Hype Cycle for Finance Analytics, 2023

Published 21 July 2023 - ID G00791435 - 99 min read

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Initiatives: Finance Data and Analytics

AI, especially generative AI, headlines an increasingly crowded finance analytics landscape fraught with hype, opportunity and risk. This Hype Cycle helps FP&A leaders evaluate the value, risk and maturity of analytics innovations, invest appropriately, and optimize analytics insights.

Strategic Planning Assumptions

By 2027, 90% of descriptive (“what happened”) and diagnostic (“why it happened”) analytics will be fully automated.

By 2027, 80% of FP&A functions will rely on AI-enabled scenario planning to produce contextualized insights that help them coordinate and optimize real-time decision making.

By 2027, 40% of organizations will use generative AI to support and/or supplement management reporting.

Analysis

What You Need to Know

Evolving analytics capabilities is a core focus for nearly all FP&A teams. The success and rapid explosion of generative AI technologies highlights the urgency to develop new analytics capabilities. However, the future of finance is more than just AI, and FP&A leaders will need to determine the right time to invest in new analytics technologies to remain relevant.

Technology vendors are quickly embracing and maturing their AI offerings. However, for FP&A leaders to reap the benefits of new AI tools, they must complement investment in AI with investments in graph databases, analytics catalogs, citizen data science and other analytics tools.

FP&A leaders should use this Hype Cycle to:

- Stay current with the rapidly changing analytics landscape.
- Disentangle innovations' overly hyped benefits from their value realities.
- Determine which innovations may require supporting investments (e.g., improving data literacy) to fully recognize benefits.
- Guide analytics planning to better sequence investments and invest with confidence.

The Hype Cycle

The Hype Cycle for Finance Analytics evaluates the analytics technologies and techniques used to explore enterprise data and create financial insights. FP&A leaders should be aware of several trends:

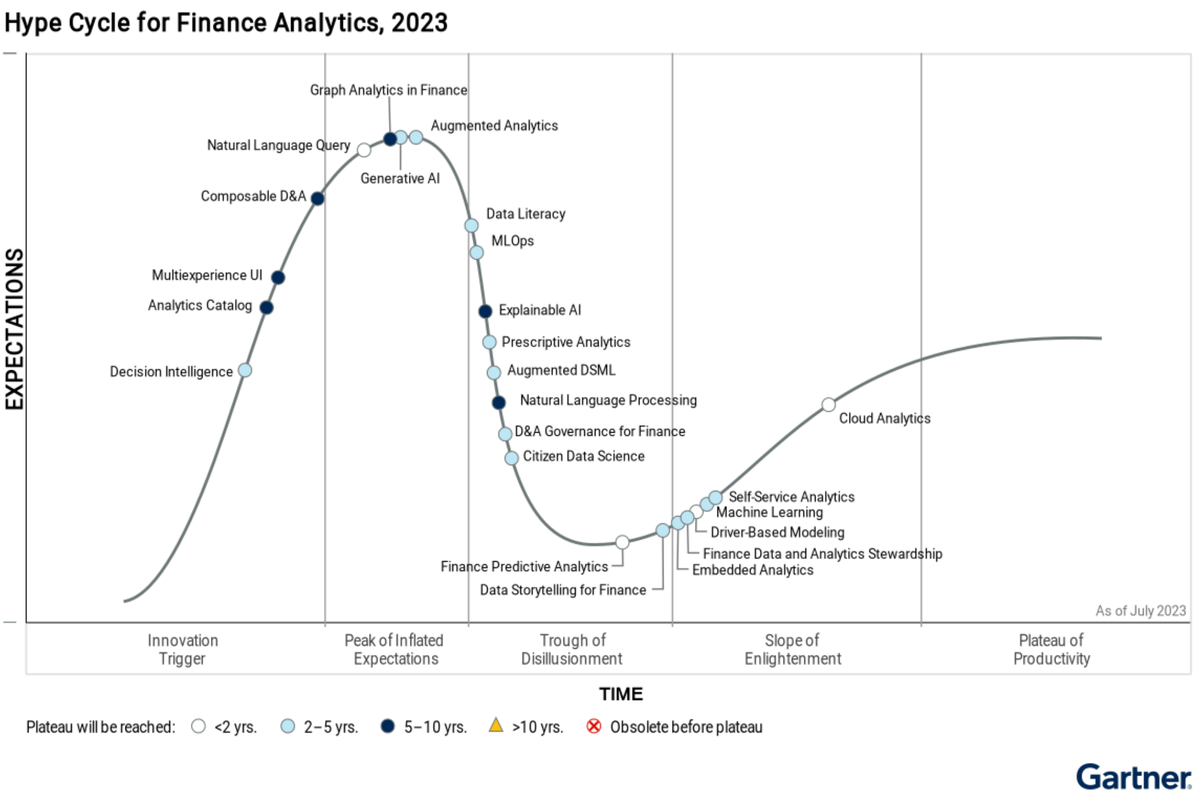
- **AI Urgency —** For teams that have yet to begin, the proliferation of generative AI tools should drive urgency to embrace AI in finance. This shift does not necessarily require significant monetary investment, and many teams can start by leveraging new AI augmentations embedded in financial applications.
- **Renewed Investments in Augmented Analytics —** Generative AI tools (e.g., ChatGPT) have brought renewed hype to augmented analytics and natural language query applications. Vendors are investing in new applications of generative AI tools such as contracts analysis and revision, data discovery and management, and report retrieval and creation.

