Hype Cycle for Analytics and Business Intelligence, 2023

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Initiatives: Analytics, BI and Data Science Solutions; Evolve Technology and Process Capabilities to Support D&A

This Hype Cycle will help data and analytics leaders evaluate the maturity of innovations across the analytics and business intelligence space. Key trends include generative AI's impact on ABI, closing the last mile of consumerization and achieving value from composable D&A ecosystems.

Analysis

What You Need to Know

The surge of generative AI capabilities brings the collision between data and analytics spaces to an unprecedented level, giving rise to new and even restored expectations around analytics and business intelligence (ABI) innovations.

This year's Hype Cycle also covers the composability and consumerization trends to reflect organizations' expectations to deliver D&A value and impact at scale.

In addition to this Hype Cycle, D&A leaders should consult the following Hype Cycles in adjacent areas:

- Hype Cycle for Artificial Intelligence, 2023
- Hype Cycle for Data and Analytics Governance, 2023
- Hype Cycle for Data and Analytics Programs and Practices, 2023
- Hype Cycle for Data Management, 2023
- Hype Cycle for Data Science and Machine Learning, 2023
- Hype Cycle for Data Security, 2023
- Hype Cycle for Natural Language Technologies, 2023
- Hype Cycle for Privacy, 2023

Together, these Hype Cycles analyze the elements required for D&A leaders to form a holistic view of the data and analytics ecosystem.

The Hype Cycle

Three main storylines stand out in this year's Hype Cycle:

- **Generative AI hype crowding the Peak of Inflated Expectations:** The ongoing collision of the data science and machine learning and the ABI worlds is intensifying as the world awakens to the possibilities of generative AI. This trend explains the crowded peak of this Hype Cycle. The impact of generative AI in ABI not only creates new technology, such as generative analytics experience, but also restores the expectations on other technologies, such as natural language query (NLQ), augmented analytics and natural language generation (NLG), which explain the crowded peak on this Hype Cycle.

- **Composability driving the Innovation Trigger stage:** The composability trend accounts for innovations still in the Innovation Trigger stage. Some of the related innovations, such as analytics collaboration and metrics store, are still in early stages of the hype, but are likely to gain increased expectation as composable D&A nearly reaches the peak and such capabilities become more mature throughout vendors in this space.

- **High expectations on value and impact delivery by D&A innovations:** A more volatile and uncertain world is increasing the expectations, and putting pressure, on D&A initiatives to drive action and deliver value and impact across the organizations. Much of the hype of the impact on generative AI is driven by expectations to deliver easier-to-consume and impactful D&A initiatives. However, many innovations associated with this trend — such as decision engineer, action frameworks and decision intelligence — are still at early stages of the Hype Cycle, making this topic likely to be persistent in the next two to five years.

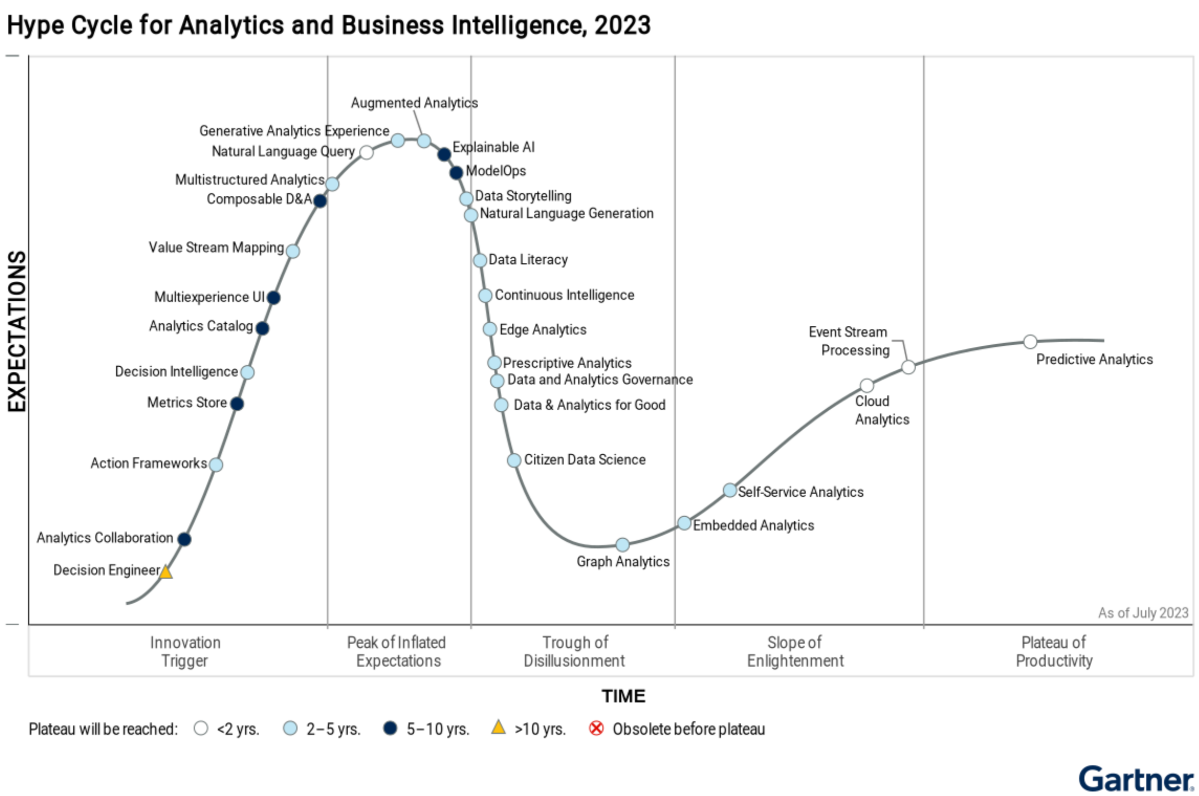
The most probable outcome is that the majority of innovations on this Hype Cycle proceed quickly (in five years or less) to the Plateau of Productivity. The unprecedented hype caused by generative AI restored the momentum on many innovations, which also are likely to advance quickly to the Trough of Disillusionment in one or two years. The ABI story remains closely tied to the data science and machine learning and artificial intelligence stories. The continued convergence and evolution of these technologies will create an entirely new wave of possibilities (and hype) by the end of the decade.

The following innovations are new to this Hype Cycle this year:

- Analytics collaboration
- Decision engineer
- Generative analytics experience

- Metrics store
- Predictive analytics
- Multistructured analytics
- Multiexperience UI
- Data and analytics governance

Figure 1: Hype Cycle for Analytics and Business Intelligence, 2023



The Priority Matrix

To help organizations prioritize investments in relation to their level of impact, we provide a Priority Matrix. Note, however, that impact is not the only factor to consider when selecting vendors and products — applicability, budget, time to implement and receive payback, and ROI are also important. The Priority Matrix shows the degree of benefit attainable from an innovation relative to its progression along the Hype Cycle.

Innovations of transformational benefit have a demonstrable, powerful impact on business operations and key metrics. Generative analytics experience and composable D&A offer transformational potential. Generative analytics has the potential to not only close the last-mile gap to D&A consumers, but also to help business leaders to ask their data better questions and have a deeper understanding of key performance drivers, for example. The impact, and hype, of generative analytics experience restored the momentum of a few profiles such as NLQ, NLG, and augmented analytics. Composability enables organizations to assemble custom-made, consumer-focused combinations of analytics services for personalized insights and experiences.

Innovations of high benefit are less likely to change an organization's business model, but they will have a significant impact on its ABI program. The majority of high-benefit innovations will progress toward the Plateau of Productivity over the next two to five years. Fundamentals for successful ABI programs, such as self-service D&A, are approaching the Plateau of Productivity, while data literacy and data and analytics for good are now perhaps overhyped and will experience periods of inflated expectations and disillusionment before achieving consistent productivity.

Although it may take five to ten years, or more, for them to achieve mainstream adoption, innovations such as composable D&A, decision engineer, explainable AI and modelOps will greatly benefit ABI programs. Innovations in this category increase the personalization, data access, depth and breadth of ABI initiatives, but require long-term investment to deliver value and trusted insights.

Table 1: Priority Matrix for Analytics and Business Intelligence, 2023

(Enlarged table in Appendix)

Benefit	*Years to Mainstream Adoption*			
↓	***Less Than 2 Years*** ↓	***2 - 5 Years*** ↓	***5 - 10 Years*** ↓	***More Than 10 Years*** ↓
Transformational	Event Stream Processing	Citizen Data Science Continuous Intelligence Data Literacy Decision Intelligence	Composable D&A	
High	Cloud Analytics Natural Language Query Predictive Analytics	Augmented Analytics Data and Analytics Governance Data Storytelling Edge Analytics Embedded Analytics Generative Analytics Experience Multistructured Analytics Natural Language Generation Prescriptive Analytics Value Stream Mapping	Explainable AI Metrics Store ModelOps	Decision Engineer
Moderate		Action Frameworks Graph Analytics Self-Service Analytics	Analytics Catalog Analytics Collaboration Multiexperience UI	
Low		Data & Analytics for Good		

Source: Gartner (July 2023)

Off the Hype Cycle

- **Analytics governance** was replaced by data and analytics governance, which currently resonates better with the ABI domain and this Hype Cycle. Analytics governance and other nuances can be found at the Hype Cycle for Data and Analytics Governance, 2023.

- **Data marketplaces and exchanges** was absorbed by the composability-related profiles. More details on data marketplaces can be found on the Hype Cycle for Data Management, 2023.

- **Data middle office** was subsumed by self-service analytics, citizen data science and composable D&A to address a broader audience.

- **Immersive analytics** was subsumed into multiexperience UI.

- **Multiexperience analytics** was subsumed into multiexperience UI.

- **In-DBMS analytics** has reached mainstream adoption and matured off the Hype Cycle.

- **Text analytics** has reached mainstream adoption and matured off the Hype Cycle.

On the Rise

Decision Engineer

Analysis By: David Pidsley

Benefit Rating: High

Market Penetration: Less than 1% of target audience

Maturity: Embryonic

Definition:

Decision engineers apply analytics and engineering skills to decision intelligence platforms and practices. This practical discipline advances decision-making experiences with design thinking by engineering how decisions are modeled and made and how outcomes are evaluated and improved via feedback. Practitioners foster multidisciplinary collaboration in decision support, augmentation and automation by applying decision engineering to processes with embedded analytics, data science and AI.

Why This Is Important

Decision engineer is a decision-centric role that operationalizes embedded decision models, monitors feedback and optimizes outcomes with decision intelligence practices and platforms. The emerging role is not only focused on implementation. It is also essential in fostering multidisciplinary collaboration to bridge the gap between business domain and process experts on the one hand, and data scientists and AI experts on the other. They collaborate with the business, inventory decision models to manage and monitor, and report on the business value of decisions under management to promote reuse and deduplication of decision models.

Business Impact

Most decisions that currently use data are or soon will be at least partially automated. Decision engineers apply process, (computational) software engineering and mathematical techniques to help organizations make better decisions. Decision engineering leverages data, analytics, DSML, optimization and simulation to support decision augmentation and automation across a range of industries and contexts.

Drivers

- Though they recognize the need to collaborate, executives report that too many stakeholders and unclear decision ownership cause problems and delays in taking action. Instead of supporting multiple decision types for a single business unit, decision engineers can support a specific decision type, such as cost management or product improvements, across a number of business units.
- The shift from data-driven to decision-centric enterprise accelerates the demand for emerging roles that apply analytics and engineering skills to decision intelligence platforms and practices.
- Gartner identifies decision intelligence as a top strategic technology trend that is disrupting decision-making culture, and a decision engineer describes “who” plays a key role in this.
- Data and analytics leaders are upgrading their operating models, especially for organizations and people, to ensure they can enable dynamic business outcomes amid disruptive market conditions.
- Challenges in executing high-impact reengineering of decisions will accelerate common definitions of embryonic roles to have a high benefit and mature into productivity in the coming decade.
- Decision engineers bring a deeper understanding of how effective decision-making processes work, and they provide human and social perspectives. Some top data science teams will be rebranded as cognitive science or science consultancies, increasing diversity in staff skills.
- Skills in demand for decision engineering include data science, simulations, optimization, SQL, Python, R, DAX, VizQL, process methods, software engineering techniques, design thinking and communication skills.

Obstacles

- Decision engineers may become a role, but not a job title. Similarities to other roles like citizen data scientist, data steward or D&A translator lead to confusion among candidates and hiring managers.
- Embryonic roles have less than 1% of target market adoption and are undifferentiated from adjacent D&A and decision-making roles. Despite different focuses and responsibilities, these roles all involve working with data and using quantitative methods to augment and reengineer decision making.

- Skill and staff shortages are the top roadblocks for success in D&A initiatives. Late adopters will struggle to recruit decision engineers and must instead focus on upskilling, motivating and retaining decision intelligence talent.
- Failure to operationalize decision intelligence or embed decision models into workflows and business processes makes for ineffectively integrated decision making.
- Not employing adaptive governance of decisions to ensure ongoing optimization of business outcomes by establishing clear decision-making processes, proactively identifying and addressing issues, continuously refining and optimizing decision models based on data-driven insights, and aligning decision intelligence with the organization's goals and values.
- Existing organizational structures silo decision intelligence approaches which, in fact, go across domains. Tactical, functional decisions are often compartmentalized by technology vendor or product (e.g., CRM, ERP, HCM, FP&A).
- Localized implementations may create fragmentation in organizational units, where decisions are very similar but regulated differently.

User Recommendations

D&A leaders responsible for analytics, BI and data science solutions should:

- Evolve their D&A approaches to support data-driven decisions by empowering and supporting business units to embed D&A in business processes.
- Assess the impact of the transition from data-driven to decision-centric and update your operating model for decision intelligence practices.
- Assess the impacts that demand for decision engineering will have upon existing skills shortages and how to fill the role by considering how other companies do this (see sample vendors).
- Define decision engineers' roles, responsibilities, requirements and qualifications (a bachelor's or master's degree in computer science, mathematics, statistics, operations research or a related discipline).
- Foster and develop decision intelligence talent to address staff shortages by recruiting decision engineers and data scientists, forming fusion teams with business experts and fostering communities of practice.

- Define the role's key responsibilities as collaboration with business functions outside of D&A, decision modeling using frameworks, decision model management (especially deduplication, reuse and mitigation of model drift), valuation and data storytelling, and continuous learning and trendspotting.
- Involve relevant stakeholders in the business, D&A and adjacencies in a collaborative way by applying best practices to fill the role through upskilling, attracting recruits, motivating and retaining decision engineers.

Sample Vendors

Airbnb; Amazon; Google; LinkedIn; Meta; Microsoft; Netflix; Philips; Uber

Gartner Recommended Reading

What Are the Essential Roles for Data and Analytics?

Maverick Research: Data and Analytics Roles Will No Longer Be a Priority

The Future of Data and Analytics: Create Competitive Differentiation Through Better Decision Making

Predicts 2023: Analytics, BI and Data Science Composability and Consolidation

Redefining Analysts as Decision Experts (Philips)

Analytics Collaboration

Analysis By: Julian Sun, David Pidsley, Anirudh Ganeshan

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Embryonic

Definition:

Analytics collaboration is the application of collaborative capabilities to analytics workstreams for organizations that want to provide an environment where users can simultaneously co-produce an analytics project, product or program, advancing from individually oriented to community-centric data and analytics (D&A).

Why This Is Important

Collecting diverse perspectives on D&A to establish a cohesive understanding is critical for complex decision making. Collaborative decision making adds context to create a shared, holistic view of the relevant information. This is also true of network effects from collaboration — where the utility that any one user derives from an analytics and business intelligence (A&BI) platform depends on the number of users. Otherwise analytics outputs fail to deliver insights with context to business processes and decision makers on time.

Business Impact

Analytics collaboration is a stepping stone to building a new style of collaborative decision making, which is decision-centric rather than just data-driven. Analytics collaboration within the team puts emphasis on communication and action, enabling the propagation of business value throughout the decision network. Organizations can enable higher employee adoption that delivers more value from their role in decision making and ROI from projects. Using collaboration in analytics can improve employee experiences and further drive data literacy.

Drivers

- Decision making has become increasingly complex with more people within the organization involved in each decision. According to the 2021 Gartner Analytics Consumerization-Democratization Survey, 55% of organizations are using hybrid (fusion team) as the most prevalent model for A&BI. This involves people from different domains collaborating on D&A in the same environment with a more consistent process from data to impact.

- Analytics collaboration is enabled by integration with digital workplace applications such as Microsoft Teams or Slack and software repository hosting manager tools such as GitLab or GitHub. For A&BI platforms, collaboration is becoming a capability that supports a collaborative community ecosystem where users annotate and socialize analytics content in a native social-media-like experience.

- Diverse business users expect their analytics to be on the same virtual canvas where they already collaborate in real time. The analysis is today embedded in conferencing and live discussion. A multipersona environment where people can contribute based on domain knowledge, not just analytical proficiency is expected.

Obstacles

- Analytics is a powerful tool that can be used for decision support, but it is only as good as the people and teams who use it. In order to get the most out of A&BI, organizations struggle to create a culture of collaboration where people are encouraged to share ideas and insights.
- Organizations usually have more than one A&BI platform as an enterprise standard, and collaboration using different tools requires more workflow management than is normally designed between tools.
- Collaboration itself is hard in organizations, and for D&A activities, collaboration sometimes starts with a data quality issue.
- One of the biggest challenges to collaboration is the lack of a common business language. Different teams and departments often use different terms and definitions, which can make it difficult to communicate effectively. This can be addressed by creating a glossary of terms and by providing training on data literacy.