- **AI Governance —** Mainstream adoption of AI will require updating and revising governance frameworks. FP&A leaders should embrace a risk-aware, not risk-averse, posture and develop guardrails and policies by experimenting in sandbox environments.

- **"Out of the Box" AI —** Vendors have long promised "out of the box" AI — meaning AI tools pretrained and requiring little data science knowledge or major infrastructure investments to deploy — and many vendors are now capable of delivering on that promise. FP&A leaders should embrace these offerings where it makes sense, but should also keep in mind that these offerings are also available to their competitors. Competitive advantage will come from homegrown AI.

- **Analytic Tunnel Vision —** Despite the tremendous potential of AI, many leaders risk overfocusing investments in AI to the detriment of other promising innovations. FP&A leaders should balance investments in AI with investments in other techniques that improve adoption (e.g., data literacy) or alignment to business outcomes (e.g., driver-based modeling).

Figure 1: Hype Cycle for Finance Analytics, 2023



The Priority Matrix

The Priority Matrix arranges analytics innovations by their relative benefits and time to mainstream adoption. For example, if your organization's analytics investment posture has been more risk-averse, the Priority Matrix enables leaders to assess emerging innovations, strike a more risk-tolerant posture and maintain a cutting-edge analytics position.

Focus on transformational innovations that will reach maturity within two to five years and identify dependencies between them. These innovations offer near-term, powerful benefits within existing analytics operations, but often require investment in several related innovations. For example, vendors are offering more mature and easy-to-use machine learning tools, but FP&A leaders should also invest in the talent required to deploy AI, such as citizen data science programs. An internal data science capability allows the enterprise to retain controls of crucial AI models that underpin investment strategies, planning and budgeting, or related competitive tools.

High-benefit innovations often help catalyze more fundamental, cultural benefits. For example, data storytelling for finance and finance data and analytics stewardship will be critical investments for many FP&A teams as analytics tools become more technically complex and difficult to understand for business colleagues. Cultural investments are as much about inspiring the imagination of end users as mitigating the risks that come with powerful new tools such as ChatGPT.

Table 1: Priority Matrix for Finance Analytics, 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		Augmented DSML Citizen Data Science Data Literacy Decision Intelligence Generative AI Machine Learning	Composable D&A Natural Language Processing	
High	Cloud Analytics Driver-Based Modeling Finance Predictive Analytics Natural Language Query	Augmented Analytics D&A Governance for Finance Data Storytelling for Finance Embedded Analytics Finance Data and Analytics Stewardship MLOps Prescriptive Analytics	Explainable AI Graph Analytics in Finance	
Moderate		Self-Service Analytics	Analytics Catalog Multiexperience UI	
Low				

Source: Gartner (July 2023)

Off the Hype Cycle

- Data and analytics services was removed, as it is now commonplace in many organizations.
- Continuous intelligence was removed due to waning relevance for finance leaders in favor of alternative technologies offering similar benefits.

On the Rise

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

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

At the Peak

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

Generative AI

Analysis By: Svetlana Sicular, Brian Burke

Benefit Rating: Transformational

Market Penetration: 1% to 5% of target audience

Maturity: Adolescent

Definition:

Generative AI technologies can generate new derived versions of content, strategies, designs and methods by learning from large repositories of original source content. Generative AI has profound business impacts, including on content discovery, creation, authenticity and regulations; automation of human work; and customer and employee experiences.

Why This Is Important

Generative AI exploration is accelerating, thanks to the popularity of Stable Diffusion, Midjourney, ChatGPT and large language models. End-user organizations in most industries aggressively experiment with generative AI. Technology vendors form generative AI groups to prioritize delivery of generative-AI-enabled applications and tools. Numerous startups have emerged in 2023 to innovate with generative AI, and we expect this to grow. Some governments are evaluating the impacts of generative AI and preparing to introduce regulations.

Business Impact

Most technology products and services will incorporate generative AI capabilities in the next 12 months, introducing conversational ways of creating and communicating with technologies, leading to their democratization. Generative AI will progress rapidly in industry verticals, scientific discovery and technology commercialization. Sadly, it will also become a security and societal threat when used for nefarious purposes. Responsible AI, trust and security will be necessary for safe exploitation of generative AI.

Drivers

- The hype around generative AI is accelerating. Currently, ChatGPT is the most hyped technology. It relies on generative foundation models, also called “transformers.”
- New foundation models and their new versions, sizes and capabilities are rapidly coming to market. Transformers keep making an impact on language, images, molecular design and computer code generation. They can combine concepts, attributes and styles, creating original images, video and art from a text description or translating audio to different voices and languages.
- Generative adversarial networks, variational autoencoders, autoregressive models and zero-/one-/few-shot learning have been rapidly improving generative modeling while reducing the need for training data.
- Machine learning (ML) and natural language processing platforms are adding generative AI capabilities for reusability of generative models, making them accessible to AI teams.
- Industry applications of generative AI are growing. In healthcare, generative AI creates medical images that depict disease development. In consumer goods, it generates catalogs. In e-commerce, it helps customers “try on” makeup and outfits. In manufacturing, quality inspection uses synthetic data. In semiconductors, generative AI accelerates chip design. Life sciences companies apply generative AI to speed up drug development. Generative AI helps innovate product development through digital twins. It helps create new materials targeting specific properties to optimize catalysts, agrochemicals, fragrances and flavors.
- Generative AI reaches creative work in marketing, design, music, architecture and content. Content creation and improvement in text, images, video and sound enable personalized copywriting, noise cancellation and visual effects in videoconferencing.
- Synthetic data draws enterprises’ attention by helping to augment scarce data, mitigate bias or preserve data privacy. It boosts the accuracy of brain tumor surgery.
- Generative AI will disrupt software coding. Combined with development automation techniques, it can automate up to 30% of the programmers’ work.

Obstacles

- Democratization of generative AI uncovers new ethical and societal concerns. Government regulations may hinder generative AI research. Governments are currently soliciting input on AI safety measures.
- Hallucinations, factual errors, bias, a black-box nature and inexperience with a full AI life cycle preclude the use of generative AI for critical use cases.
- Reproducing generative AI results and finding references for information produced by general-purpose LLMs will be challenging in the near term.
- Low awareness of generative AI among security professionals causes incidents that could undermine generative AI adoption.
- Some vendors will use generative AI terminology to sell subpar “generative AI” solutions.
- Generative AI can be used for many nefarious purposes. Full and accurate detection of generated content, such as deepfakes, will remain challenging or impossible.
- The compute resources for training large, general-purpose foundation models are heavy and not affordable to most enterprises.
- Sustainability concerns about high energy consumption for training generative models are rising.

User Recommendations

- Identify initial use cases where you can improve your solutions with generative AI by relying on purchased capabilities or partnering with specialists. Consult vendor roadmaps to avoid developing similar solutions in-house.
- Pilot ML-powered coding assistants, with an eye toward fast rollouts, to maximize developer productivity.
- Use synthetic data to accelerate the development cycle and lessen regulatory concerns.
- Quantify the advantages and limitations of generative AI. Supply generative AI guidelines, as it requires skills, funds and caution. Weigh technical capabilities with ethical factors. Beware of subpar offerings that exploit the current hype.
- Mitigate generative AI risks by working with legal, security and fraud experts. Technical, institutional and political interventions will be necessary to fight AI's adversarial impacts. Start with data security guidelines.
- Optimize the cost and efficiency of AI solutions by employing composite AI approaches to combine generative AI with other AI techniques.

Sample Vendors

Adobe; Amazon; Anthropic; Google; Grammarly; Hugging Face; Huma.AI; Microsoft; OpenAI; Schrödinger

Gartner Recommended Reading

Innovation Insight for Generative AI

Emerging Tech Roundup: ChatGPT Hype Fuels Urgency for Advancing Conversational AI and Generative AI

Emerging Tech: Venture Capital Growth Insights for Generative AI

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

ChatGPT Research Highlights

Graph Analytics in Finance

Analysis By: Clement Christensen, Mark D. McDonald

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Graph analytics comprises a series of techniques and database technologies that enable the exploration of relationships between entities, such as organizations, people or transactions. It uses nodes and vertices to analyze the relationship between such entities (commonly termed “objects”). It uncovers, with relatively low complexity, linkages between seemingly disparate data points and enables analysis in users’ natural language without the need for burdensome SQL queries.

Why This Is Important

Exploring interconnected data relationships among multiple sources daunts many financial planning and analysis (FP&A) leaders. Legacy, relational (SQL) query works well when data is known, but falters in environments when data is unfamiliar and evolving. Graph analytics recognizes that most data is connected, simplifies interfaces and evaluates its most relevant linkages without changing its underlying structure. This enables exploration of new and previously hidden relationships within data.

Business Impact

Graph analytics enable analysis of underleveraged data for insights that address evolving demand for insights, assess risk and suggest proactive resolutions. Now possible at scale, graph techniques have proven effective as recommendation engines, market basket analysis, merchandising decisions, fraud analysis, route optimization, clustering analysis, outlier detection, and more. When combined with business process models, graph analytics successfully identifies patterns to exploit or optimize.

Drivers

- A steady increase in data volume increases the complexity of data and makes finding relevant relationships between data points more difficult.
- As the number and diversity of data sources grows, graph analytics adds the ability to quickly link disparate sources into a logically cohesive data structure.
- Data relationship insights are often lost when using traditional data storage. Since graph analytics does not modify data's underlying structure, it preserves data's richness. It enables data's relationships to be explored, discovered and analyzed — especially when relationships are complex and there is no existing data model.
- Use cases requiring analysis across highly complex models are developed and used within machine learning (ML), with the output stored in graph databases. Graph analytics can traverse millions of relationships in a matter of seconds, whereas traditional relational database management systems (RDBMSs) take minutes or hours (potentially crashing systems).
- Graph databases are ideal for linking internal and external data for storage, manipulation, and analysis. Graph-specific processing languages such as graph query, capabilities and computational power enable storage, manipulation, and analysis across a wide variety of perspectives. For example, graph analytics might be used to compare financial ERP trade data with social, geographical or other data to detect fraud or cyberattacks.
- Some vendors have developed graph solutions (such as SPARQL or GQL) that enable graph analytics to use more commonly available SQL.
- Established AI techniques (such as Bayesian networks) increase the power of knowledge graphs and the usefulness of graph analytics.
- Use cases that span many industry verticals in a horizontal fashion are seeing early-to-moderate levels of adoption (such as route optimization, market basket analysis, fraud detection, social network analysis or location intelligence).