User Recommendations

- Orchestrate teamwork for analytics by exploring the emerging collaborative capabilities of A&BI platforms and digital workplace applications for multipersona collaboration across technology application silos and business functions.
- Transform data and analytics into business insights and action by implementing the integration between A&BI platforms and workstream collaboration applications.
- Improve analytics content delivery with an agile, iterative process by bridging the D&A team with the software engineering practice.

Sample Vendors

atoti; Coginiti; Deepnote; Domo; Einblick Analytics; Hex Technologies

Gartner Recommended Reading

Innovation Insight: Analytics Collaboration

Market Guide for Augmented Analytics

Market Guide for Embedded Analytics

Critical Capabilities for Analytics and Business Intelligence Platforms

Action Frameworks

Analysis By: David Pidsley, Julian Sun

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Embryonic

Definition:

Action frameworks for analytics and BI platforms help users compose and automate data-driven decision workflows. Triggers include buttons (no-code), conditional drag-and-drop thresholds (procedural or functional), automated insights (AI-powered), reusable blocks/recipes (low-code) from marketplaces, or bring-your-own-model (code). These write back to operational systems, cloud applications or datasets. Embedded analytics actions make prescriptive analytics contextual in the business moment.

Why This Is Important

Action frameworks:

- Enhance collaboration, responsiveness, efficiency and adaptability in closed-loop decision making.
- Fulfill the last mile, bridging ABI, collaboration apps, CRM, ERP and supply chain systems in multicloud ecosystems via domain business technologist-led integration.
- Drive intelligent composable business with timely, context-specific outcomes, and provide agility to reengineer decisions.
- Reframe the ABI/DSML enterprise value story from “dashboard quantity” to “business actions driven” by decision intelligence.

Business Impact

In their transition toward becoming more decision-centric, organizations are adopting action frameworks to:

- Make data-driven decision making more actionable within ABI platforms.

- Decrease integration costs and reduce friction in tool reconfiguration.
- Reduce the need for application and software engineers as bottlenecks for integration.
- Enable multipersona collaboration across technology application silos and business functions for workflow automation and collaborative work management.

Drivers

- Action frameworks close the loop of a decision intelligence process where “action” is the vital step. They are especially helpful for decision augmentation (e.g., using prescriptive analytics about a geographical location to determine where to invest and pushing that insight to an expert deployed in the field).
- Business technologists are using low-code/no-code composable analytics to build new packaged analytics experiences for operational business functions. They’re starting from the data and analytics (D&A) side rather than starting with stand-alone low-code application platforms (e.g., Salesforce Lightning and Microsoft Power Automate).
- The rise of the augmented consumer means that users expect a drag-and-drop workflow-builder experience, rather than having to build upon the API.
- Architectures in client and vendor platforms are becoming decoupled (e.g., microservices and APIs), enabling users to interact with heterogeneous tools, technologies and ecosystems to deliver insights.
- Writing back to data sources without delay is a demand from LOB users, who wish to make corrections at the speed of business. Action frameworks support governance to overcome data management concerns about users writing directly to source systems.
- New tools like collaborative work management and workplace collaboration are being introduced into decision-making environments and helping leaders realize value from their D&A initiatives.
- Within a few years, most self-service analytics activities will be initiated in — and many will be completed entirely within — digital workplace applications, such as Microsoft Teams, Slack and Jira. The composable, embedded nature of the action is just as important as the action itself.
- Organizations wanting to benefit from prescriptive analytics are increasingly maturing.
- Cloud-based analytics is on the rise. In addition, application integration platforms for consumer and enterprise users, into which ABI platform vendors have integrated, have become more widely available and cover more applications.

Obstacles

- The noise of too many action alerts reduces the relevance of notifications.
- A lack of cloud strategy leaves ABI platforms disconnected from downstream business process integration.
- In-platform collaboration environments can create user lock-in. They can also further isolate siloed communities from cross-platform workstream collaboration tools and existing systems of action, such as email, productivity applications, workflow tools, and ERP, CRM, HR and supply chain systems.
- Security privileges and access control mechanisms span across ABI platforms and the systems they are acting on or being triggered by, preventing users from gaining access to integration application platforms and connecting systems.
- Poorly implemented action frameworks can result in suboptimal or noncompliant actions due to low data quality, inadequate governance and insufficient compliance measures (e.g., U.S. Sarbanes-Oxley Act [SOX]).

User Recommendations

- Use action frameworks to create LOB applications infused with prescriptive analytics that can trigger workflows via recipes/blocks. Measure triggers and actions via analytics catalogs and user telemetry.
- Integrate ABI platforms with digital workplace applications and conversational analytics (chatbots) to push actions into applications (e.g., Teams and Slack, CRM, and ERP), and enable updates the other way too.
- Evaluate composite AI solutions that offer visual decision workflow design, decision flow execution and orchestration features.
- Evaluate action frameworks in existing and candidate ABI platforms in relation to the cloud stacks and business applications popular in the organization.
- Work with DevOps, development and product teams to determine when to use ABI platforms with action frameworks versus when to use conventional custom-built applications.
- Assess how vendors incorporate generative AI into analytics workflows to trigger business actions from within ABI platforms, especially their natural language query capabilities to orchestrate and connect insights to a digital ecosystem.

Sample Vendors

Domo; Google; Microsoft, Salesforce; SAP; ThoughtSpot; TIBCO Software; Zoho

Gartner Recommended Reading

Market Guide for Embedded Analytics

Critical Capabilities for Analytics and Business Intelligence Platforms

Innovation Insight for Decision Intelligence Platforms

Video: How Decision Intelligence Improves Business Outcomes

Is Your Business Intelligence Enabling Intelligent Business?

Metrics Store

Analysis By: Christopher Long, David Pidsley, Julian Sun

Benefit Rating: High

Market Penetration: Less than 1% of target audience

Maturity: Embryonic

Definition:

A metrics store is a virtualized semantic layer capability that allows users to create and define business metrics as code. It governs those metrics from data warehouses, and serves the downstream analytics, data science and business applications. The metrics store often provides an API-centric way to deliver analytics uniformly across consuming use cases, including reporting, BI, DSML and integrated applications — a headless form decoupling the metrics definition and delivery from consumption.

Why This Is Important

Organizations wrestle with consistency across metric definitions in the age of decentralized analytics and self-service-enabled users. Decentralized development of metrics allows different versions of the truth for metric definitions. As a result, metrics end up siloed, leading to duplication and fragmentation of metric development. These differing definitions lead to confusion and a lack of trust in the data, which undermines the data-driven decision-making process.

Business Impact

Through decentralized ownership, storing metrics as code, and providing open-source access for consumption, metrics stores can achieve:

- **Agnostic layer for ABI/DSMLs and data warehouses:** This flexible interface enhances interoperability, maintains metric consistency while streamlining data management and fostering collaboration.
- **Enhanced connection with DSML and feature stores:** Integrating metrics stores with feature stores not only streamlines the analytics pipeline but also fosters collaboration between data science and machine learning teams.

Together, these improve development efficiency, ultimately accelerating the organization's ability to make data-informed decisions.

Drivers

- **Increasingly decentralized analytical delivery:** As the proliferation of distributed analytics continues, it becomes increasingly crucial to maintain consistency over definitions of common metrics used across the organization.
- **Increasingly diverse analytical use cases:** Organizations have more use cases to consume metrics, including interactive dashboards, enterprise reporting, data science and machine learning, and integrated applications and workflows.
- **Need for operational integration in DevOps practices:** As DevOps mature in organizations, the analytics components need to be treated as services (analytics-as-code) that can be easily integrated in XOps practices like DataOps, MLOps and overall CI/CD.
- **Redundant metric development**: Diverse use cases often represent individual analytical pipelines that duplicate existing development creating multiple artifacts and pipelines to manage, ultimately increasing costs.
- **Drift in common metric definitions:** Redundant pipelines built to serve analytical use cases can cause risks for decision makers across the organization. Metrics relied on in different systems that should be the same could either drift apart from their origin or — worse — could be misaligned from the beginning.

Obstacles

- **Unclear and embryonic market:** Metrics stores are an emerging concept that attempt to fill the need for business user collaboration and governance with enterprise-level distribution capabilities. It is still unclear whether the metrics store represents a new tool (or layer) in the analytics stack or if this is a capability fulfilled by existing toolsets. Existing semantic layers and new vendors are rushing to bring tools to market to fulfill these needs. Emerging stand-alone tools currently lack broad integration support with database management and ABI tools.

- **Lack of business user-focused interface:** Current tools implementing metrics stores are still code-centric in their application. A successful metrics store implementation will include a UI that is feature-rich for business analysts with lower technical coding skills.

- **Tools don't solve for low-maturity organizations not having defined metrics:** Implementing a metrics store alone won't ensure adoption if users don't agree with the underlying metrics. Addressing this issue is crucial to preventing variance in metric definitions across the organization.

User Recommendations

- Evaluate how metrics store capabilities may help manage the analytics life cycle, specifically related to metrics generation.

- Achieve consensus on metric definitions and calculations by actively involving business users in the decision-making process.

- Invest in development skills required and related skill gaps to successfully create metrics as code in existing metrics store products in preparation of implementing metrics store capabilities.

- Develop and implement the foundational governance policies and procedures to ensure enterprise and business developers are equipped to operationalize metrics in a guided environment.

Sample Vendors

AtScale; Cube; dbt Labs; Denodo; GoodData; Kyligence; Trace

Gartner Recommended Reading

Innovation Insight: Metrics Stores

Video: Demystifying the Metrics Store

Quick Answer: How Can Metrics Stores and Analytics Catalogs Help Govern ABI Platforms?

Demystifying Semantic Layers for Self-Service Analytics

The Future of Data and Analytics Is Headless by Design and Opportunity

Decision Intelligence

Analysis By: Erick Brethenoux

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Emerging

Definition:

Decision intelligence (DI) is a practical discipline that advances decision making by explicitly understanding and engineering how decisions are made and how outcomes are evaluated, managed and improved via feedback.

Why This Is Important

The current hype around automated decision making and augmented intelligence, fueled by AI techniques in decision making (including generative AI), is pushing DI toward the Peak of Inflated Expectations. Recent crises have revealed the brittleness of business processes. Reengineering those processes to be resilient, adaptable and flexible will require the discipline brought by DI methods and techniques. A fast-emerging market (DI platforms) is starting to provide resilient solutions for decision makers.

Business Impact

Decision intelligence helps:

- **Reduce technical debt and increase visibility.** It improves the impact of business processes by materially enhancing the sustainability of organizations' decision models based on the power of their relevance and the quality of their transparency, making decisions more transparent and auditable.

- **Reduce the unpredictability of decision outcomes.** It does so by properly capturing and accounting for the uncertain factors in the business context and making decision models more resilient.

Drivers

- **A dynamic and complex business environment, with an increasingly unpredictable and uncertain pace of business.** Two forces are creating a new market around decision intelligence platforms (DIPs). The first is the combination of AI techniques such as natural language processing, knowledge graphs and machine learning. The second is the confluence of several technology clusters around composite AI, smart business processes, insight engines, decision management and advanced personalization platforms.
- **The need to curtail unstructured, ad hoc decisions that are siloed and disjointed.** Often uncoordinated, such decisions promote local optimizations at the expense of global efficiency. This phenomenon happens from both an IT and a business perspective.
- **Expanding collaboration between humans and machines.** This collaboration, supplemented by a lack of trust in technologies (such as AI), is increasingly replacing tasks and promoting uneasiness from a human perspective. DI practices promote transparency, interpretability, fairness, reliability and accountability of decision models critical for the adoption of business-differentiating techniques.
- **Tighter regulations that are making risk management more prevalent.** From privacy and ethical guidelines to new laws and government mandates, it is becoming difficult for organizations to fully understand the risk impacts of their decisions. DI enables an explicit representation of decision models, reducing this risk.
- **Uncertainty regarding decision consistency across the organization.** Lack of explicit representation of decisions prevents proper harmonization of collective decision outcomes. DI remedies this issue.
- **Emergence of software tools in the form of decision intelligence platforms.** DIPs will enable organizations to practically implement DI projects and strategies.
- **Generative AI.** The advent of generative AI is accelerating the research and adoption of composite AI models, which are the foundation of DIPs.

Obstacles

- **Fragmentation:** Decision-making silos have created data, competencies and technology clusters that are difficult to reconcile and that could slow down the implementation of decision models.
- **Subpar operational structure:** An inadequate organizational structure around advanced techniques, such as the lack of an AI center of excellence, could impair DI progress.
- **Lack of proper coordination between business units:** The inability to impartially reconsider critical decision flows within and across departments (also because of fragmentation) diminishes the effectiveness of early DI efforts.
- **Lack of modeling in a wider context:** In organizations that have focused almost exclusively on technical skills, the other critical parts of human decision making — psychological, social, economic and organizational factors — have gone unaddressed.
- **Lack of AI literacy:** Many organizations still suffer from a lack of understanding when it comes to AI techniques. This AI illiteracy could slow down the development of DI projects.

User Recommendations

- **Promote the resiliency and sustainability of cross-organizational decisions** by building models using principles aimed at enhancing traceability, replicability, pertinence and trustworthiness.
- **Improve the predictability and alignment of decision agents** by simulating their collective behavior while also estimating their global contribution versus local optimization.
- **Develop staff expertise** in traditional and emerging decision augmentation and decision automation techniques, including predictive and prescriptive (optimization, business rules) analytics. Upskill business analysts, and develop new roles, such as decision engineer and decision steward.
- **Tailor the choice of decision-making technique** to the particular requirements of each decision situation by collaborating with subject matter experts, AI experts and business process analysts.
- **Accelerate the development of DI projects** by encouraging experimentation with generative AI and expediting the deployment of composite AI solutions.

Gartner Recommended Reading

Innovation Insight for Decision Intelligence Platforms

Reengineer Your Decision-Making Processes for More Relevant, Transparent and Resilient Outcomes

How to Choose Your Best-Fit Decision Management Suite Vendor

AI Security: How to Make AI Trustworthy

Top Strategic Technology Trends for 2023: Adaptive AI

Analytics Catalog

Analysis By: Anirudh Ganeshan, Peter Krensky

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Analytics catalogs apply portal-like curation and collaboration functions to analytics and BI (ABI) content. This enables users to share, find, search, comment and certify dashboards, reports and datasets from a diverse range of platforms in one place. They also help those managing portfolios of ABI platforms to monitor, manage content sprawl and migrate usage across technologies.

Why This Is Important

Many large organizations use multiple ABI technologies to support a wide range of analytics processes, and portfolio deployments are commonplace. As such, there is a need to help business decision makers get to the right content from more than one underlying technology. Analytics catalogs address a real pain point impacting organizations using multiple ABI tools by giving business users a single, personalized point of access.

Business Impact

Analytics catalogs:

- Help decision makers find the analytics content they need and reuse trusted analytics assets.
- Assist in tool rationalization and ABI platform portfolio management. Usage and lineage data collected by the analytics catalog allows D&A leaders to better understand where decision makers spend the majority of their time.
- Drive wider adoption of ABI tools by delivering a one-stop shop and allow internal users to find content and rank and review its relevance and business value.

Drivers

- Managing access to multiple ABI platforms is not a new problem. Historically, organizations have built their own custom access points using standard intranet portal tools (commonly Microsoft SharePoint). However, that can be costly to do and requires ongoing maintenance, to the extent that Gartner has spoken to customers that have abandoned this build-it-yourself approach. Analytics catalogs productize that requirement into a commercial off-the-shelf (COTS) application.
- Integration of ChatGPT and generative AI with ABI platforms will only proliferate analytics content creation by acting as an accelerant for self-service analytics. Analytics catalogs make this process less cumbersome by allowing users to easily find relevant analytics assets.
- Analytics catalogs are an enabling technology that can help businesses better operationalize and scale their analytics initiatives by providing metrics on usage and adoption across the full range of ABI technology used. This enables organizations to better plan ABI tooling strategy and allow them to understand how different users interact with analytics content.
- Some of these products go beyond simply identifying content at the report or dashboard level, decomposing content down to individual charts or tables and maintaining full interactivity (for example, via sorting, filtering or revisualization). Organizations that want to compose analytics applications drawing together granular content from a variety of BI tools may select an analytics catalog for this capability.
- Organizations that are looking to migrate from an old, possibly on-premises BI platform to a newer cloud-based analytics technology need to know what content to migrate (and what not to). An analytics catalog provides visibility into usage patterns that can help this use case.

Obstacles

- Lack of buyer awareness: There is little hype around these tools but a clear need for them in many organizations.
- Lack of support from large vendors: Vendors from large ABI platforms want customers to leverage their own product ecosystems rather than use competing products and thus don't promote this functionality or the metadata interoperability needed for aggregation and personalization of analytics assets.
- Aspiration to single vendor standardization: If aiming for a single-vendor solution, then a portal-like tool is of less relevance. However, this is not a realistic aim in many cases. No single vendor or tool offers everything at the same level of functionality; departments may demand specific analytics tools; new capabilities may become available that are not offered by incumbent software providers; and M&A activity often brings different, nonstandard tools into the organization.