Obstacles

- Many FP&A leaders are still evolving their team's data and analytics (D&A) and query skills. Graph analytics requires new skills related to graph-specific knowledge (such as Resource Description Framework [RDF], property graphs, SPARQL Protocol, RDF Query Language, Python or R). Low availability of graph skills gaps have slowed adoption and limited growth, within FP&A and finance.
- Graph analytics complements RDBMSs, but will not replace them. Where there is a need to record parallel or serial business process data (such as transactional detail), traditional RDBMSs remain highly valuable for certain use cases (especially for compliance and audit purposes).
- Despite the healthy startup market of vendors pushing to integrate graph analytics in multimodel platforms, much of the technology is developed either in-house or integrated via resale agreements with specialist vendors.

User Recommendations

- Test graph analytics where overly complex, traditional SQL-based coding, queries and visualizations inhibit insight development.
- Use graph analytics to complement and enhance traditional pattern analysis, focusing on the use cases noted above.
- Transition metadata analytics from simple catalog search and discovery into a graph analysis model.
- Implement interactive user interfaces from vendors that use graph elements to find insights and analytic results, and the store outputs for reuse in a graph database.
- Train FP&A staff how to align data assets, develop statistical processes or author algorithms to create training datasets and build identification processes that detect data changes to evolve analytical models.
- Prioritize efforts to clean metadata across the landscape since graph analytics leverages metadata. This includes having a consistent definition of metadata elements across systems.

Sample Vendors

Cambridge Semantics; Elastic; Neo4j; Siren; Smarsh; SparkCognition (Maana)

Gartner Recommended Reading

Understanding When Graph Analytics Are Best for Your Business Use Case

Quick Answer: When to Use Graph Analytics in Finance

Quick Answer: What Is Graph Analytics in Finance?

CFO Podcast: Graph, the Future of Databases With Grant Nelson

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

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

MLOps

Analysis By: Peter Krensky, Pieter den Hamer, Jim Hare, Erick Brethenoux

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Emerging

Definition:

Machine learning operationalization (MLOps) aims to streamline the end-to-end development, testing, validation, deployment and instantiation of ML models. It supports the release, activation, monitoring, experimentation and performance tracking, management, reuse, updating, maintenance, version control, risk and compliance management, and governance of ML models.

Why This Is Important

Operationalization of machine learning projects is often an afterthought, which keeps organizations from realizing the true value of their investments. MLOps aims to standardize the development, deployment and management of ML models by supporting the release, activation, monitoring, performance tracking, management, reuse, maintenance, risk and compliance management, and governance of ML artifacts.

Business Impact

MLOps supports the following:

- **Integration:** Integrate advanced analytics and ML platforms to provide a unified ML operationalization pipeline that rapidly reduces time to value.
- **Catalogs:** Store and secure data, analytical artifacts and ML artifacts for ease of collaboration and reusability.
- **Governance:** Ensure auditability, enforce adherence to internal and external security policies and procedures, and address potential privacy issues.
- **Coherence:** Provide functional bridges between the development and operationalization cycles.

Drivers

- Organizations often face machine learning model debt, which keeps them from realizing the true value of their investments. MLOps helps organizations pave a clear path from experimentation to production.
- Organizations want to ensure the integrity (technical and business), transparency and sustainability of deployed ML models by establishing a systematic operationalization process for their machine learning projects — one that differs from the process for traditional software engineering projects.
- Organizations want to maximize their operationalization success by securing the help of domain experts, ML engineers, IT professionals and business practitioners, in addition to existing data science talent. MLOps brings all these personas together by providing a common management and governance framework.
- Organizations seek to simplify the maintenance of deployed machine learning models by monitoring and revalidating their business value on an ongoing basis.
- The number of deployed ML models is increasing rapidly. In the 2021 Gartner AI in Organizations Survey, some respondents said they have hundreds of thousands of models, making MLOps a must-have capability.

Obstacles

- Organizations tend to think of MLOps as a technology or procedure, rather than a collaborative way of working. MLOps brings different personas together to productionize ML workflows.
- MLOps tools and platforms primarily focus on the management, monitoring and governance of machine learning models. In most cases, they do not assist in the end-to-end development, deployment, management and governance of machine learning pipelines.
- Most organizations overlook the critical aspect of operationalization.
- The vendor landscape for MLOps is rapidly evolving, creating confusion for organizations seeking the most efficient way to operationalize their machine learning workflows.
- MLOps focuses on the end-to-end management and governance of ML models, whereas ModelOps focuses on the end-to-end governance of all logic-based models and decision models, including knowledge graphs, heuristics, ML-based models and other AI models. This subtle distinction adds a layer of confusion for organizations making platform decisions.

User Recommendations

- Establish a systematic MLOps process through Gartner's MLOps framework.
- Consider implementing a wider ModelOps strategy if you are a mature organization with a variety of AI models, such as heuristics, agent-based models, knowledge graphics and ML models.
- Make active investments to upskill your workforce for operationalization.
- Ensure the business value of ML deployments while prioritizing use cases by establishing close, ongoing dialogue with, and explicit buy-in from, business counterparts. The earlier the dialogue happens, the more successful the model operationalization will be.
- Distribute delivery, but centralize oversight, by organizing for MLOps. Connect delivery and oversight within the data science lab, IT or the LOBs, depending on the expected business outcomes, size of the ML project team and complexity of the initiatives.
- Define roles and responsibilities of data scientists, IT and MLOps by aligning team members with stages in the ML life cycle.

Sample Vendors

Amazon Web Services; Databricks; Dataiku; DataRobot; Datatron; Google; Microsoft; Valohai

Gartner Recommended Reading

A Mandate for MLOps, ModelOps and DevOps Coordination

Use Gartner's MLOps Framework to Operationalize Machine Learning Projects

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

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

Augmented DSML

Analysis By: Peter Krensky, Carlie Idoine

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Augmented data science and machine learning (augmented DSML) uses artificial intelligence to help automate and assist, in variable degrees, key aspects of a DSML process. These aspects include data access and preparation, feature engineering and model selection, as well as model operationalization, model explanation, model tuning and management.

Why This Is Important

Augmented DSML, a subcategory under the augmented analytics umbrella, reduces the requirement for specialized skills to generate and operationalize advanced analytical models. It enables citizen data scientists to create, manage and embed ML models into business applications. Highly skilled data scientists can use augmented DSML to increase productivity by automating time-consuming, labor-intensive and mundane, simple steps, while reducing error or bias inherent in manually developed models.

Business Impact

Augmented DSML learning fosters:

- Data-driven decision making by democratizing access to advanced analytics
- Reduced time to build and deploy models, while offering more flexibility and business responsiveness
- Reduced reliance on scarce data science experts, while enabling those with domain knowledge to practically use DSML

- Organic growth and expansion of analytics portfolios by enabling access and collaboration among various personas, which fosters trust and acceptance of advanced analytics outputs

Drivers

- Increasingly decentralized business users have a need for more advanced analytics that incorporate analytics in ad hoc decision making and embed analysis directly within their business processes and systems.
- Shortages of expert data science skills and high costs to secure and retain data science talent are driving new approaches to enable use of advanced analytics without solely relying on traditional experts.
- Specific steps in the ML pipeline are time-consuming and mundane (e.g., data preparation, feature engineering, model optimization), and so are ripe for automation.
- There is an increased need for collaboration between those possessing knowledge of advanced analytical techniques and those with strong business acumen and organizational experience.
- Augmented capabilities are increasingly included by vendors across the complete analytics process within all DSML platforms.

Obstacles

- Expert data scientists often underestimate the net business value provided by augmentation that enables nonexperts or themselves to be more productive.
- Business-user-led analysis often surfaces issues in how data is collected, organized and managed. D&A leaders must be prepared for new utilization of data.
- Lack of collaboration processes and tools between citizen data scientists and data scientists.
- Upskilling in advanced analytics techniques as well as providing augmented DSML tools is necessary to fully use augmented DSML approaches. Learning how to apply these approaches to real, prioritized business problems takes time and guidance from experienced data scientists.
- Expectations for a fully automated approach often are not met, except in narrow use cases and limited scenarios.
- Citizen data science used in silos with no oversight or collaboration may lead to duplication of efforts, lack of operationalization and limited visibility.

User Recommendations

- Use augmented DSML to extend, but not replace, traditional DSML approaches.
- Recruit/upskill and enable citizen data scientists to increase accessibility and grow use of augmented DSML. In addition, support the use of augmented DSML to increase efficiency and mitigate bias in models.
- Extend and integrate with the existing analytics and DSML technology stack when possible. Prioritize vendor solutions that include augmented capabilities.
- Manage and guide your augmented DSML approach, with significant focus on governance and explainability, data access and data quality. Leverage collaboration between experts and nonexperts to validate and audit the models and approach.
- Incorporate collaboration tools and processes to enable citizen and expert data scientists, business analysts and application developers to work together to define, build and manage models.

Sample Vendors

Aible; Alteryx; Dataiku; DataRobot; H2O.ai; 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

Market Guide for Augmented Analytics Tools

Natural Language Processing

Analysis By: Bern Elliot, Erick Brethenoux

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Emerging

Definition:

Natural language processing (NLP) enables an intuitive form of communication between humans and systems. NLP includes computational linguistic techniques aimed at parsing, interpreting and, sometimes, generating human language. NLP techniques deal with the pragmatics (contextual), semantics (meanings), grammatical (syntax) and lexical (words) aspects of languages. The phonetic part is often left to speech-processing technologies that are essentially signal-processing systems.