User Recommendations

- Build a business case for managing increasing analytics asset sprawl to allow more analytics content governance.
- Run a proof of concept (POC) to evaluate analytics catalogs and explore the benefit that a managed single access point for ABI content could provide to users.
- Compare the functionality and cost of any custom-built BI portals versus that offered by commercial analytics catalog tools.
- Evaluate how these platforms help manage the life cycle of the ABI tools portfolio, particularly when it comes to retiring older content or products and smoothing the user experience through transition.

Sample Vendors

Digital Hive; Enquero; Metric Insights; Visual BI Solutions; ZenOptics

Gartner Recommended Reading

Quick Answer: How Can Metrics Stores and Analytics Catalogs Help Govern ABI Platforms?

Predicts 2023: Analytics, BI and Data Science Composability and Consolidation

Multiexperience UI

Analysis By: David Pidsley

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

A multiexperience user interface (UI) for analytics and business intelligence (ABI) aligns modes of interaction and analytics capabilities, which optimize a user's experience of analytics development and consumption of content for a given decision-making process. The increase in possible combinations of approaches is due to advancements in technologies such as augmented analytics, generative AI, data storytelling, natural language query, virtual reality (VR) and augmented reality (AR).

Why This Is Important

Much like the customized user experiences we are used to in our day-to-day interactions with technology, consumer-oriented analytics experiences are needed to drive adoption of data-driven decisions. Organizations must be able to deliver the most relevant, contextualized and consumable analytics outputs possible. This requires tapping into the unique intersection of various devices, interaction modalities and analytics capabilities that can augment users' ability to consume insights.

Business Impact

Transitioning from static analytics outputs to dynamic contextualized insights, embedded or automated, means analytics are delivered with increased relevance closer to the point of decision. Aligning analytics with an optimal interface and consumption modality will impact the approach to measuring ABI adoption. Quantifying adoption must shift from counting how many users leverage a tool to how many people consult data in making a decision and what pathway of capabilities they use.

Drivers

- Multiexperience is closely coupled to advancements in both hardware, in the form of interfaces such as desktops, mobile devices, wearable devices, virtual reality simulators or smart speakers; and software, in the form of augmented analytics, data storytelling and natural language query capabilities.

- The various modalities in which users can interact with data (chat, click, touch, voice, etc.) are generally accepted, yet organizations are only scratching the surface when it comes to maximizing the cross-section of these interfaces and capabilities. Many organizations are already using embedded forms of analytics as a starting point for multiexperience.

- Because capabilities, such as augmented and automated data storytelling, are almost entirely enabled by cloud-based architectures, adoption will be accelerated proportionate to organizations' movement to cloud-based data and analytics tools.

- AI-powered assistants enabled by generative AI (similar to ChatGPT, Copilot) that vendors make available within (or connect to) ABI platforms have changed the way analytics developers and consumers experience their work. This shifts the focus from drag-and-drop to prompt-and-refine.

Obstacles

- While there is a wide variety of multiexperience UIs available to users, the roles and skills needed to compose these remains a challenge.

- Data and analytics (D&A) resources must learn how to maximize the combination of new interaction modalities and analytics capabilities. The time needed for this will be in direct competition with the time needed for day-to-day analytics requests that many D&A teams are already inundated with.

- While unique best-of-breed user experiences may be ideal, potential buyers may default to using existing ABI platforms that will add augmented capabilities without time-consuming migration, consolidation or additional new investments.

- Automation of decisions, accelerated by the adoption of AI, may lessen the need for humans to create analytic content for decision support. Data literacy may decline as business users transition from analytics consumers to a role where their input simply validates recommended decisions.

User Recommendations

- Account for multiexperience approaches to consuming data by aligning the right analytic capability to the right user interface and experience.
- Evaluate where new consumption mechanisms could add value to decision-making processes, rather than simply lifting and shifting the same traditional analytics outputs to a modern cloud platform.
- Evaluate, on a regular basis, your existing ABI tools and innovative startups to offer new augmented user experiences beyond the predefined dashboard, such as AI-powered coding assistants.
- Place analytics capabilities as close to relevant business decision makers as possible, by evaluating when ABI platform capabilities are best embedded in line with other business applications or workflows.
- Take a data-driven approach to analytics adoption by leveraging the usage data available within today's ABI platforms. If not prebuilt, discuss with vendors the options available to tap into such data.

Sample Vendors

BadVR; D6 VR; Google; SAS; TIBCO Software; Virtualitics

Gartner Recommended Reading

Market Guide for Augmented Analytics

Top Trends in Data and Analytics, 2023

Emerging Technologies: Find Success With Head-Mounted Displays Despite Modest Market Growth Expectations

Cool Vendors in Analytics and Data Science

Multiexperience Will Be the New Normal for Consuming Analytics Content in the Augmented Era

Value Stream Mapping

Analysis By: Saul Brand, Mike West

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Value stream mapping is a technique that visualizes and combines sequences of business processes that represent the ways that an enterprise provides end-to-end visibility and customer value, from receiving customer requests to delivering products, services or experience to its consumers. Each step in the value stream cuts across and connects siloed business capabilities and links lower-level and detailed business processes.

Why This Is Important

Over the past decade, business capability models and business process models have become widely used by enterprise architects. However, in the past five years, there has been a shift in focus from projects to products, and a greater emphasis has been placed on democratized or distributed organizational design and customer and employee experiences. As a result, an increasing number of organizations have started to use value stream maps (VSMs) to bridge the strategy-to-execution gap.

Business Impact

Enterprise architects must help plan, design, innovate, orchestrate, navigate and operationalize digital business. Designing products and services that support the operating model is a challenge for many organizations. Enterprise architects can use VSMs to connect the design process with the underlying technology platform in a way that also links business and technology architecture, thereby ensuring that the value created in the software will enhance the value delivered to customers.

Drivers

- The hype around VSMs continues to increase, but at a slower pace. Between April 2022 and April 2023, Gartner saw a 10.4% year-over-year increase in the number of client inquiries concerning value stream mapping. However, this growth rate declined 10% from that between April 2021 and April 2022.
- An increasing number of clients have seen the importance of VSMs and are interested in using VSMs as an integral part of enterprise and business architectures, or using them as part of product management and agile development.
- Gartner's clients show keen interests in VSMs, business capability modeling (BCM) and business process modeling (BPM), and the relations between them.
- The Scaled Agile Framework (SAFe), the leading enterprise agile framework for scaling, strongly recommends understanding and mapping business or product value streams as well as development value streams. The latter is for optimizing and managing software delivery and the former for identifying the actions that need to be taken to improve flow and value delivery to customers.
- After the value stream concept was introduced into the software delivery process, software engineers started to apply it to the processes that their software is designed to support.

Obstacles

- Traditional project and application funding has long targeted improvements in business capabilities from a siloed perspective.
- The greatest challenge that enterprise architects face is knowing why, when and how to use VSMs.
- Enterprise architects often don't understand the relationships between value streams and other key business architecture deliverables that are essential to link business and technology architecture.
- The perspectives of both IT and business leaders are limited, constrained by the functional domain in which they have authority and by their application-centric — rather than customer-centric — views.

User Recommendations

- Know why, when and how to use VSMs to close the strategy-to-execution gap.
- Deliver an end-to-end visualization of the flow of value to the customer through VSM to focus strategy, investment and success metrics around delivering customer value.
- Equip product teams to fine-tune their delivery by using ongoing value stream management to navigate with both leading and lagging indicators.
- Use value streams to guide multiple decentralized agile teams to develop collaborative and consistent insights across functions and to identify optimization opportunities for making decisions.

Sample Vendors

Atlassian; Creately; Edraw; LinearB; Lucid Software; Microsoft; Miro; Panaya; SmartDraw; Visual Paradigm

Gartner Recommended Reading

Use Value Streams to Design Service and Operating Models and Enable Application Composability

Ignition Guide to Value Stream Mapping of DevOps Process

Optimize Decision Making and Business Value Creation by Aligning D&A With Value Streams

Align D&A With Value Streams to Optimize Decision Making and Business Value Creation

Market Guide for Value Stream Management Platforms

Composable D&A

Analysis By: Peter Krensky, Erick Brethenoux, Julian Sun, Carlie Idoine

Benefit Rating: Transformational

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Composable data and analytics (D&A) utilizes container or microservices architectures and data fabric to assemble flexible, modular and consumer-friendly D&A capabilities from existing assets. This transforms monolithic data management and analytics applications into assemblies of D&A building blocks. This is achieved via composition technologies enabled by low- and no-code capabilities, supporting adaptive and intelligent decision making.

Why This Is Important

Organizations are looking for flexibility in assembly/reassembly of D&A capabilities, enabling them to blend more insights into actions. Time to insight, reuse and agility are top requirements. Modular D&A capabilities enable faster and more proactive insight delivery.

Business Impact

The transition from monolithic D&A applications to composable D&A capabilities can be used with application development to assemble AI-augmented decision-making solutions. The focus of collaboration will transition from technology integrations to business problem solving. Organizations can create advanced analytics capabilities by composing the best capabilities from different vendors, rather than using them separately. Composability also relates to data fabric and data mesh in terms of being able to correctly identify data objects that exhibit wide reuse and separating them from those that are business-process-unique.

Drivers

- Container- or microservices-based analytics and business intelligence (ABI) and data science and machine learning (DSML) platforms with improved APIs enable the assembly of analytics applications in a more flexible way than custom code-based solutions.
- For most organizations, AI is still at the piloting stage, but ABI has been in production for years. Organizations can use composition to connect ABI to AI, extending ABI capabilities and empowering users with a comprehensive, tailored and even personalized solution without having to use different applications.
- Organizations need to assemble descriptive, diagnostic, predictive and prescriptive analytics capabilities dynamically to generate insights along with the decision-making process. Use analytics to inform decision making and drive effective actions in a more connected, continuous and contextual way.
- Both D&A and software development teams will need composable data and analytics to enable emerging business technologies.
- As more data and analytics are integrated into digital platforms, traditional embedded analytics will need more modular capabilities to be assembled and reassembled for faster delivery.
- Embedded analytics are usually implemented by IT, but business users can use low- or no-code capabilities to source more data and compose more capabilities, such as interactive data visualization and predictive modeling, independently enriching more comprehensive embedded analytics.
- Cloud-based marketplaces are becoming an effective channel for organizations to distribute and share analytics applications, and composable D&A enables them to easily find the required components and add value to their applications by infusing analytics.

Obstacles

- New technologies and data have been the key drivers to evolve an analytics platform, resulting in less of a connection with business outcomes. Making data more accessible and composable often raises quality, governance and security concerns, among others.
- Software application development teams and data and analytics teams have not collaborated closely before. Composable D&A requires more involvement from the application development side, including applying XOps practices to maximize its value.
- Today's ABI and DSML markets are not zero-sum games. Many vendors of all sizes and specialties can thrive. No single vendor or tool offers all functions at the same level. It is unrealistic to implement a full D&A stack all at once, so many companies do so in stages. The composability of the existing products is not mature enough without technology partnership.

User Recommendations

- Improve decision making and business impact of data and analytics by incorporating and assembling modular, reusable D&A capabilities.
- Leverage composable analytics to drive innovation by incorporating advanced DSML capabilities into analytics applications.
- Exploit opportunities to add analytics capabilities to applications by building a joint team of application developers and business analysts with ongoing collaboration. Rethink organization, processes and skills to support agile assembly and reassembly of analytics services.
- Pilot composable analytics in the cloud, establishing an analytics marketplace to drive and support collaboration and sharing.

Gartner Recommended Reading

Use Gartner's Reference Model to Deliver Intelligent Composable Business Applications

Adopt Cloud Analytics to Drive Innovation

3 Steps to Build and Optimize a Portfolio of Analytics, Data Science and Machine Learning Tools

Generative Analytics Experience

Analysis By: Julian Sun, Edgar Macari, Peter Krensky

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Generative analytics experience is an analytics evolution that uses business terminology expressed as natural language via prompts to augment the entire data and analytics process, connecting qualitative and quantitative analytics. It leverages generative AI to empower business users by linking the interpretation of business problems and D&A problems in both directions, autogenerating code (Python, R and SQL) that interacts with the data, and narrating the insights with the business context.

Why This Is Important

Enterprises are using generative AI to improve the experience of analytics for business by better understanding the business questions, translating them into analytical questions and curating into a business-friendly data storytelling. Generative AI enhances augmented analytics with autogenerated content including data, text and code. Technology providers are developing new product lines and innovative customer engagement by integrating generative AI into the main augmented analytics offering.

Business Impact

Enterprises can implement generative analytics experience to:

- Enable business executives without an in-depth understanding of D&A context or who have low data literacy to answer critical business questions and improve decision support.
- Evolve the enterprise's analytics capabilities with more advanced analytical functions triggered by autogenerated R and Python code.
- Improve both quality and quantity of analytics content with more business users acting as analytics creators, and with more narrative business context.
- Improve and expand composable analytics by using generative analytics as the new interface to connect to insight engines.

- Activate the metadata usage to autogenerate the business context of data by incorporating generative AI with semantic layer.

Drivers

- Achieving the business outcome of data and analytics requires connection from insights to actions — a closed-loop activity. Generative analytics experience expands the connections of D&A solutions to a broader generative AI business application with natural language.
- Enterprises are accelerating the adoption of analytics to support more complex decision makings that used to have to use code-oriented data science and machine learning (DSML) solutions. Generative analytics experience can work as a unified experience layer to compose both analytics and business intelligence (ABI) and DSML solutions with better explainability compared to many augmented analytics solutions today, as the code (Python, SQL and R) is clearly generated during the process.
- The market lacks talent. Few people have both the business domain knowledge and advanced analytics skills. Generative analytics experience can fill the gap by enabling more business users with domain knowledge to ask complex business questions.
- ABI and DSML solution providers, especially the search-first vendors, have good technological foundations to integrate with generative AI technologies, which will bring immediate value to the clients if integrated properly. These include semantic layer, MLOps, knowledge graph, natural language query and catalog technologies.
- Digital workplace applications such as Slack and Teams have already integrated with ABI and DSML solutions. The use of natural language from digital workplace applications to perform analytics will form the generative analytics experience as both sides incorporate large language models.
- Enterprises that adopt a data-centric AI approach will proceed with generative analytics experience as one use case among many to achieve the outcome of new technology innovation.

Obstacles

- Natural language query is not a capability in high demand, according to Gartner client interactions over the past year. Enterprises still consider it a nice-to-have feature, and incorporating generative AI would not improve the adoption in the short term.

- Generative AI, and all the ChatGPT hype, is still new to the market. Vendors are still innovating new product lines with immature capabilities. It remains a challenge to incorporate large language models with the right governance to seamlessly integrate with the existing analytics capabilities, especially considering that the accuracy of generative AI is based on activating D&A metadata across multiple vendors.

- Use of generative analytics experience will bring extra cost as most vendors are incorporating GPT-3 or GPT-4 APIs. The usage from broader business users will drive more cost concerns.

User Recommendations

- Target the automation of certain closed-loop business outcomes of D&A by piloting use cases that leverage generative analytics experience to connect insights to action by natural language.

- Start with generative analytics experience in digital workplace applications, mobile BI and natural language query capabilities by evaluating and monitoring existing vendors' roadmap items.

- Establish the governance of generative analytics experience to minimize errors and "hallucinations" by assessing vendor's accuracy and veracity of their outputs and its feedback loop to correct and monitor the errors.

Sample Vendors

Aible; AnswerRocket; Hex Technologies; Microsoft; Pyramid Analytics; Tellius

Gartner Recommended Reading

Emerging Tech: Generative AI Needs Focus on Accuracy and Veracity to Ensure Widespread B2B Adoption

Quick Answer: What Are the Short-Term and Midterm Implications of ChatGPT for Data and Analytics?

At the Peak

Multistructured Analytics

Analysis By: David Pidsley, Stephen Emmott, Tim Nelms, Anthony Mullen

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Multistructured analytics describes techniques applied to unlocking the value of wide data — the spectrum of multistructured information (structured, semi-structured, and unstructured) of any formats, including language (text/audio) and vision (image/video), sourced internally or externally. Multistructured analytics decomposes meaningful features of human-generated data for DSML modeling. It composes machine-generated data into context-enriched analysis for expert decision making.

Why This Is Important

D&A leaders must bridge the gap between the analytics of today and the context-enriched analysis for decision makers to uncover unique insights. Exponential growth in the spectrum of multistructured information sources/formats requires techniques beyond traditional, structured, transactional or relational data. To get a grip on business complexity, harness multistructured analytics to support expert decision making with richer situational awareness, augment business workflows and automate decisions.

Business Impact

Across industries/business functions, organizations accelerate their application of multistructured analytics to wide data sources/formats to reduce costs, address new uncertainties, drive growth and enable innovation in

the use cases for analytics. Multistructured analytics of audio/video streams in sales and marketing can identify behaviors and sentiments of customers and influencers across channels for new insight, experience optimization, real-time dynamic pricing and competitive intelligence.