Why This Is Important

NLP enables the automated processing and leveraging of vast quantities and types of text-based information. These can include documents, literature, email, text messages, invoices and receipts. With speech-to-text, NLP can process speech, including livestreams of text and speech. As a result, NLP enables a vast array of applications and automation that was previously unachievable by machine, offering businesses significant process improvement.

Business Impact

- NLP is an enabler that is typically useful when built into applications that support business workflows.
- Because so many tasks involving text rely on human labor, the potential for savings and new business processes is vast.
- Business value reported from some applications using NLP, such as machine translation, are thousandfold efficiency improvements and operational cost savings.

Drivers

- Growth in transcription and translation services.
- Language-generation applications (chatbots, text summarization) that produce natural language descriptions of tabular data, making it easier for many to understand.
- Keyword tagging in documents, making it easier to determine relevant sections or to extract other information, such as intent and entities.
- Autocorrect and autocompletion tools and services.
- Content moderation services that analyze user-generated content (text or images) to flag potentially offensive content or identify fake news in social media.
- Sentiment analysis to identify the effective states and subjective information in statements — for example, from negative to neutral to positive.
- Search improvements through better understanding of the intent of a search query or through summaries of the retrieved content.
- Text analytics and intelligent document processing (IDP) to quickly process large numbers of an organization's documents and determine compliance or legal validity.
- Advances in insight engine text capabilities combined with more-advanced NLP functionality.
- The introduction of new machine learning (ML) techniques, including transformer-based large language model (LLM) approaches, such as BERT and GPT-3. This has enabled new use cases and improvements to existing use cases, with special regard to those involving text generation.

Obstacles

- Despite progress made in NLP methods, many subtle nuances properly processing the complex and enormous variety found in human languages are deeply influenced by cultural and other idiosyncratic conditions. Significant customization of tools and products is often needed.

- Although recent NLP methods that leverage deep neural networks have provided significant and useful improvements to many applications, some are experimental and are not yet mature.

- Support for low-resource languages. Although common languages have support for templates, data and algorithms, lesser-used languages can be difficult to develop for, and require more custom-made effort.

- Despite advances in new techniques, the hyped expectations surrounding NLP may result in unrealistic expectations, leading to disappointing results.

- Many of the new use cases of emerging NLP opportunities are poorly understood and face issues with meeting expectations or defining a clear business value to companies.

User Recommendations

- Select the strongest and most-immediate use cases for NLP. Examples include customer service (affecting cost, service levels, customer satisfaction and upselling) and employee support (including augmenting them as they perform tasks). Another example is automation of paper- and document-based tasks (e.g., contract analysis, compliance enforcement, document generation, translation and transcription).

- Demonstrate success in initial projects by starting with modest goals. As experience is obtained, projects should iterate, and scope can increase. As enterprises enhance their NLP initiatives, new skills should be explored that better leverage new NLP methods.

- Verify the effectiveness of solutions before making significant commitments, because the quality of NLP solutions can vary.

- Evaluate master metadata implications. Ensure that language assets are considered from a master metadata management point of view to ensure reuse and portability of assets between algorithms and systems.

Sample Vendors

Baidu; Expert.ai; Google; IBM; Microsoft; Narrative Science; NLTK; Openstream; Rasa

Gartner Recommended Reading

Applying AI — A Framework for the Enterprise

Applying AI — Techniques and Infrastructure

Tool: Vendor Identification for Natural Language Technologies

Use-Case Prism: Artificial Intelligence for Customer Service

Cool Vendors in Natural Language Technology for Processing Enormous Volumes of Unstructured Data

Cool Vendors in Conversational and Natural Language Technology

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

D&A Governance for Finance

Analysis By: Ash Mehta, Andrew White, Debra Logan

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Data and analytics (D&A) governance for finance is the framework for the specification of decision rights and accountability to ensure appropriate behavior in the valuation, creation, consumption and control of D&A, in the context of the finance function. It includes the processes, roles, policies, standards, and metrics that ensure the effective and efficient use of D&A for finance.

Why This Is Important

D&A governance is critical for managing finance data assets. Though traditionally the domain of CIOs or CDOs, governance of financial data and analytics assets is shifting to finance department leaders who have better visibility into how decision makers use data in practice. Finance leaders responsible for enterprise analytics require good governance practices to ensure analytical consistency across business lines and departments and to deliver analytical insights that support key outcomes.

Business Impact

Finance leaders should anticipate the following impacts:

- Stronger governance over D&A decision rights across the enterprise and within business areas.
- Tighter regulatory compliance leading to lower risk of infractions and fines.
- Increased levels of business collaboration with data stewards to engage, orchestrate, innovate and drive governance to support enterprise business outcomes.
- Greater understanding of how key business outcomes relate to data quality metrics.
- Governance enabling data literacy.

Drivers

- As organizational D&A capabilities mature, organizations are recognizing that enterprise — as opposed to siloed — governance yields better business results.
- Accelerating investment in advanced (artificial intelligence, machine learning) analytics requires an enterprise governance approach.
- The level of data quality required for FP&A leaders to deploy advanced analytics requires an active role in governance.
- Decision-ready data required to deliver actionable insights in the decision making requires sufficient version of truth-based governance.
- Multiple business units within organizations are building and investing in their own D&A teams leading to conflicting metrics and KPIs.
- Organizations are investing heavily in technologies that are based on loose foundations without proper data governance leading to lower-than-anticipated ROIs.
- Shadow data and metrics continue to proliferate across organizations even as technology investments and digital transformation initiatives accelerate.

Obstacles

- Enterprise data governance has long been thought of as the domain of IT and CDOs.
- Overly restrictive data governance principles are created when policymakers write data governance principles as fixed rules with specific do's and don'ts for employee actions, burdening (rather than enabling) productive practices and behaviors.
- Top-down evaluation process where policymakers seek policy approval from the data governance steering committee and do not address end-user concerns regarding policy language and implementation.
- Control-oriented data governance approaches have proven ineffective at achieving the data quality level desired by business leaders, creating a one-size-fits-all approach that is ill-suited for advanced analytics.
- Centralized data governance results in data governance that causes data owners and stewards to disengage, casting them as passive recipients of data governance mandates rather than active participants in data quality improvement efforts.

User Recommendations

- Define data governance policy objectives and establish a finance-led steering committee to implement enterprise data governance.
- Detect whether a CxO leads any existing governance efforts; if so, then we recommend a finance D&A leader serve as co-chair.
- Appoint a member of the leading governance committee to oversee the policy creation.
- Strengthen governance accountability by establishing roles that encourage a collaborative, enterprisewide data governance model.
- Build a business case and appoint an executive champion to coordinate and arbitrate governance opportunities and business outcomes.
- Increase the consistency of interactions between data governance councils and data stewards by establishing a data governance charter.
- Establish guidelines, not rules, using natural business language (free from technical or other jargon). Draft broad principles that empower employees with the autonomy to make decisions and value judgments where appropriate.

Gartner Recommended Reading

Finance's Role in Enterprise Data Governance: Executive Champion and Lead Steward

Ignition Guide to Creating a Finance Data Governance Policy

Ignition Guide to Building a Data and Analytics Governance Program for Finance

Use Value Streams to Create a Common Language for Finance Data Definition Governance

How to Align Finance's Data and Analytics Governance Strategy With a Metrics Cascade

Finance Predictive Analytics

Analysis By: Clement Christensen, Matthew Mowrey

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Finance predictive analytics is a form of advanced analytics that examines data or content to answer the questions, “what will happen?,” “when will it happen?,” or “why will it happen?” It is characterized by algorithms that are trained to use historical data to predict and add context to future events or trends.

Why This Is Important

Predictive analytics answers “what is likely to happen?” It incorporates legacy approaches (for trend analysis and statistical inference) with more advanced approaches (such as pattern matching or cluster analysis). Where forecasting is common to FP&A leaders, the appeal for predictive, contextual insights and for resource reallocation decisions to enhance performance compels continued interest; and, adopters are infusing predictive ML and AI techniques into traditional forecasting processes.

Business Impact

Finance predictive analytics generates likely future values, behaviors or trends for proactive (vs. reactive) decision making. Proven use cases include demand forecasting and collections risk or fraud detection. Since interest and investment continue to grow, new AI and ML use cases are rapidly evolving. Predictive analytics investments are not limited to technology. Leaders must consider people (training, roles), process (workflow) and data (governance) investments to fully realize value.

Drivers

- Improved data availability, lower-cost (cloud) computing and a growing body of proven use cases continue to drive interest. Predictive models are no longer produced by data science and machine learning (DSML) platforms; predictive analytics are embedded in more business applications than ever.
- In addition to top-down demand, predictive analytics interest is often driven by new-to-company analytics business interpreters or citizen data science (CDS) roles. Interpreters and CDS broaden stakeholder interest by proactively anticipating, explaining, and coordinating predictive analytics with context or within existing workflows.
- As finance teams mature their D&A skill sets, more demand for predictive analytics is anticipated. This suggests predictive technology will soon enter the Slope of Enlightenment.
- Traditional D&A tools and techniques struggle to keep pace with growth in data and business expectations. New DSML investments are not only intended to meet these demands, but also enable a predictive analytics' reality.
- FP&A leaders report increasing demands to improve forecast agility and adaptability to support continuous or event-driven forecasting. In response, leaders are more apt to consider technology — like predictive analytics — to respond more efficiently and more precisely.
- Application developers are accelerating innovations with low-code/no-code or pretrained models (such as AutoML) and introducing them as improvements to existing applications. This is more prevalent in cloud-based applications (such as Financial Planning or ERP), which many finance teams are considering.
- D&A literacy programs continue to increase stakeholders' ability to read, write and communicate D&A in context. Additionally, the prevalence of online and in-person education has increased. These trends give rise to growing numbers of data-literate employees capable of leveraging predictive analytics in practice.