Drivers

- Decisions are more complex, with more stakeholders and choices than two years ago. Scenarios need context-sensitive evaluation, beyond individual events, using multidimensional models of real-world uncertainties. Lacking the right variety of data stifles this.
- By 2025, 70% of organizations will shift their focus from big to wide data, providing more context for analytics. Internal (digital workplace) and external (business ecosystem) data sources continue to increase silos, leaving hidden intelligence for competitive advantage. Data marketplaces and exchanges make larger, pretrained and more diverse data assets widely available.
- Organizations are adopting multistructured analytics to move beyond storing content, to extract meaningful features and insights. By 2023, over 80% of organizations will use some form of computer vision to analyze images and videos.
- All forms of wide data can now be processed. Document topics can be tagged, speech transcribed, imaged environments annotated, emotions predicted from video, gauges digitized, opening new doors for analytics, data science and machine learning (DSML) and AI.
- Transformer models (via BERT and GPT techniques), advanced text analytics and deep learning have been a catalyst for linguistic and visual analysis. By 2025, AI for video, audio, vibration, text, emotion and other content analytics will trigger major innovations and transformations in most global enterprises.
- Improved price/performance ratio of cloud AI developer services has made experimenting accessible and scalable.
- Multistructured analytics enriches structured data with categorization and tagging. Analytics and BI and DSML platforms are adding multistructured analytics and graph capabilities so that by 2025, context-driven analytics and AI models will replace 60% of existing models built from traditional data sources, consolidating a mix of analytics solutions.

Obstacles

- Although different forms of (text) content analytics have been deployed for years, many organizations avoid leveraging multistructured information due to limited competencies, specialized tools and their perceived difficulty fueled by confusion around terminology.

- While the tools now exist to deploy multistructured analytics uniting the spectrum of multistructured information to model complex context, it's a shift in the way D&A teams undertake data modeling especially in natural language processing.
- The difficulty of combining techniques (composite AI) to handle specific formats/sources — like deep learning for videos, symbolic algorithms for text analytics, and knowledge graphs — is a challenge.
- Data sourcing, quality and privacy are common challenges that can be cost prohibitive for large datasets. Finding suitable data for a specific use case can be difficult and require governance.
- The market for multistructured analytics tools is fragmented and will likely require leveraging multiple vendors, increasing costs.

User Recommendations

- Leverage multistructured analytics for richer situation awareness and expert decision support.
- Conduct proof of value/pilots and understand the data, technical and organizational gaps.
- Apply text analytics for supply chain optimization, image analytics for diagnostic maintenance, video analytics for conferences and audio analytics for fraud prevention.
- Provide context-enriched analysis for decision makers by applying multistructured analytics to multistructured information.
- Explore multistructured analytics capabilities and roadmaps of vendors, including insight engines for text content and cloud AI developer services for image, video and audio analytics.
- Engage startups and hyperscale cloud providers for innovation.
- Estimate your compute and storage needs to train/run effective ML models that leverage multistructured information.
- Invest in taxonomy/ontology skills to accelerate the refinement and automation of information tagging/classification.
- Revise data collection, management and integration practices to take advantage of multistructured analytics.

Sample Vendors

Amazon Web Services; Databricks; Elastic; Google; IBM; Microsoft; OpenAI

Gartner Recommended Reading

Use Multistructured Analytics for Complex Business Decisions

Quick Answer: What Are the Short-Term and Midterm Implications of ChatGPT for Data and Analytics?

Buyer's Selection Spotlight: Insight Engines

Magic Quadrant for Cloud AI Developer Services

Working With Semistructured and Unstructured Datasets

Natural Language Query

Analysis By: David Pidsley, Rita Sallam

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Early mainstream

Definition:

Natural language query (NLQ) allows business users to query information using business terms typed into a search box or chatbot, or via voice. Vendors' techniques differ in analytical complexity of queries, data volumes and types supported. These keyword searches translate terms into natural language questions using natural language processing technologies and LLM like ChatGPT. Some support querying structured data, and others enable semantic search of multistructured information.

Why This Is Important

- Business users need to make faster data-driven decisions and get context-enriched analysis that includes reasoning about location and time-sensitive situations.
- Despite significant advances in the usability of the point-and-click visual-based analytics, business intelligence (ABI) platforms and other knowledge bases, traditional access paradigms are still too hard for most business users.
- Flattening the learning curve for ABI platform users enables adoption by the remaining two-thirds of employees in organizations that do not use them.

Business Impact

NLQ drives adoption by nontechnical users, offering the ability to ask questions to gain insights, overcoming resistance to visual-based self-service analytics interfaces. NLQ is an increasingly important interface for analytic content development and consumption in data-driven decision making accessible to those unfamiliar with SQL. For data pipelines to enable multistructured analytics across a spectrum of structured data and unstructured content, NLQ can unify a multiexperience user interface.

Drivers

- Foundation models like BERT, large language models (LLMs) and ChatGPT see NLQ repositioned at the Peak of Inflated Expectations and a high benefit rating with less than 2 year time to plateau.
- Generative AI hype is accelerating NLQ capabilities with advanced text analytics and deep learning as catalysts of natural language technologies, including natural language generation (NLG) and NLQ. They enable two-way communication between the human questioner and the machine-generated answer based on the data.
- Demand for generative D&A is substantial with the substantial increase in entrants in 2023. Established ABI platform vendors responded to ChatGPT by improving support for and innovations in NLQ, which is a well-established critical capability of the platforms. Adoption continues to grow as NLQ awareness, availability and solution capabilities improve.
- Orchestration of the entire analytics workflow will increasingly become NLQ-driven and used to manage the analytics and application development activities.
- Augmented analytics capabilities make the analytics consumer of tomorrow a power user by today's standards. Most analytics consumers enter the data story workflow when viewing content that has been created from prepared components and existing data visualizations. Their interaction is typically followed by NLQ or conversational analytics.
- NLQ is becoming central to personalized, consumer-oriented user experiences that combine augmented analytics or automated insights into automated data stories, scenario analysis and conversational analytics. Analytics collaboration enables NLQ engines to learn from team-usage preferences.
- Increasingly mobile workforces using handheld devices and voice interfaces need NLQ to interpret geospatial questions and immediately deliver location-based answers and business insights as a best-fit map visualization. Geospatial analytics and algorithm advances enable NLQ to deliver geospatial reasoning of distance, route calculations and analytics about entities near, farther than or within a certain proximity or boundary, based on business-defined regions or geocoded reference data.

Obstacles

- Limitations in real-time type ahead search-bar suggestions can frustrate users, reduce usefulness and hinder adoption. Some users may not understand the implicit structure of underlying data, rendering queries uninterpretable by the NLQ parser.
- Unindexed datasets often hinder bringing search into an ABI platform. The effort/costs to map/model wide data are high, although generative AI is enabling NLQ of unstructured data to expand the scope and enable multistructured analytics.
- A substantial variety exists in the analytical complexity of queries, NLQ reasoning, support for suggestions for the next questions to ask, NLG to explain findings and support for large data volumes, structured and formats.
- Poor support of spoken languages beyond English, limited domain and industry ontologies, difficulty in configuration, and the need to be predefined in advance means optimizing NLQ implementations often requires customizing the platform and curating synonyms.
- Consistency is lacking for where users can ask questions across platforms and where implementations embed NLQ into the decision making or business process.

User Recommendations

- Help users adopt NLQ for decision making and orchestrating workflows.
- Promote NLQ-specific data literacy training for augmented consumers, business analysts and analytics developers.
- Assess the NLQ roadmaps of vendors and augmented analytics startups.
- Prioritize vendors based on how and what a platform learns (from activate metadata for personalization) via a proof of concept with real data and users.
- Evaluate how NLQ fits into analytics solution architectures. Involve IT in evaluation, data preparation and deployment of ABI platforms.
- Support multiple use cases with multiexperience UIs including evaluating enterprise conversational AI platforms.
- Invest in design thinking on dialogue flows and in competencies to connect conversational analytics to the ecosystem of APIs; for example, ABI platforms and insight engines that enable semantic search and analyzing results sets of wide data with multistructured analytics.

Sample Vendors

ConverSight; iGenius; Pyramid Analytics; Qlik; Tellius; ThoughtSpot

Gartner Recommended Reading

Magic Quadrant for Analytics and Business Intelligence Platforms

Is Your Business Intelligence Enabling Intelligent Business?

Quick Answer: What Are the Short-Term and Midterm Implications of ChatGPT for Data and Analytics?

Magic Quadrant for Insight Engines

Magic Quadrant for Enterprise Conversational AI Platforms

Augmented Analytics

Analysis By: David Pidsley, Anirudh Ganeshan

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Augmented analytics uses AI to automate analytics workflows in platforms, contextualizing user interfaces with automated insights, generative storytelling explanations and collaborative exploration. Driven by ML and generative AI, it enables natural language queries and personalized analytics catalogs. It democratizes advanced analytics with augmented data ingestion, preparation, analytics content and DSML model development. It also curbs human biases and accelerates insights for diverse users.

Why This Is Important

Many activities associated with data, including preparation, pattern identification, transformation, model development and insight sharing, remain highly manual. This friction limits the user adoption and business impact of analytics. Enhancing these capabilities with generative AI democratizes analytics and reduces barriers to entry by allowing users to perform complex analytics tasks with low/no code.

Business Impact

Augmented analytics is transforming how users interact with analytics content. Features like conversational interfaces are making analytics more accessible, explainable and expedient. Generative AI is changing how people interact with augmented analytics, enabling access to deeper insights from data. Once confined to experts only, insights from advanced analytics are now in the hands of business analysts, decision makers and operational workers across the enterprise. These augmented consumers are driving new sources of business value.

Drivers

- Organizations increasingly want to analyze more complex datasets combining diverse data from both internal and external sources. With an increasing number of variables to explore in such harmonized data, it is practically impossible for users to explore every pattern combination. It is even more difficult for users to determine whether their findings are the most relevant, significant and actionable. Expanding the use of augmented analytics will reduce the time users spend on exploring data, while giving them more time to act on the most relevant insights.

- Generative AI has accelerated market interest in dynamic data stories and other combinations of augmented analytics features that automate insights. Generative AI combines augmented analytics with natural language query, natural language generation, and anomaly detection to dynamically generate data stories for users in their contexts. This type of multiexperience UI will reduce the use of predefined dashboards for monitoring and analysis, and increase the use of augmented analytics.

- Vendor technology innovation is pushing augmented analytics forward. With the explosion of generative AI, augmented analytics is receiving heightened attention. ABI platforms are now integrating large language models like GPT-4, allowing users to generate, debug and convert code, create data stories, and aid in data preparation. This integration has also enabled newer users to emerge, fueling analytics adoption. In a next wave of generative analytics experiences, users may see the entire workflow become AI-driven.

- Most organizations leverage multiple ABI platforms, causing exponential proliferation of analytics content. Coupled with a lack of governance, this proliferation often leads to inconsistencies in metrics and insights, duplication of reports and dashboards, and an overall decline of trust in data. Hence, analytics catalogs, powered by augmented analytics capabilities with generative AI, are becoming key in allowing users to find and recommend analytics content.

- By integrating with digital workplace applications (e.g., Microsoft Teams and Slack), augmented analytics features allow users to share and collaborate on insights.

Obstacles

- **Lack of trust in autogenerated models and insights:** Organizations must ensure that the augmented approach is transparent and auditable for accuracy and bias. They must establish a process to review and certify analyses created. These guardrails are especially important with generative AI being included within ABI platforms.

- **Training and rapidly evolving skills needs:** Obtaining desired skill sets and data literacy standards is a never-ending challenge, and leaders need broad and diverse training for multiple personas.

- **Ecosystem requirements:** It will be critical to build an ecosystem that includes not only tools, but also data assets, people and processes to support the use of augmented analytics.

- **Cultural barriers:** Analytics developers writing analytics-as-code and business analysts accustomed to visual self-service analytics may regard augmented analytics as a “nice to have” feature. However, they neither utilize nor rely on it in their analytics content production workflows.

User Recommendations

- Identify the personas and use cases that will benefit most from augmented analytics capabilities.

- Ensure that users can get value from new augmented analytics features by providing targeted and context-specific training. Invest in data literacy to ensure responsible adoption.

- Focus on explainability as a key feature to build trust in autogenerated models. Create learning opportunities for those who wish to know more about the theory and inner workings of augmented analytics solutions.

- Assess the augmented analytics capabilities and roadmaps of ABI platforms, data science platforms, data preparation platforms and startups as they mature. Look into the upfront setup and data preparation required, the range of data types and algorithms supported, the integration with existing tools, the explainability of the models, and the accuracy of the findings.

- Provide incentives for citizen data scientists to collaborate with, and be coached by, specialist data scientists who still need to validate models, findings and applications.

Sample Vendors

AnswerRocket; iGenius; Microsoft; Oracle; Pyramid Analytics; Qlik; Sisense; Tableau; Tellius; ThoughtSpot

Gartner Recommended Reading

Market Guide for Augmented Analytics

Magic Quadrant for Analytics and Business Intelligence Platforms

Critical Capabilities for Analytics and Business Intelligence Platforms

Is Your Business Intelligence Enabling Intelligent Business?

Top Trends in Data and Analytics, 2023

Data Storytelling

Analysis By: Aura Popa, Peter Krensky

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Early mainstream

Definition:

Data storytelling combines interactive data visualization with narrative techniques to deliver insights in compelling, easily assimilated forms. Analytic data stories aim to prompt discussion and collaborative decision making. Data stories can take several forms (data-connected slideshows/storyboards, annotated dashboards and graphic-design-style infographics). In contrast to dashboards used for monitoring, data storytelling techniques are used to inform and educate decision makers.

Why This Is Important

Too many decision makers still overlook the data insights delivered to them, going with their gut feeling rather than decision making based on data facts. This can be a cultural issue; however, there is also a simpler factor at play — how data insights are delivered. In many cases, even where the insight does spark interest, it may lack the context required to drive a decision. Data storytelling can help break down managerial inertia and apathy toward data by adding context and making it more accessible.

Business Impact

The impact of data delivered as a story can be much higher than dashboards and reports, as a story form is familiar to everyone. From an ROI perspective, data storytelling can help drive adoption of analytics tools by repositioning them from just data visualization tools to becoming the key medium for effective communication of data insights. This is important, as our research shows that adoption of ABI platforms is still less than what it should be to be most impactful.

Drivers

- KPI-centered dashboards are not the only or even the most effective way of delivering data. A data storytelling approach can transform how analytics and data science teams work by getting them to focus on their audience and the business decisions they need to take based on insights and the data provided. The audience, made out of nontechnical decision makers, often needs data to be presented to them in narrative format to be most compelling and actionable.

- The functional capabilities to create data stories are now widely available. Most ABI platforms now include a basic functionality to create and share data stories. These stories can take several forms — most frequently these are data-connected slideshows or storyboards, annotated dashboards, and graphic design-style infographics, but they can also be simple alerts in a chat.

- A considerable proportion of vendors have already implemented ChatGPT within their platform, enabling news-style headlines and narratives generated automatically and specifically personalized for individuals.

- As self-service analytics matures, users are beginning to use data storytelling tools and techniques to better communicate to decision makers.

Obstacles

- The use of data storytelling draws on an evolving set of skills, practices and behaviors around how data is socialized and used in organizations. Many organizations do not have these skills in place.
- Data storytelling is a part of a broader movement oriented around data literacy, and explaining and expressing data and analytics in a consumable, engaging and relevant way. Poor data literacy is a chronic inhibitor to effective data storytelling.
- There should be no compromise on quality from content governance in the world of data storytelling. Data storytelling may allow bias or overfitting to create false narratives both from the human creation form or the machine-generated route.
- Machine-generated data stories may not gain traction if they are not relevant, understandable or explainable to the intended recipients. Metadata and context around data stories may need to be automated and utilized to prevent this.

User Recommendations

- Evaluate and experiment with the data storytelling capabilities of ABI platforms. Examine how their incumbent portfolio of technologies supports the creation of storyboard-style presentations with embedded analytical content.
- Leverage the power of machine-generated data stories, collecting as much metadata and context information as possible for enrichment, but making sure human peer reviews and content governance rules are put in place for a continuous sustainable quality.
- Task members of your analytics team with investigating data storytelling as an extension to their use of interactive visual exploration and analytic dashboarding. This will provide a richer delivery of information by adding narrative and context.
- Prepare programs to develop and instill the mix of data visualization design, narration and presentation skills needed to support effective data storytelling. Identify a team of business analysts and citizen data scientists to act as a virtual team of data storytellers.

Sample Vendors

Domo; Oracle; Pyramid Analytics; Qlik; Salesforce (Tableau); ThoughtSpot; TIBCO Software; Toucan; Yellowfin

Gartner Recommended Reading

Communicate Insights Effectively With Augmented Data Visualization and Storytelling

Market Guide for Augmented Analytics

Data Storytelling: Analytics Beyond Data Visualizations and Slideshows

Engage and Influence Business Stakeholders Using Data-Enabled Storytelling

Data-Centric Translators Are Crucial for Facilitating Data Literacy

ModelOps

Analysis By: Joe Antelmi, Erick Brethenoux, Soyeb Barot

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Model operationalization (ModelOps) is primarily focused on the end-to-end governance and life cycle management of advanced analytics, AI and decision models (models based on machine learning [ML], knowledge graphs, rules, optimization, linguistics, agents and others).

Why This Is Important

ModelOps helps companies challenged in standardizing, scaling and augmenting their analytics and AI initiatives that leverage a combination of statistical and ML models. It helps organizations to move their models from the lab environments into production. MLOps primarily focuses on monitoring and governance of ML models, while ModelOps assists in the operationalization and governance of all advanced analytics, decision and AI models (including ML models).

Business Impact

ModelOps delivers business impact in multiple ways. As a practice, it:

- Lays down the foundation for the management of various knowledge representation models, reasoning capabilities and composite model integration.
- Augments the ability to manage decision models and integrate multiple analytics techniques for robust decision making.
- Ensures collaboration among a wider business, development and deployment community, and the ability to correlate analytics and model outcomes with business KPIs.

Drivers

- As the number of advanced analytics, AI and decision models at organizations increase, and as projects become more complicated, organizations will have to manage different types of prepackaged or custom-made models. All will require different operationalization and governance procedures, especially when they are built from scratch.
- Organizations want to be more agile and responsive to changes within their advanced analytics and AI pipelines, not just with models, but also with data, application and infrastructure.
- The operationalization aspects of ML models are not new, but they are in their early stages. However, with ModelOps, the functionalities provided by MLOps are now extended to other non-ML models.
- ModelOps provides a framework to separate responsibilities across various teams for how models (including generative AI, foundational models, analytics, ML, physical, simulation, symbolic, etc.) are built, tested, deployed and monitored across different environments (for example, development, test and production). This enables better productivity and collaboration, and it lowers failure rates.
- There's a need to create resilient and adaptive systems that use a combination of various analytical techniques for decision support, augmentation and automation.
- There is a wide range of risk management concerns across different models — drift, bias, explainability and integrity — that ModelOps helps address.

Obstacles

- Organizations using different types of models in production often don't realize that for some analytics, decision and AI models (rule-based, agent-based, graph, generative AI or simulation models), end-to-end governance and management capabilities can and need to be expanded further.
- Not all analytical techniques currently benefit from mature operationalization methods. Because the spotlight has been on ML techniques, MLOps benefits from a more evolved AI practice, but some models, like agent-based modeling, rule-based models and optimization techniques, require more attention in ModelOps practices and platforms. The creation of applications that leverage generative AI has increased the focus of integrating ModelOps with generative and foundational models, also known as LLMOps in the industry.
- The lack of knowledge relevant to leveraging multiple analytics and AI techniques could prevent organizations from considering the techniques particularly suited to solving specific problems.
- Organizations that are siloed create redundancy in effort with respect to operationalization.

User Recommendations

- Leverage different analytics and AI techniques to increase the success rate of data and analytics initiatives.
- Utilize ModelOps best practices across data, models and applications to ensure transition, reduce friction and increase value generation.
- Extend the skills of ML experts to operationalize a wider range of models. Recruit/upskill additional AI experts to also cover graph analytics, optimization or other required techniques for composite AI
- Establish a culture that encourages collaboration between development and deployment teams, and empowers teams to make decisions to automate, scale and bring stability to the analytics and AI pipeline.
- Collaborate with data management and software engineering teams to scale ModelOps. Offloading operationalization responsibilities to multiple teams enables increased ModelOps specialization and sophistication across the ecosystem of complex AI-enabled applications.
- Optimize the adaptability and efficiency of your AI projects by considering a composite AI approach — integrating various AI techniques to solve business problems.

Sample Vendors

DataRobot; Datatron; IBM; McKinsey & Company (Iguazio); ModelOp; Modzy; SAS; Subex; Valohai; Verta

Gartner Recommended Reading

Top 5 Priorities for Managing AI Risk Within Gartner's MOST Framework

Market Guide for AI Trust, Risk and Security Management

Use Gartner's MLOps Framework to Operationalize Machine Learning Projects

A Mandate for MLOps, ModelOps and DevOps Coordination

Toolkit: Delivery Metrics for DataOps, Self-Service Analytics, ModelOps and MLOps

Natural Language Generation

Analysis By: Bern Elliot

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Emerging

Definition:

Natural language generation (NLG) solutions automatically convert structured and unstructured data into text-based narratives. This is achieved either through rule-based methods, which have been in use for over 15 years, or the one based on recent large language model (LLM) and generative AI methods. Both approaches have strengths and weaknesses; however, they can also be combined into hybrid solutions.

Why This Is Important

NLG solutions improve understanding and operational efficiencies by making it easier to generate content or appraise, via summary or extraction, large or complex material and data. Recent advances in generative AI have enabled significantly more fluid and creative language generation. However, those methods may also introduce erroneous content, an unacceptable risk in many use cases. Leading solutions combine rule-based and generative-AI-based approaches, enabling selectable control over which method is used.

Business Impact

NLG supports multiple productivity-enhancing use cases by augmenting human editors and writers. It can increase the speed at which textual information can be produced and shared, reducing cost and time to market for new content on multiple channels. It also allows applications to communicate with users via conversational UIs in a more fluid and natural manner, such as by supporting interpretation of complex information like analytic reports. Generative AI functionality has expanded the scope, variability and creativity of what can be generated.

Drivers

The most common uses cases for NLG driving adoption fall into several categories:

- **Enhance understanding of business analytics:** For instance, integrating NLG functionality with existing analytics and business intelligence (BI) and data science initiatives.
- **Article-type short summaries:** For instance, writing summaries or analysis of business data, financial data, wealth management information, personalized marketing copy or sports — perhaps in conjunction with abstractive text summarization technology.
- **Conversation responses:** For instance, writing personalized communications to customers via email or text.
- **Easing data access:** For instance, writing short, prose-based product descriptions as per database product information. These might then be posted as a reply to website information requests.
- **Generating variants of outbound messaging and marketing copy:** The last four years have seen growth in the number of short-form NLG specialist vendors.

Emerging, complex use cases include:

- **The combination of NLG with automated pattern/insight detection and self-service data preparation:** This can drive the user experience of next-generation augmented analytics platforms. Users have varying degrees of analytics skills to correctly interpret and act on statistically significant relationships in visualization. This use case could also expand the benefits of advanced analytics to a wider audience of business users, as well as make existing analysts and data scientists more efficient.
- **Tighter integration with BI workflows and experiences:** Context-based narration will reinforce mobile BI use cases, where a lack of screen space is a major impediment to information consumption. It will also expand the use of conversational analytics that combine natural language query (NLQ), chatbots and NLG via virtual personal assistants.
- **Complementing conversational experiences:** Conversational solutions, including virtual assistants, will be able to use NLG methods to enable more complex and natural-sounding interactions.

Obstacles

- The rule-based NLG solutions are mature but are limited in the range of language and complexity of content types that they can generate. However, their output is deterministic and accurate, which is required for many applications, and hence, their use cannot be eliminated.

- Generative-AI-based NLG solutions are emerging, with best practices for their architecture and use still being defined. Additionally, the potential introduction of inaccurate content makes them unsuitable for many use cases. While generation can be "grounded" or based on a narrow set of information, it only reduces, and cannot completely eliminate, the likelihood of errors.

- Hybrid approaches, while promising, are new and may be more complex to use as they involve two different underlying techniques.

- Generative AI approaches require a foundation model which is difficult to develop. Many will rely on existing foundation models, including Generative Pre-trained Transformer (GPT). Usage may incur significant expenses.

User Recommendations

- Be aware of a solution's maturity, particularly in terms of its ability to deliver hybrid functionality.

- Be aware of the platform data integration and preparation requirements, the platform's self-learning capabilities, and the upfront set-up and configuration required.

- Define the languages that need to be supported, the extent of narration, the degree of story automation and control supported, and the accuracy requirements of the findings and narration.

- Investigate and understand potential drawbacks relating to multilingual user scenarios, as NLG requires specific libraries for each language in use. Additionally, industry-specific use cases need to be considered carefully with respect to jargon, tone and specialized ontologies.

- Identify how NLG could be attractive to organizations wishing to make their analytics, BI solutions and other classes of visual information accessible to visually impaired audiences (for instance, to comply with the U.S. Americans with Disabilities Act and similar mandates in other countries).

Sample Vendors

Arria NLG; AX Semantics; Marlabs; neuroflash; OpenAI; Retresco; Salesforce (Narrative Science); ThoughtSpot; Yseop

Gartner Recommended Reading

ChatGPT Research Highlights

Magic Quadrant for Enterprise Conversational AI Platforms

Magic Quadrant for Cloud AI Developer Services

Magic Quadrant for Analytics and Business Intelligence Platforms

Sliding into the Trough

Data Literacy

Analysis By: Alan D. Duncan, Donna Medeiros, Sally Parker

Benefit Rating: Transformational

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Data literacy is the ability to read, write and communicate data in context, with an understanding of the data sources and constructs, analytical methods and techniques applied. Data-literate individuals have the ability to identify, understand, interpret and act upon data within business context and influence the resulting business value or outcomes.

Why This Is Important

Data and analytics (D&A) are pervasive in all aspects of businesses, communities and our personal lives. Thus, data literacy is foundational to the digital economy and society. It helps stakeholders:

- Draw a directlink between D&A and desired outcomes
- Unlock knowledge workers' business acumen
- Explain how to identify, access, integrate and manage datasets
- Draw insights relevant to specific use cases
- Describe advanced analytics techniques and enable AI
- Reduce risk through improved decision making

Business Impact

To become data-driven and equipped to use data and analytics to their competitive advantage, enterprises require explicit and lasting organizational change. Chief data and analytics officers (CDAOs) need to promote and orchestrate “leadership moments” where they act as role models, exemplifying new cultural traits at critical points. To be successful, they will need to guide the workforce by addressing both data literacy and data-driven culture.

Drivers

- The continued growth in digital transformation is amplifying a focus on D&A best practices. Employee data literacy is becoming increasingly recognized as an important factor in an organization’s overall digital dexterity.
- The role of the D&A function has evolved. It is now at the core of an organization’s business model and digital platforms, and with everyone being an information worker, the footprint of business use of data and analytics is broader than ever before.
- Effective D&A strategies require an increased focus on change management. Higher-performing CDAOs prioritize their emphasis, energy and effort on change management requirements, including data literacy.
- Defining what data-driven behaviors are expected — using a “from/to/because” approach — is central to employee development plans. It ensures that creators, consumers and intermediaries have the necessary D&A skills, knowledge and competencies.
- Data literacy is not a one-off project. CDAOs need to take immediate action to create and sustain data literacy through assessment of maturity, awareness, and education. Quick wins build momentum, but lasting and meaningful change takes time because it requires people to learn new skills and behave in new ways. (For example, there is a hunger for this type of skills development within Gen Z, especially in order to future-proof their careers.)

Obstacles

- Lack of common data literacy models/frameworks/standards and terminology.
- Varying interpretations of the term “data literacy” in terms of training, curriculum and understanding, ranging from enhanced data visualization skills to fostering business curiosity about data.
- Failure to measure contribution of data to business outcomes.

- A sporadic and inconsistent approach to training and certification.
- Not recognizing that data use is a behavioral change or change management initiative.
- Lack of talent and poor data literacy within the current workforce.
- Lack of initiatives to address cultural and data literacy challenges within strategies and programs.
- Overall adoption will still take years, due to the complexity of upskilling entire workforces.
- Data literacy is treated as a checkbox activity, especially when delegated to more junior (and unempowered) resources.
- Lack of a designated leader accountable for the development and execution of the program, roadmap and communication plan.

User Recommendations

- Make the business case for data literacy by identifying stakeholder outcomes and linking these to underlying learning needs.
- Designate a leader who will be accountable for developing and executing the roadmap.
- Foster data literacy during D&A requirements gathering by bringing data and business experts together around the problem to be solved.
- Call out examples of “good” and “bad” data literacy to promote desired behaviors.
- Nurture data literacy by rewarding stakeholders who recognize this as a factor for success and sharing their stories.
- Partner with HR and business leaders to incorporate data literacy learning outcomes into job descriptions, career paths and employee value proposition.
- Use data literacy assessments to evaluate current skill levels and desire to participate.
- Go beyond vendor product training to focus on people’s role- and industry-related D&A skills. Improve learning effectiveness by using a mix of training delivery methods (classroom, online, community, on the job).

Sample Vendors

Avado; The Center of Applied Data Science (CADS); Coursera; The Data Lodge; Data To The People; Pluralsight; Skillsoft; Udacity; Udemy

Gartner Recommended Reading

How CDAOs Must Lead Data Literacy and Data-Driven Culture

Address Both 'Skill' and 'Will' to Deliver Data-Driven Business Change

Drive Business Outcomes by Measuring the Value of Data Literacy

Tackle Data Literacy Head-On to Avoid Data and Analytics Program Failure

Partner With Data Literacy Providers to Accelerate the Time to Value for Data-Driven Enterprises

Continuous Intelligence

Analysis By: Pieter den Hamer

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Continuous intelligence (CI) is a design pattern in which real-time analytics are integrated into business operations to process current and contextual data and prescribe actions in response to events. It provides decision automation, augmentation or support. CI leverages multiple technologies such as augmented analytics, event stream processing, optimization, business rule management and machine learning.

Why This Is Important

CI plays a major role in digital business transformation and optimization projects. A key benefit is improved situational awareness and a common operating picture across business functions by providing real-time dashboards, alerts and next-best-action recommendations. Equally important is the capability to trigger automated responses by sending signals to machines or initiating business processes in cases where the decision on what to do can be automated.

Business Impact

The current hype is focused on holistic, integrated CI solutions that share real-time information from myriad sources with various departments and applications to support multiple business functions. This is a further evolution of many existing but more local CI point solutions for specific applications. Examples of more integrated CI include real-time 360-degree views of customers, supply chain networks and "enterprise nervous systems" in airlines, railroads and other transportation operations.

Drivers

- **CI systems leverage real-time and contextual data to support, augment or automate decisions** for customer interaction, manufacturing, fraud detection, supply chain management or other areas. CI is also used for real-time (re)scheduling and optimization; for example, to allocate resources in the most efficient manner possible.
- **CI goes beyond real-time descriptive, diagnostic and predictive analytics by supplying prescriptive information about the best available action in the current context.** It applies to situations in which real-time data from the last few seconds or minutes significantly improves business decisions. It is not relevant where equally good decisions can be made with data that is hours, days, weeks or older.
- **The hardware and software technologies for holistic, integrated CI are available and affordable.** These include inexpensive sensors, publish-and-subscribe messaging systems, such as Apache Kafka, event stream processing platforms and augmented analytics. CI may also leverage decision management tools, machine learning, business process automation platforms, IoT platforms or other development, middleware and analytics products.
- **The growing complexity, and the desired scalability, speed and automation of decision making fuel the adoption of decision intelligence.** This discipline includes the explicit modeling of decisions as a foundation to understand, assess and, where needed, reengineer decisions. It also encompasses the combination of connected insights, contextual analytics and CI.
- With increasing dynamics and disruptions in business, companies need to be more adaptive and resilient. **CI enables constant monitoring for threats and opportunities, including suggested or automated responses to those events.** To further improve this, adaptive machine learning combined with CI paves the way for what ultimately may become autonomous, constantly adapting and self-learning processes and organizations.

Obstacles

- **CI can be very challenging in terms of the full integration of real-time analytics with business processes** and their supporting applications, which, as a result, need to be redesigned. This requires close collaboration between disciplines such as data and analytics, IT application teams and business process designers.
- **Holistic, integral CI is applied at a cross-functional enterprise or ecosystem level,** resulting in a more complete situational awareness and more optimal decisions. However, to achieve this, resistance to change and a silo-oriented culture need to be overcome.
- **Many companies lack the skills necessary to develop custom-built solutions for CI.** These skills include streaming data processing and time-series data analysis, which are significantly different from processing and analyzing data "at rest."
- **Real-time integration of multiple data sources leaves little room for dealing with semantic differences or data quality issues,** implying the need for mature data management practices.

User Recommendations

- **Involve and work with business managers and subject-matter experts** as early as possible in the requirements-gathering and implementation processes, because when CI is implemented, it fundamentally affects the design of business processes.
- **Choose CI offerings in multidisciplinary collaboration among business domain experts, change managers, architects and developers.** Subscribe to SaaS offerings or acquire packaged applications or devices that provide internal continuous intelligence as a point solution to reduce the effort of achieving CI. However, more integral, cross-functional CI will still entail custom design and integration with multiple applications.
- **Hire outside service providers or train your staff on the new disciplines** if your enterprise wants to build its own solutions and does not already have staff expertise in messaging, stream analytics, machine learning and decision management disciplines.

Sample Vendors

Datapred; IBM; Nstream; Quantexa; Radicalbit; SAS; Spindox; TIBCO Software; TransVoyant; Workato

Gartner Recommended Reading

5 Essential Practices for Real-Time Analytics

How to Use Real-Time Analytics When Building an Enterprise Nervous System

Market Guide for Event Stream Processing

Innovation Insight for Decision Intelligence Platforms

What Comes After Digital Business? Exploring the Era of Autonomous Business

Edge Analytics

Analysis By: Peter Krensky

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Analytics is the discipline that applies logic (e.g., “rules”) and mathematics (“algorithms”) to data to provide insights that drive organization strategy and decision making. “Edge” analytics means that the analytics are executed in distributed devices, servers or gateways located outside of data centers and public cloud infrastructure closer to where the data and decisions of interest are created and executed.

Why This Is Important

Gartner client inquiries about the impact of edge on data and analytics continue to increase. With a growing relevance, by 2025, more than 50% of enterprise-managed data will be created and processed outside the data center or cloud. Demand for real-time decision making closer to where the data of interest is created and stored is one of many drivers for edge analytics.

Business Impact

The origins of edge analytics offerings were primarily in the support of decentralized deployments for device-isolated insights. However, connectivity advances, demands for cross-device analytics and innovations surrounding IoT have dramatically increased the scale and complexity of edge analytics use cases. Real-time event analytics and decision making, autonomous behavior of assets, and fault-tolerant applications hold tremendous potential value for enterprises in many industries.

Drivers

- Advantages of edge analytics include faster response times, reduced network bottlenecks, data filtering, reliability, increased access to data and reduced communications costs.
- Data sovereignty and governance issues related to sensitive/regulated data can constrain D&A teams from adopting centralized/cloud-based environments — moving data outside its originating geography can violate sovereignty regulations. By locating analytics in edge environments, the data remains in the originating locations, increasing the likelihood of compliance.
- The increase of distributed cloud and hyperconverged solutions from public cloud providers, including Amazon Web Services (AWS Outposts), Microsoft (Azure Stack Hub) and Google Cloud (Anthos), are further decentralizing previously cloud-restricted workloads. This perimeter expansion of the cloud brings compute and storage closer to the edge — creating new possibilities for edge-centric analytic workloads.
- 5G networks continue to grow in relevancy and, combined with mobile edge computing, will increase edge analytics use cases — particularly for latency-sensitive deployments.
- More analytics solutions, such as those supporting IoT use cases, need to operate in disconnected (or intermittently connected) scenarios. By bringing more powerful analytics capabilities to edge environments, these solutions need not rely on centralized data centers or cloud resources. As demand grows for “smarter” physical assets in many industries, supporting autonomous behavior will be a common requirement.

Obstacles

- Some of the disadvantages of edge analytics include increased complexity, lack of cross-device analytics, overhead of device maintenance and technical currency demands.
- Architectural design and development best practices for traditional or cloud-resident analytics typically assume or prioritize data/analytics centrality and do not carry over directly for edge analytics use cases.
- Vendor choices include two extremes in terms of provider scale — with early and unknown startups competing head-to-head with global megavendors. This drives a mix of platform/protocol standards and complicates going concern considerations for prospective buyers.
- Edge analytics can increase the complexity of enterprise standards and governance (data privacy, security, etc.), which has the potential to delay overall value realization objectives.

User Recommendations

Analytics leaders should consider edge analytics across the following five imperatives:

- Provide analytic insights for individual devices, assets or a larger distributed site even in the midst of disconnection from cloud or data center infrastructure and resources (e.g., driverless cars).
- Provide data sovereignty. Many regulations or data privacy laws require data be kept in the location of origin or the organization deems the transfer of data to introduce too many security vulnerabilities.
- Adapt to scenarios where network connectivity does not have the ability to support desired latency or stability requirements.
- Address scenarios where cross-device interdependencies serving as part of a larger system require edge-resident analytics.
- Redesign analytic strategies where it costs too much to upload the full volume of generated data and where there is no benefit to moving device-level data to a central location for aggregated analysis.

Sample Vendors

Amazon Web Services; Arundo; CloudPlugs; FogHorn; Microsoft; PTC; Samsara; TIBCO Software

Gartner Recommended Reading

Market Guide for Edge Computing

Innovation Insight for Edge AI

The Edge of the Edge Overview

Emerging Technologies Impact Radar: Edge AI

Explainable AI

Analysis By: Peter Krensky, Sumit Agarwal

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Explainable AI (XAI) is a set of capabilities that describes a model, highlights its strengths and weaknesses, predicts its likely behavior, and identifies any potential biases. It can clarify a model's functioning to a specific audience to enable accuracy, fairness, accountability, stability and transparency in algorithmic decision making.

Why This Is Important

XAI gives visibility into how a model arrived at a particular decision. This helps in building trust, confidence and understanding in AI systems. In highly regulated sectors such as insurance or banking, regulations directly or indirectly mandate the need for model explainability to properly manage model risk.

Business Impact

XAI is the responsibility of both vendors (data scientists and solution developers) and also of end-user organizations that consume them. Not supporting this capability puts businesses and decision making at risk. However, different levels of explainability are required for customers, the organization's IT and management, society, and regulators to direct AI governance.

Drivers

- The lack of model transparency or interpretability among model users, managers and consumers impacted by models' decisions severely limits an organization's ability to manage AI risk. Fairly or unfairly, consumers hold the originating organization responsible for the performance and behavior of AI.
- Not ensuring explainability invites model risk that can lead to financial loss, poor business and strategic decision making, or damage to organizational reputation.
- A lot of organizations are shifting to augmented decision-making capabilities with the use of AI models. As a result, they should be able to explain how an AI model arrived at a particular prediction or decision.
- XAI capabilities are prebuilt into both platforms and innovations in the open-source community to explain and interpret models are on the rise.
- Ethical and moral considerations need to be accounted for while relying on augmented decision making, often supported by thorough governance and auditing capabilities for these models.
- New regulations and legal interventions are taking place that mandate the use of explainable AI methodologies.
- Explainable models also help with attrition, so data scientists who quit the job do not leave black boxes behind them. Models that are interpretable help business audiences gain trust in AI.

Obstacles

- Explainability is often confused with ML interpretability. Although the latter serves data scientists, the former applies to different personas interacting with the AI life cycle.
- XAIs are often looked at as a task or a step required while creating AI projects toward the end of the AI life cycle, but they have to be continuous and tested throughout training, development and production phases.
- An inherent lack of trust exists in AI systems that keeps organizations from adoption, since they're simply not aware of XAI techniques or frameworks.
- Explainability tools are fragmented, and XAI is often consumed in an oversimplification such as showing feature importance to end users. Although that approach works in the beginning, XAI is much wider than that, and requires a deep understanding of the subject.
- Organizations that focus on the accuracy of the models rather than on the interpretability stall their decisions on creating a more explainable AI.

User Recommendations

- Define a range of actions that can be taken independently that identify unacceptable results and that flag those results for human intervention. Minimizing the number of incorrect results derived from AI is critical, because users will lose trust in a poorly performing system.
- Educate, train and foster ongoing conversations with key stakeholders, including line-of-business managers, legal and compliance, to understand the AI model's explainability requirements, challenges and opportunities.
- Strive for XAI for each model along the dimensions of business, data, algorithms, models and production.
- Accept deficiencies in explainability as a natural consequence of systems becoming increasingly complex. Document notable deficiencies or potential biases so that they can be used to make corrections in the future.
- Establish the role of AI model validator, a data scientist whose job is to ensure that models are explainable and robust, and meet all possible constraints.

Sample Vendors

Dataiku; EazyML; Fiddler AI; Google; H2O.ai; IBM; Microsoft; Modzy; Superwise; TruEra

Gartner Recommended Reading

Innovation Insight for Bias Detection/Mitigation, Explainable AI and Interpretable AI

Top 5 Priorities for Managing AI Risk Within Gartner's MOST Framework

Market Guide for AI Trust, Risk and Security Management

Incorporate Explainability and Fairness Within the AI Platform

Data & Analytics for Good

Analysis By: Jorgen Heizenberg, Carlie Idoine, Kevin Gabbard

Benefit Rating: Low

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

"Data & Analytics for Good" is a movement in which D&A is pursued because of its ability to deliver a social impact. These initiatives may deliver incidental enterprise value, but this is not their motivation, and they intentionally exclude leveraging social causes to market products or services.

Why This Is Important

"Data and analytics for good" (DA4G) is a movement that transcends organizational boundaries to use data for social impact. Corporate philanthropy is one way commercial organizations can advance societal needs and generate competitive advantage. They can use this human-centric approach as a differentiator in skills enhancement, company engagement and recruiting.

Business Impact

The “Data & Analytics for Good” movement gives resources to a good cause, the public sector or NGOs through free or reduced-cost technology, data and expertise. In the commercial sector, participation in DA4G initiatives can be through philanthropic benefits that attract and retain workers and provide resources. DA4G initiatives can signal social responsibility to investors.

Drivers

Focus on “Data & Analytics for Good” initiatives is growing with increased visibility and understanding of the value provided from these efforts.

- DA4G efforts initially focused on educational enhancement and on providing clean water, reliable food, ecological management, and arts and science community support.
- The number of organizations — from universities and communities to vendors — having a focus on DA4G has increased.
- D&A has the potential to identify, describe, diagnose and address the root causes of human suffering.
- Significant market momentum for DA4G comes from vendors (both software and services) and has been especially evident in relation to sustainability efforts.
- DA4G initiatives within organizations can provide impetus and incentive for attracting and retaining talent as well as incentive to develop new products to alleviate human suffering.

Obstacles

- Justification for “Data & Analytics for Good” is difficult to initiate and maintain because the goals and objectives are considered altruistic, and lose influence relative to business delivery-driven efforts.
- DA4G programs are often dismissed because the funding stream is considered temporary, or at least inconsistent.
- Some DA4G programs are rejected when they seek to qualify inclusion or delivery based on personally identifiable information or data that is considered ethically dangerous.
- Lack of transparency can lead to negative unintended consequences. Data ethics and trust must be incorporated to mitigate the risk of potential data misuse.
- Low levels of data literacy get in the way of effectively using the contributed data and analytics to achieve the desired social impact.
- Legal impediments, technical data format standards and the practical issue of data cataloging and aggregation have also hindered efforts.

User Recommendations

- Leverage free resources (expertise/services, software, technology, data) from organizations that support “Data & Analytics for Good” projects.
- Participate in community events to collaborate on DA4G. Contribute to open data in support.
- Allow employees time to work on philanthropic initiatives. Use this HR benefit as a differentiator in recruiting and skills’ enhancement.
- Evaluate internal, external and open data to assess its usefulness for social purpose while adhering to privacy and security policies. Instill data ethics considerations in data use and sharing.
- Drive data literacy to help identify, understand and recommend controls for DA4G use cases in an effort to provide transparency without endangering individuals’ privacy or sensitivities.
- Grow awareness about DA4G. Share internal and external case studies as well as resources that demonstrate what DA4Gis and what its impact can be.

Gartner Recommended Reading

Quick Answer: How Can We Start a 'Data and Analytics for Good' Initiative?

Prescriptive Analytics

Analysis By: Peter Krensky

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Prescriptive analytics is a set of capabilities that specify a preferred course of action and, at times, take automated actions to meet a predefined objective. The most common types of prescriptive analytics are optimization methods, a combination of predictive analytics and rules, heuristics, and decision analysis methods. Prescriptive analytics differs from descriptive, diagnostic and predictive analytics in that the technology explores multiple outcomes and provides a recommended action.

Why This Is Important

Prescriptive analytics capabilities either automate or augment decision making to improve business responsiveness and outcomes. From a "purist" perspective, the term "prescriptive analytics" is a broad category with little hype, encompassing components with varying positions across the Hype Cycle and various levels of maturity. Such components include optimization, rules combined with predictive techniques and decision intelligence. The increasing focus on composite AI is further propelling the importance of prescriptive analytics.

Business Impact

Prescriptive techniques support:

- Strategic, tactical and operational decisions to reduce risk, maximize profits, minimize costs, or more efficiently allocate scarce or competing resources
- Recommendations for a course of action that best manages the trade-offs among conflicting constraints and goals

- Exploration of multiple scenarios and comparison of recommended courses of action
- Strategic and tactical time horizons as well as real-time or near-real-time decision making

Drivers

- Prescriptive analytics benefits from maturing and expanding data science initiatives, better algorithms, more cost-effective cloud-based computing power, and a substantial increase in available data.
- With improvements in analytics solutions, data quality and user skills, prescriptive analytics will continue to advance.
- The increasing popularity of graph techniques provides a great substrate for prescriptive analytics. Graph techniques highlight early signals, causality links and paths forward, facilitating the implementation of decisions and actions.
- Demand is shifting away from traditional reactive reporting to actionable, proactive insight, placing greater focus on optimization, advanced techniques, composite AI and prescriptive analytics.
- AI platforms and decision management tools increasingly include prescriptive techniques, driving user acceptance and potential value to the organization.
- Prescriptive analytics continues to evolve, ranging from relatively straightforward rule processing to complex simulation and optimization systems. To respond to ever-greater complexity in business, organizations need more advanced prescriptive analytics and composite AI (e.g., combining rules/decision management with machine learning or optimization techniques).
- Organizations continue to improve, optimize and automate their decision making by applying decision intelligence and decision modeling. Prescriptive analytics is a key enabler of this approach.

Obstacles

- Expertise on how and where to apply prescriptive techniques is lacking.
- The industry lacks formal operationalization methods and best practices.
- Historically, organizations have required separate advanced analytics software specializing in prescriptive techniques. Such point solutions offer little cohesion across the analytics capability continuum from descriptive to diagnostic to predictive to prescriptive.
- Even established use cases can fall victim to common data science challenges, such as data quality issues, bias and talent shortages.
- Although it is a necessary competency, prescriptive analytics does not automatically result in better decision making.

User Recommendations

- Start with a business problem or decision involving complicated trade-offs, multiple considerations and multiple objectives.
- Explore the breadth of prescriptive analytics approaches and decision models available. Identify the ones that best cater to your specific business problems and skills.
- Analyze packaged applications to determine which provide specific vertical or functional solutions, and which service providers have the necessary skills.
- Make sure that the enterprise is willing to rely on analytics recommendations, by gaining buy-in from stakeholders — ranging from senior executives to frontline workers carrying out the recommended actions.
- Ensure that your organizational structure and governance program will enable the enterprise to implement and maintain functional, as well as cross-functional, prescriptive analytics recommendations.

Sample Vendors

AIMMS; Amazon Web Services; FICO; Frontline Systems; Google; Gurobi Optimization; IBM; Microsoft; River Logic; SAS

Gartner Recommended Reading

Combine Predictive and Prescriptive Analytics for Better Decision Making

Innovation Insight for Composite AI

How to Use Machine Learning, Business Rules and Optimization in Decision Management

Data and Analytics Governance

Analysis By: Saul Judah, Andrew White

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Data and analytics governance is the specification of decision rights and an accountability framework to ensure the appropriate behavior in the valuation, creation, consumption and control of data, analytics and AI. It includes the processes, roles, policies, standards and metrics that ensure the effective and efficient use of data and analytics in enabling an organization to achieve its goals.

Why This Is Important

Data and analytics governance allows organizations the oversight to drive better behaviors relating to information-related assets in the enterprise, enabling better business outcomes and mitigation of risk. Data and analytics leaders need good governance practices to enable key business outcomes, such as market growth, cost optimization, merger and acquisition scenarios, and compliance management.

Business Impact

Data and analytics leaders should anticipate the following impacts:

- Better governance oversight, accountability and understanding of decision rights relating to data and analytics across the enterprise and within business areas
- Increased levels of business collaboration, transparency, engagement and innovation to drive mission-critical priorities in the enterprise
- Increased levels of data literacy and cultural change enabled by better governance

Drivers

- Higher levels of risk appetite and growth expectations in organizations are based on digital as an implicit part of growth strategies. This requires data and analytics governance capabilities that enable flexibility, scale and resiliency. Data and analytics governance is hence recognized by CDAOs as among the top three critical enablers for successful data and analytics initiatives.

- Investment in data and analytics is widespread across enterprises, with business functions spending as much as central IT teams on these initiatives, causing proliferation of information silos. The need for effective governance capabilities has therefore become an increasing concern for data and analytics leaders as a framework for enabling the connected enterprise, while also addressing the local information needs of business functions.

- Organizations with higher information maturity increasingly recognize that taking a data and analytics governance approach — rather than one focusing on individual information asset types (e.g., data governance) — yields better business results. Elsewhere, we have seen organizations recognize the urgent need to establish governance “to get the ball rolling,” even if it is for only data governance or analytics governance. This significant increase in effort and hype relating to data and analytics governance is being seen in all industries, geographies, organization types and maturity levels.

- Hype and interest are also growing in many areas related to data and analytics governance. These areas include AI model governance, analytics governance in data warehouses and data lakes, trust-based governance, IoT data governance, and ethics as a discrete governance policy type.

Obstacles

- Data and analytics governance is complex, organizationally challenging and politically sensitive. It is often difficult to get executive-level consensus for data and analytics governance programs, and as a result, they are led by IT, with a view to "bringing in the business later." Because these initiatives are not business-outcome-based, they typically result in failure.
- Despite the diversity and complexity of business scenarios, most organizations continue to take a one-size-fits-all, command-and-control approach to their data and analytics governance. Furthermore, most organizations have a poor understanding of executive leader accountability and decision rights for information. Establishing an effective governance for data and analytics is therefore difficult to achieve. As organizations' expectations of what can realistically be achieved through data and analytics governance decline, we see its position on the Hype Cycle descend into the Trough of Disillusionment.

User Recommendations

- Identify critical business outcomes that need good data and analytics to be successful. Focus your governance work there to maximize your investment, developing a business case if needed.
- Engage key business stakeholders and the CDAO in sponsoring and driving the initiative to enable information culture change.
- Focus on the least amount of data with the maximum business impact, while managing your risk to embed data and analytics governance in the full business context.
- Clearly define the scope of work related to data and analytics governance: policy evaluation and setting, policy interpretation and enforcement, and policy execution. The first two must be led by the business; the latter can be enabled by IT.
- Examine how data standards and metadata management can be used to implement data and analytics governance in the enterprise. Though business leaders may not fully understand their importance, an industrial governance capability needs enterprise-scale data and analytics capabilities.

Gartner Recommended Reading

7 Must-Have Foundations to Build a Modern Data and Analytics Governance Program

2022 Strategic Roadmap for Data and Analytics Governance

Quick Answer: How Can I Apply Composable Design Principles to Data and Analytics Governance Organization Capabilities?

Next Best Actions to Improve Your Data and Analytics Governance

5 Steps to Build a Business Case for Data and Analytics Governance That Even Humans Will Understand

Citizen Data Science

Analysis By: Peter Krensky, Rita Sallam, Carlie Idoine, Shubhangi Vashisth, Frances Karamouzis

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Citizen data science is the collective set of capabilities applied to deliver analytic insights where the personnel are not the experts and their role or job function may not be within the data and analytics (D&A) discipline. Citizen data scientist is a persona rather than a title or role within an organization.

Why This Is Important

- The collective personnel (citizen data scientists) delivering these insights add to the impact of the D&A discipline on the organization through the creation and delivery of insights.
- The functional knowledge of citizen data scientists adds a dimension of efficiency, efficacy and depth to the solutions and experience. Citizen data scientists often unlock new insights beyond the use of basic descriptive and diagnostic capabilities.
- Citizen data scientists serve to reduce the talent gap caused by the shortage and high cost of data scientists.

Business Impact

The business impact can range from a synergistic force multiplier effect to governance challenges. The most powerful and impactful business benefits come when citizen data scientists are actively recruited to fusion teams, are provided tools, and perform specific phases of the analytics life cycle (such as feature generation and selection, and algorithm selection) to best leverage their expertise. Ultimately, this puts the power of the tooling in the hands of those who know best how to apply it and align to making business decisions. The challenges arise when the citizen data scientists are reaching beyond their expertise and the appropriate guardrails are not in place.

Drivers

The most significant drivers of citizen data science include:

- **Talent gap —** The sheer volume of personnel needed continues to outstrip demand. Citizen data scientists help fill a portion of that gap. Historically, building data science and machine learning (DSML) models required expert data scientists, who are difficult and expensive to hire and retain. Citizen data science helps overcome such limitations.

- **Generative AI excitement and possibilities —** The popularity of ChatGPT and the dawning of the generative AI era has had a profound effect on citizen data science. The full user spectrum from experts to beginners is experimenting with novel approaches and techniques for low-code/no-code data science. Data preparation exploration and model development will be dramatically accelerated and democratized, contributing to a rewritten art of the possible for citizen data science.

- **Functional knowledge —** Citizen data scientists' primary knowledge base is an in-depth understanding of the business domain. It is the combination of functional knowledge, data science skills and technology that drive results.

- **Vendor offerings —** Vendors have recognized this additional population as a target-rich environment for their offerings. As such, many vendor offerings now commonly include tools and features designed specifically for usage by citizen data scientists.

- **Augmented analytics capabilities —** These include automated, streamlined data access and data engineering; augmented user insight through automated data visualization and exploration; modeling and pattern detection including feature engineering, model selection and validation; automated deployment and operationalization; and capabilities to support collaboration and sharing.

Obstacles

- Upskilling in advanced DSML techniques and approaches is important to derive value from citizen data science. Classroom learning provides a foundation but must be supported by on-the-job learning and experimentation.
- Tools with augmented analytics capabilities and additional processes to manage creation and sharing of models will be required to support citizen data science.
- There is still a need to (statistically) validate results of citizen data science by expert data scientists.
- Expert data scientists often resist or underestimate the effectiveness of citizen data science approaches.
- Citizen data science is often deemed to be just a preliminary, elementary step and not a fully functional DSML approach.
- Citizen data science leveraged in silos with no oversight or collaboration among experts and others with a vested interest in DSML success could lead to duplication of data engineering and analytic effort, lack of operationalization, and limited visibility and standards.

User Recommendations

- **Success starts with leadership —** Educate business leaders and decision makers about the potential impact of a broader range and larger pool of delivery capability. Work with leadership to scan opportunities for citizen data science to complement existing analytics and expert data science initiatives across the data science life cycle.

- **Inviting and inclusive environment —** Create communities of practice, and provide training and tools to make an inviting and supportive environment for all to explore the value of the citizen data scientist persona. This involves defining the citizen data scientist as a formal persona. Define its “fit” relative to other roles, and identify those who fit the citizen data scientist profile.

- **Expert data scientist value —** Acknowledge that you still need specialist data scientists to validate and operationalize models, findings and applications.

- **Tools and technologies —** Provision augmented analytics tools (including but not limited to augmented data science and machine learning tools), platforms and processes to support and encourage collaboration between business users, application developers and data science teams. Track the capabilities (technology) and roadmaps of existing business intelligence (BI) and data science platforms and emerging startups for support of augmented features.

Sample Vendors

Aible; Alteryx; Dataiku; DataRobot; H2O.ai; Microsoft; Qlik; SAS; Tellius

Gartner Recommended Reading

Build a Comprehensive Ecosystem for Citizen Data Scientists to Drive Impactful Analytics

Maximize the Value of Your Data Science Efforts by Empowering Citizen Data Scientists

Best Practices to Enable Effective Citizen Data Science

Graph Analytics

Analysis By: Afraz Jaffri, Rita Sallam, Jim Hare, Mark Beyer

Benefit Rating: Moderate

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Graph analytics techniques allow for the exploration and discovery of relationships between entities and concepts such as organizations, people or transactions. Graph analytics consists of models that determine the connectedness across data points. Graph analytics is typically portrayed via data visualization where surfacing relationships can lead to better-informed insights and decisions.

Why This Is Important

- Graph analytics has proven value in specific use cases (disease tracking, supply tracing, crime prevention).
- Graph analytics can often be the only effective way of analyzing data where connections and links between data items need to be identified.
- Graph analytics is an enabler of knowledge graphs, which are also accelerating in terms of market adoption.
- Graph analytics enable the exploration of connected data without the limitation of legacy data models.

Business Impact

Graph analytics helps in the following ways:

- Analyzes data for insights into relationships in complex, connected data.
- Highly effective at assessing risks to analyze fraud, route optimization, clustering, outlier detection, Markov chains and more.
- Application to digital twin scenarios where network effects and impacts of proposed changes need to be simulated.
- Identifies outlier and unusual patterns that cannot be detected by other methods.
- Augments data discovery capabilities in augmented analytics and business intelligence platforms.

Drivers

- Rapid uptake in use cases that require analysis across complex models or datasets is developed and used within machine learning (ML) with the output stored in graph databases.
- The availability of low- or no-code tools for domain experts and business users to take advantage of graph analytics techniques for complex investigations.
- The increasing maturity of graph databases for storing, manipulating and analyzing the widely varied perspectives in the graph model due to their graph-specific processing languages, capabilities and computational power.

- Established AI techniques (such as Bayesian networks) are increasing the power of knowledge graphs and the usefulness of graph analytics by adding further representational power.

Graph analysis on data can be further augmented by leveraging metadata from unexpected sources adds to the graph analysis capabilities in the following ways:

- Certain evaluations can build data “push” models by analyzing data access logs and users’ analytical model development, graph analytics can track and recommend data based on data’s relationships and users’ acceptance.
- Augmented data profiling combined with graphs can evaluate unfamiliar assets for similarities as compared to currently used datasets — identifying characteristics that are aligned to production AI techniques or ML features.

Obstacles

- Transforming data into graph data models suitable for analysis remains a substantial challenge for large-scale usage. The tooling available is largely concentrated on facilitating end-user ease of use but there is still a need for low code tools that can manage complete graph analytics workflows and life cycles or “GraphOps.”
- Graph analytics and closely related graph databases are driving demand for new skills related to graph-specific knowledge, which may limit growth in adoption. Some vendors have created graph analytic solutions that make it possible to execute graph analytics using SQL.
- New skills required include knowledge and experience with graph algorithms and applying the right algorithm to solve a problem.

User Recommendations

- Prototype graph analytics techniques to address use cases that exhibit development, coding and data models that are overly complex using traditional SQL-based queries and visualizations.
- Examine graph analytics to enhance pattern analysis — especially in verticals and core use cases.
- Transition data catalog search and discovery into a graph analysis model to identify user communities' usage patterns and drive personalization applied to shared datasets.
- Implement multiexperience user interfaces with graph elements to find insights and analytic results, and store the outputs/results for repeated use in a graph database.
- Train existing personnel on how to align data assets, statistical processes and algorithms to create training datasets and build identification processes to detect data changes that will drive changes in the analytical models.
- Evaluate existing tools to determine their graph capabilities.

Sample Vendors

DataWalk; Linkurious; Neo4j; Siren; TigerGraph; Virtualitics

Gartner Recommended Reading

Graph Technology Applications and Use Cases

3 Ways to Enhance AI With Graph Analytics and Machine Learning

Use Multistructured Analytics for Complex Business Decisions

Climbing the Slope

Embedded Analytics

Analysis By: Kevin Quinn, Julian Sun

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Embedded analytics are delivered within a user's natural workflow, without the need to toggle to another application. The embedded analytics market definition is changing as the availability of low-/no-code interfaces increases, drawing on the services originally exposed via APIs to support embedding. Next-generation embedded analytics capabilities include embedding predictive analytics, prescriptive recommendations (next best action), automated insights and natural language virtual agents.

Why This Is Important

Embedded analytics enables nondevelopers to compose stand-alone composable analytic applications. More platforms are now offering automated insights like key driver analysis, outlier/anomaly detection, clustering and forecasting as capabilities are evolving. These capabilities enable citizen developers to extend the reach and connectedness of how analytics and business intelligence (ABI) platforms are used. They may enter the embedded space from adjacent markets as headless services to enhance decision support and augmentation.

Business Impact

Embedding analytics and data science functionalities (predictive and prescriptive analytics) within websites or business applications via APIs reduce change management and increase analytics adoption close to decision points. The new landscape for embedded analytics will include vendors from adjacent markets (e.g., DSAI, low-code application platforms and CAIDS).

Drivers

- **A trend toward composable architectures:** Composable architectures based on containers and microservices have enabled organizations to more easily assemble a best-of-breed environment out of preexisting components. Additionally, low-code application development platforms are enabling citizen developers to “compose” their applications through an assembling experience (e.g., Microsoft Power Apps for Power BI and Viz Lightning for Tableau).

- **AI and market convergence:** Traditional embedded analytics products have come from the ABI market; however, embedded analytics can originate in data science and AI platforms, which can employ (machine learning) ML to offer automated key drivers, make predictions, and prescribe the next best action. To fight back, ABI vendors have been adding AutoML capabilities by building or acquiring companies that offer it. Case in point: Both Tableau and Qlik offer AutoML.

- **Intelligent applications with embedded AI delivered as managed services:** Organizations want to be smart, efficient and innovative AI companies but after experimentation with AI and ML, they have found the tremendous complexities in operationalizing and scaling AI. Instead, they are finding myriad intelligent applications with embedded advanced analytics that are delivered as managed services.

- **Consumerization of analytics and ChatGPT:** Many vendors in the ABI space have shifted focus from enabling business analysts to empowering business consumers to ask and answer questions. Technologies like ChatGPT from OpenAI have demonstrated that nontechnical people can have intelligent conversations with AI bots trained on historical data. In business, these conversations can be about analytics like key drivers, outliers and anomalies even recommendations for the next best action.

Obstacles

- ABI vendors and embedded analytics vendors have shifted focus away from building reports and dashboards to providing functionality for generating predictive and prescriptive analytics leveraging AI and ML. The challenge is that AI and ML technologies are the domain of data science and AI platforms as well as many open-source tools. This has put the two markets on a collision course. End-user organizations have a choice of embedding advanced analytics via either offering.

- Besides huge open-source libraries of prebuilt components for R and Python, there are libraries of open-source D3 charts that offer the potential for internal development teams to build their solutions at a much lower cost.

- Users have the perception that embedding analytics is hard and it requires IT (e.g., API's SDKs, JavaScript, etc.). This perception will need to be overcome, and this will be the role of new no-code platforms.

User Recommendations

- Build upon existing D&A investments by evaluating the embedded analytics capabilities offered by your enterprise standard ABI and DSML platforms. Explore vendors that have specialized in embedded analytics, particularly when deploying large user-scale experiences and/or to stakeholders outside your organization.
- Plan for growth in the number of citizen developers and business technologists using low-/no-code capabilities to extend how they use self-service analytics by providing training in foundational software development practices.
- Scan the market for intelligent applications and managed services — as an alternative to developing analytics to embed in your applications — that provide advanced analytics, including predictions, recommendations and embedded chatbots/virtual assistants that can act as an analytics advisor.

Sample Vendors

GoodData; Google; Infor; Microsoft; MicroStrategy; Oracle; Salesforce; Sisense; Syncfusion; ThoughtSpot

Gartner Recommended Reading

Market Guide for Embedded Analytics

Magic Quadrant for Analytics and Business Intelligence Platforms

Critical Capabilities for Analytics and Business Intelligence Platforms

Self-Service Analytics

Analysis By: David Pidsley, Alys Woodward, Peter Krensky, Sharat Menon, Anirudh Ganeshan, Edgar Macari

Benefit Rating: Moderate

Market Penetration: 20% to 50% of target audience

Maturity: Mature mainstream

Definition:

Self-service analytics (SSA) refers to technology and processes in which line-of-business professionals are enabled to autonomously prepare and visualize data, perform queries, and generate reports, with nominal IT support or involvement. SSA is often characterized by low-code/no-code tools that are increasingly augmented via AI. These tools provide increasingly sophisticated data preparation and analytics capabilities, but are simplified for ease of understanding and frictionless data access.

Why This Is Important

Self-service analytics fosters agility by enfranchising business analysts. It gives analysts direct access to data, enabling them to blend data, derive insights and collaborate on data visualizations. This approach reduces IT bottlenecks, accelerates decision making and enhances efficiency. While SSA is useful for rapid prototyping, complex scenarios may still necessitate IT support and analytics developer intervention for data integration, cataloging, pixel-perfect reporting or advanced analytics.

Business Impact

Self-service analytics is critical to scaling the benefits of data-driven decision making. Many centralized D&A functions struggle to keep up with requests for data and insights coming from decentralized teams. Emerging business technologists or citizen data scientist personas who understand the business context of the data are able to use powerful no-code/low-code data preparation and analytics platforms to quickly discover insights.

Drivers

- **Enhanced vendor offerings:** Analytics and business intelligence (ABI) platforms and vendors in adjacent markets continue to improve SSA capabilities, ensuring alignment with the abilities of less technical users, such as business analysts.
- **Evolving business-user needs:** As business users' information requirements advance, they expect SSA to extend into data management. Tasks such as adding data sources, selecting from data catalogs and integrating external data sources are anticipated capabilities for advanced business analysts (power users or citizen developers).
- **Decentralized budgets and spending patterns:** Compared with central IT teams, lines of business allocate a larger proportion of their overall IT budgets to D&A, emphasizing the need for self-service solutions that cater to their specific requirements.
- **Demand for timely insights:** Business users require prompt insights, but centralized teams may struggle to provide the necessary support. This support gap drives users to seek modern BI tools enabling SSA.
- **Decision-making empowerment:** SSA allows business users to access critical information and make data-driven decisions faster, uncovering valuable insights that might have been overlooked by centralized teams.
- **Analytics collaboration:** Organizations are increasingly seeking to provide environments where a diverse range of users can simultaneously co-produce analytics projects. This collaboration enables users to share knowledge, streamline workflows and drive collective decision making, further boosting the adoption of SSA.
- **Metrics stores and governance:** A virtualized layer that allows users to define and manage metrics as code supports governing metrics from data warehouses and servicing all downstream SSA, data science and business applications.
- **Generative AI:** ABI platforms are increasingly integrating large language models like GPT, which can be leveraged in data preparation, code generation, debugging, and creation of data stories and visualizations. Generative AI accelerates SSA, allowing newer users to enter this workflow. However, intelligent prescriptive applications lessen the need for visual SSA.

Obstacles

- **Governance challenges:** Inadequate user enablement and training often lead to overwhelming governance issues, hindering self-service tools' effectiveness.
- **Struggles between agility and control:** Organizations grapple with striking the right balance, risking either stifled innovation or jeopardized data integrity.
- **Intense data engineering collaboration:** The increased need for data engineering involvement creates collaboration requirements, potentially disrupting workflows and causing metric inconsistencies.
- **Cumbersome DataOps practices:** DataOps introduces complex processes that challenge organizations to adapt effectively, making analytics collaboration more difficult for business analysts.
- **Persistent data quality issues:** Organizations continue to battle poor data quality, risking misunderstandings and detrimental misuse of data.
- **Overhyped vendor claims:** Many exaggerated claims have yet to be fully realized in products, necessitating advancements in augmented analytics and data literacy programs.

User Recommendations

- Segment your users by their ability and inclination to become self-servicing, and deliver to the most prepared users first. Build data literacy and certification programs to ensure users are best prepared to add value from self-service without mistakenly delivering bad or siloed information. Success often compounds and drives further successes, and aids in improving D&A maturity over time.
- Evaluate analytics catalogs and SSA capabilities to allow business users to add curated or external sources to their data landscapes.
- Form communities (analytics franchises) consisting of both business analysts doing self-service and augmented consumers. Self-service should not be self-serving. Communities where sharing, collaboration, education, project overviews and success evangelism occur are critical as analytics audiences grow.

Sample Vendors

Domo; Microsoft; Oracle; Pyramid Analytics; Salesforce (Tableau); TIBCO Software

Gartner Recommended Reading

Critical Capabilities for Analytics and Business Intelligence Platforms

Toolkit: Create a RACI Matrix for Self-Service Analytics

Infographic: Self-Service Analytics and BI Adoption Roadmap

How to Balance Control and Agility in Your Self-Service Analytics

Rethink Self-Service by Establishing Analytics Franchises to Drive Adoption and Break Bottlenecks

Cloud Analytics

Analysis By: Julian Sun, Fay Fei, Jamie O'Brien

Benefit Rating: High

Market Penetration: More than 50% of target audience

Maturity: Mature mainstream

Definition:

Cloud analytics delivers analytics capabilities as a service. It often comprises database, data integration and analytics tools. As cloud deployments continue, the ability to connect to both cloud-based and on-premises data sources in a hybrid model is increasingly important. Cloud-native architecture and multicloud deployments are also becoming popular in order to cater to the cloud ecosystem.

Why This Is Important

Adoption of cloud analytics is growing, with most analytics deployments originating in the cloud. The majority of respondents to the 2022 Gartner State of Data and Analytics Cloud Adoption Survey say they are using or plan to use the cloud for analytics and data science. Cloud capability among analytics and BI vendors is also expanding, with emerging capabilities coming from cloud-first. The cloud is an ideal place to build modular analytics capabilities that enable greater agility and reuse of existing investments in support of composable business.

Business Impact

A cloud-enabled, composable platform can innovate by assembling modular analytics capabilities on demand. More advanced analytics can complement key components of the analytics infrastructure in the cloud. The high computational power needed to process tasks such as ML and advanced analytics can be more easily accessed and scaled in the cloud. Business users can pilot cloud-first augmented analytics within a sandbox provisioned by the cloud. Cloud deployment offers faster time to value and more targeted analytics for specific business areas.

Drivers

- To better leverage scalability and elasticity from the cloud, many platforms have rearchitected themselves to be cloud-native.
- To bring more flexibility for organizations that are already using multicloud, vendors are adding more deployment options and management capabilities. These additions enable portability through microservices architectures that are readily supported via containerization across multiple clouds.
- Startups continue to join the analytics market with cloud-first or cloud-only solutions, which are complementary to established platforms.
- The range of capabilities is growing too. Reporting and data visualization were already commodified capabilities. Customers can now also subscribe to self-service data preparation; augmented data discovery; predictive modeling; other advanced capabilities, such as ML or streaming analytics; and even data/context broker services from several vendors.
- The growing cloud DBMS market naturally supports and expands the cloud analytics market as companies embrace the cloud for managing their data.

Obstacles

- Security is a top concern for organizations moving to the cloud. Organizations need to plan how they will integrate their growing cloud analytics deployments with additional data sources, provide access to more advanced (potentially open-source) analytics tools, and embed analytics in business processes. Such planning becomes even more challenging across multiple cloud and on-premises ecosystems.

- Organizations' adoption of the cloud is closely tied to data gravity. Data gravity refers to data's attractive force: As data accumulates and the need for customization, integration and access grows, data has greater propensity to "pull" data services, applications and other data/metadata to where it resides. Thus, smaller organizations with data originating in the cloud have higher adoption rates than larger organizations with data predominantly in on-premises legacy solutions.

- Even as cloud analytics becomes more predominant and mature, organizations with deployment and governance challenges face growth obstacles.

User Recommendations

- Establish a measured approach to move to the cloud incrementally — rather than simply "lifting and shifting" — as cloud analytics becomes a dominant option in most scenarios in the analytics space.

- Include innovative cloud analytics solutions in your portfolio, renovating on-premises components or complementing your on-premises platform, to gain competitive advantage through analytics and BI. Completely disregarding cloud analytics solutions means risk for many organizations, as most vendors don't focus their R&D efforts on legacy products.

- Be aware of extra costs and the total cost of ownership (TCO) as you adopt new capabilities and offerings within your vendor's cloud stack. Although cloud analytics solutions do not require significant upfront investment like on-premises solutions do, the former will likely be more expensive to license over four or more years. Also be aware of the performance downgrade in the cloud — benchmark the platform, and carefully plan the data integration approach.

Sample Vendors

Alibaba Cloud; Amazon Web Services; Databricks; Domo; Google; Microsoft; Oracle; Qlik; Sigma Computing; ThoughtSpot

Gartner Recommended Reading

Adopt Cloud Analytics to Drive Innovation

Use Cloud to Compose Analytics, BI and Data Science Capabilities for Reusability and Resilience

Magic Quadrant for Analytics and Business Intelligence Platforms

Critical Capabilities for Analytics and Business Intelligence Platforms

Event Stream Processing

Analysis By: W. Roy Schulte, Pieter den Hamer

Benefit Rating: Transformational

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Event stream processing (ESP) is computing that is performed on streaming data (sequences of event objects) for the purpose of stream analytics or stream data integration. ESP is typically applied to data as it arrives (data "in motion"). It enables situation awareness and near-real-time responses to threats and opportunities as they emerge, or it stores data streams for use in subsequent applications.

Why This Is Important

ESP enables continuous intelligence and real-time aspects of digital business. ESP's data-in-motion architecture is a radical alternative to the conventional data-at-rest approaches that have historically dominated computing. ESP platforms have progressed from niche innovation to proven technology, and now reach into the early majority of users. ESP will reach the Plateau of Productivity in less than two years and eventually be adopted by multiple departments within every large company.

Business Impact

ESP transformed financial markets and became essential to telecommunications networks, smart electrical grids, and some IoT, supply chain, fleet management and other transportation operations. However, most of the growth in ESP during the next 10 years will come from areas where it is already established, especially IoT and customer engagement. Stream analytics from ESP platforms provide situation awareness through dashboards and alerts, and detect anomalies and other significant patterns.

Drivers

Six factors are driving ESP growth:

- Organizations have access to ever-increasing amounts of low-cost streaming data from sensors, machines, smartphones, corporate websites, transactional applications, social computing platforms, news and weather feeds, and other data brokers. Many new AI and other analytical applications need this streaming data to satisfy business requirements for situation awareness and faster, more-accurate decisions.

- The wide use of Apache Kafka and similar streaming messaging systems is reducing the cost and complexity of ingesting, storing and using streaming data.

- Conventional data engineering pipelines take hours or days to prepare data for use in BI and analytics, causing delays that are unacceptable for some purposes. Therefore, an increasing number of data engineering pipelines are being reimplemented as real-time data flows (continuous ETL) in ESP platform products or stream data integration tools with embedded ESP. These real-time data flows filter, aggregate, enrich, and perform pattern detection and other transformations on streaming data as it arrives.

- ESP products have become widely available, in part because open-source ESP technology has made it less expensive for more vendors to offer ESP. More than 30 ESP platforms or cloud ESP services are available. All software megavendors offer at least one ESP product, and numerous small-to-midsize specialists also compete in this market. Cloud ESP platforms have lowered the cost of entry.

- Vendors are embedding ESP platforms into a wide variety of other software products, including industrial IoT platforms, stream data integration tools, unified real-time platforms (aka continuous intelligence platforms), insider threat detection tools and AI operations platforms.

- Vendors are adding highly productive development tools that enable faster ESP application development. Power users can build some kinds of ESP applications via low-code techniques and off-the-shelf templates.

Obstacles

- ESP platforms are overkill for many applications that process low volumes of streaming data (i.e., under 1,000 events per second), or that do not require fast response times (i.e., less than a minute). Conventional BI and analytics tools with data-at-rest architectures are appropriate for most stream analytics with these less-demanding requirements.
- Many architects and software engineers are still unfamiliar with the design techniques that enable ESP on data in motion. They are more familiar with processing data at rest in databases and other data stores, so they use those techniques by default unless business requirements force them to use ESP.
- Some streaming applications are better-implemented on unified real-time platforms that process both data in motion and data at rest. Some unified platforms use embedded open-source ESP platform products, while others get their ESP capabilities from custom internal code.

User Recommendations

- Use ESP platforms when conventional data-at-rest architectures cannot process high-volume streams fast enough to meet business requirements.
- Acquire ESP functionality through a SaaS offering, an IoT platform or an off-the-shelf application that has embedded ESP logic if a product that targets specific business requirements is available.
- Use vendor-supported closed-source platforms or open-core ESP products that mix open-source with closed-source extensions for applications that need enterprise-level support. Use free, community-supported, open-source ESP products if developers are familiar with open-source software, and license fees are more important than staff costs.
- Use ESP platforms or stream data integration tools to ingest, filter, enrich, transform and store event streams in a file or database for later use.
- Choose a unified real-time platform with embedded ESP capabilities over a plain ESP platform if the application uses both data at rest and data in motion.

Sample Vendors

Confluent; EsperTech; Google; Hazelcast; IBM; Microsoft; Oracle; SAS; Software AG; TIBCO Software

Gartner Recommended Reading

Market Guide for Event Stream Processing

5 Essential Practices for Real-Time Analytics

Create an Optimal IoT Architecture Using 5 Common Design Patterns

Adopt Stream Data Integration to Meet Your Real-Time Data Integration and Analytics Requirements

Entering the Plateau

Predictive Analytics

Analysis By: Peter Krensky

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Predictive analytics is a form of advanced analytics that examines data or content to answer the question, “What will happen?” or more precisely, “What is likely to happen?” It is characterized by techniques such as regression analysis, multivariate statistics, pattern matching, predictive modeling and forecasting.

Why This Is Important

Predictive analytics was in early mainstream adoption before the COVID-19 pandemic and adoption has accelerated since. Early adopters have proven and refined use cases with clear value. Most organizations have numerous initiatives underway related to predictive analytics, and many organizations are just getting started. In addition, client searches on gartner.com for “predictive analytics” continue to trend upward.

Business Impact

Predictive analytics prioritizes identifying and providing an understanding of likely future outcomes to enable improved decision making, as well as threat/opportunity identification. As a result, organizations can be proactive, rather than reactive (e.g., predictive maintenance of equipment, demand prediction, fraud detection and dynamic pricing). Interest and investment continue to grow in new use cases, as well as more traditional applications of predictive analytics.

Drivers

Project underperformance and ROI failure are low, and this technology is on the doorstep of the Plateau of Productivity. Although related artificial intelligence (AI) and machine learning (ML) innovations continue to be hyped, this technology's journey on the Hype Cycle is nearly at an end. The value derived from predictive analytics is well-aligned with expectations. Interest continues to be driven by improved availability of data, lower-cost compute processing (especially in the cloud) and a growing body of proven, real-world use cases. Predictive models are no longer just produced by data science platforms; predictive analytics is embedded in more business applications than ever. Additional drivers of predictive analytics hype and adoption include:

- Lessons learned from the COVID-19 pandemic on the need for agile and adaptable predictions
- Application developers leveraging pretrained models and cloud AI services to add predictive analytics to applications
- Embedded predictive analytics in enterprise applications and other software
- Augmented analytics capabilities and support for low-code/no-code model building
- Education and upskilling programs for citizen data scientists and augmented consumers
- Growing numbers of practicing expert data scientists
- Emerging roles, such as ML engineer and chief data scientist

Obstacles

- Poor data quality/availability, combined with the data engineering burden placed on data scientists
- Technical debt — i.e., deploying predictive models without proper consideration of ongoing maintenance costs and need for IT support
- Properly defining, designing and supporting XOps (MLOps, ModelOps, DataOps, PlatformOps, etc.)
- Talent recruitment, development, retention and organization
- Predictive model value estimation and project prioritization, and ongoing collaboration with consumers of predictive analytics

- Reliance on black-box models, and evolving standards and regulations around model explainability and bias detection

User Recommendations

- Prepare to manage a heterogeneous portfolio across multiple analytics communities.
- Evaluate the buy option first. Predictive analytics can be quite easy to deploy and use if delivered via a packaged application or a cloud AI developer service. However, packaged applications pretrained models do not exist for every analytics use case. Packaged applications and AI cloud services often may not provide enough agility, customization or competitive differentiation.
- Build solutions through an external service provider (ESP), or with skilled in-house staff using a combination of open-source technologies and a data science platform.
- Use a combination of these tactics (buy, build, outsource) and explore vendors with offerings that combine two or more of these approaches.
- Focus on an operationalization methodology, including ML engineering roles, formal processes and investment in vendor platforms in the initial stages of planning.

Gartner Recommended Reading

Magic Quadrant for Data Science and Machine Learning Platforms

Critical Capabilities for Data Science and Machine Learning Platforms

Maximize the Benefits of Augmented Analytics With a Strategic Action Plan

Top Trends in Data and Analytics for 2021: The Rise of the Augmented Consumer

When and How to Combine Predictive and Prescriptive Techniques to Solve Business Problems

Appendixes

See the previous Hype Cycle: Hype Cycle for Analytics and Business Intelligence, 2022

Hype Cycle Phases, Benefit Ratings and Maturity Levels

Table 2: Hype Cycle Phases

(Enlarged table in Appendix)

Phase ↓	Definition ↓
Innovation Trigger	A breakthrough, public demonstration, product launch or other event generates significant media and industry interest.
Peak of Inflated Expectations	During this phase of overenthusiasm and unrealistic projections, a flurry of well-publicized activity by technology leaders results in some successes, but more failures, as the innovation is pushed to its limits. The only enterprises making money are conference organizers and content publishers.
Trough of Disillusionment	Because the innovation does not live up to its overinflated expectations, it rapidly becomes unfashionable. Media interest wanes, except for a few cautionary tales.
Slope of Enlightenment	Focused experimentation and solid hard work by an increasingly diverse range of organizations lead to a true understanding of the innovation's applicability, risks and benefits. Commercial off-the-shelf methodologies and tools ease the development process.
Plateau of Productivity	The real-world benefits of the innovation are demonstrated and accepted. Tools and methodologies are increasingly stable as they enter their second and third generations. Growing numbers of organizations feel comfortable with the reduced level of risk; the rapid growth phase of adoption begins. Approximately 20% of the technology's target audience has adopted or is adopting the technology as it enters this phase.
Years to Mainstream Adoption	The time required for the innovation to reach the Plateau of Productivity.

Source: Gartner (July 2023)

Table 3: Benefit Ratings

Benefit Rating	*Definition*
Transformational	Enables new ways of doing business across industries that will result in major shifts in industry dynamics
High	Enables new ways of performing horizontal or vertical processes that will result in significantly increased revenue or cost savings for an enterprise
Moderate	Provides incremental improvements to established processes that will result in increased revenue or cost savings for an enterprise
Low	Slightly improves processes (for example, improved user experience) that will be difficult to translate into increased revenue or cost savings

Source: Gartner (July 2023)

Table 4: Maturity Levels

(Enlarged table in Appendix)

Maturity Levels ↓	*Status* ↓	*Products/Vendors* ↓
Embryonic	In labs	None
Emerging	Commercialization by vendors Pilots and deployments by industry leaders	First generation High price Much customization
Adolescent	Maturing technology capabilities and process understanding Uptake beyond early adopters	Second generation Less customization
Early mainstream	Proven technology Vendors, technology and adoption rapidly evolving	Third generation More out-of-box methodologies
Mature mainstream	Robust technology Not much evolution in vendors or technology	Several dominant vendors
Legacy	Not appropriate for new developments Cost of migration constrains replacement	Maintenance revenue focus
Obsolete	Rarely used	Used/resale market only

Source: Gartner (July 2023)

Document Revision History

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Hype Cycle for Analytics and Business Intelligence, 2019 - 18 July 2019

Hype Cycle for Analytics and Business Intelligence, 2018 - 20 July 2018

Hype Cycle for Analytics and Business Intelligence, 2017 - 28 July 2017

Hype Cycle for Business Intelligence and Analytics, 2016 - 25 July 2016

Hype Cycle for Business Intelligence and Analytics, 2015 - 4 August 2015

Hype Cycle for Business Intelligence and Analytics, 2014 - 31 July 2014

Hype Cycle for Business Intelligence and Analytics, 2013 - 31 July 2013

Hype Cycle for Business Intelligence, 2012 - 13 August 2012

Hype Cycle for Business Intelligence, 2011 - 12 August 2011

Hype Cycle for Business Intelligence, 2010 - 16 August 2010

Hype Cycle for Business Intelligence and Performance Management, 2009 - 27 July 2009

Hype Cycle for Business Intelligence and Performance Management, 2008 - 22 July 2008

Hype Cycle for Business Intelligence and Performance Management, 2007 - 23 July 2007

Hype Cycle for Business Intelligence and Corporate Performance Management, 2006 - 14 July 2006

Recommended by the Authors

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Understanding Gartner's Hype Cycles

Tool: Create Your Own Hype Cycle With Gartner's Hype Cycle Builder

Over 100 Data and Analytics Predictions Through 2028

Analytics, BI and Data Science Solutions Primer for 2023

Quick Answer: What Are the Short-Term and Midterm Implications of ChatGPT for Data and Analytics?

Magic Quadrant for Analytics and Business Intelligence Platforms

Market Guide for Multipersona Data Science and Machine Learning Platforms

Market Guide for DSML Engineering Platforms

Table 1: Priority Matrix for Analytics and Business Intelligence, 2023

Benefit	*Years to Mainstream Adoption*			
↓	***Less Than 2 Years*** ↓	***2 - 5 Years*** ↓	***5 - 10 Years*** ↓	***More Than 10 Years*** ↓
Transformational	Event Stream Processing	Citizen Data Science Continuous Intelligence Data Literacy Decision Intelligence	Composable D&A	
High	Cloud Analytics Natural Language Query Predictive Analytics	Augmented Analytics Data and Analytics Governance Data Storytelling Edge Analytics Embedded Analytics Generative Analytics Experience Multistructured Analytics Natural Language Generation Prescriptive Analytics Value Stream Mapping	Explainable AI Metrics Store ModelOps	Decision Engineer
Moderate		Action Frameworks Graph Analytics Self-Service Analytics	Analytics Catalog Analytics Collaboration Multiexperience UI	

Benefit	*Years to Mainstream Adoption*			
	Less Than 2 Years	***2 - 5 Years***	***5 - 10 Years***	***More Than 10 Years***
Low		Data & Analytics for Good		

Source: Gartner (July 2023)

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