Obstacles

- Without assurance that predictive analytics won't threaten their jobs, end users resist solutions that may replace them.
- Initial, poorly-scoped and overly-promised predictive pilots often fall short of inflated managerial expectations — driven by media hype — discouraging further investment.
- Embedded predictive capabilities in vendor-created software are often developed for the most common use cases. Distinct DSML platforms are required to address more specific predictive needs.
- Poor data quality and availability increases the predictive development burden; poor data literacy discourages predictive adoption.
- Technical debt (effort, rework, or expense incurred as a result of poor technology deployment).
- Poor support from XOps (MLOps, ModelOps, etc.).
- Low availability (or lack thereof) of advanced analytics talent.

User Recommendations

- Evaluate buy options first. Predictive may deploy easily via embedded vendor solutions. Explore functional use cases (ex., AP or AR). Vet whether customized DSML platforms are required. Embedded solutions may be too basic for your needs.
- Generate predictive demand via technical upskilling and adjust ways of working. For example, employees formerly responsible for creating forecasts may devote efforts to increasing the likelihood of outperforming predictions.
- Focus training on complete capabilities usage and conquering the fear-of-the-unknown, boosting buy-in and scale.
- Start small — predictive analytics introduces new levels of technical complexity. Pilot functional solutions with precise predictions and create prediction-informed action plans.
- Orchestrate vendor partnerships enabling both prepackaged and customized approaches. Fuse buy and build tactics to develop in-house skills while increasing predictive maturity and scale. Explore outsourcing for cost-saving opportunities.

Gartner Recommended Reading

Business Drivers Unlock the Power of AI Forecasting

Automate Scenario Planning With AI-Driver-Based Forecasts

Build Your Own AI-Driven Use Cases in Finance

How Leading Finance Organizations Achieve AI Success

Quick Answer: What Is the Difference Between Predictive and Prescriptive Analytics in Finance?

Data Storytelling for Finance

Analysis By: Valeria Di Maso

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Early mainstream

Definition:

Data storytelling is an approach that combines interactive data visualizations with narrative techniques to deliver insights in compelling, easy-to-understand forms. FP&A leaders practice data storytelling by using these techniques to increase their efficacy at guiding discussions, share potential options or prompt actions. Often, analysts develop storylines through analytic frameworks and capture findings in a data-driven, visually enriched narrative.

Why This Is Important

Data storytelling aims to improve partners' understanding of the relationship between business actions and financial results. Decision makers often overlook or selectively use finance insights and struggle to relate functional performance and financial results. Data storytelling enables FP&A teams to weave together descriptive (KPI), diagnostic (driver), predictive (forecast) and prescriptive (guidance) insights, improving stakeholder intuition and decision quality.

Business Impact

When finance reports quantitative data without context, it rarely stimulates data-driven decision making. Presenting data within a narrative stimulates thoughts and emotions that drive partners to decisions. Storytelling helps drive analytics and business intelligence (A&BI) adoption and makes data more intuitive, improves recalls, stimulates debate and urgency to act, and helps build high-performing cultures.

Drivers

- P&L-centered dashboards (especially balanced scorecards) are not the most effective way of delivering data and insights to operational decisions makers. A data storytelling approach, instead, helps finance analytics to present data in a more relevant and actionable format.
- KPIs are not used only as descriptive performance indicators, but support narratives about which key actions can be taken today, to optimize future results.
- Artificial intelligence (AI) and machine learning (ML) advances can detect meaningful patterns in big data better than most humans. Provided with context, these insights stimulate intuition and help driving decisions.
- A wide array of maturing A&BI platforms now include easy-to-use, native functionality to create and share data stories. These stories can take several forms — most frequently natural language generation (NLG), data-connected slideshows or storyboards, annotated dashboards and occasionally more graphic-design-style infographics.
- Machine-generated data storytelling (via applied ML) continues to gain market traction, offering the promise of news-style headlines and narratives generated automatically and tailor-made to individuals. This is almost inevitable as there are not enough human analysts for the analyzable available data.

Obstacles

- Delivering insights within a narrative context increases the responsibility of FP&A teams to improve their business acumen. The use of data storytelling draws from an emerging set of A&BI skills, practices and behaviors about how insights are socialized and used in organizations. Many FP&A teams are still developing these skill sets.
- Data storytelling is a part of a broader movement related to data literacy: the ability to read, write and communicate data in context. Poor data literacy inhibits effective storytelling.
- Machine-generated data stories will not gain traction if they are not consumable, relevant or explainable to the intended recipients. To date, few ML or AI solutions have proven capable of creating analyst-quality finance narratives. What they can do is to point humans toward concepts/POIs that might be overlooked. They also help build more effective data stories — NLG, for example, addresses basic data narratives about the numbers, but struggles with the diagnostic analyses.

User Recommendations

- Experiment with the data storytelling capabilities of A&BI platforms. Examine how the growing portfolio of technologies supports the creation of storyboard-style presentations with embedded analytics.
- Partner with decision makers to specify their business objectives and socialize data sources relevant to decision makers.
- Task FP&A teams with investigating data storytelling as an extension of current interactive visualizations and analytic dashboarding.
- Explore ML and AI limitations in storytelling. Since we are still several years away from using AI as an autonomous storytelling avatar, augmented storytelling — where analysts leverage ML to enrich insights and narratives — is required.
- Prepare programs to develop 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; Outlier; Qlik; Tableau (Narrative Science); Toucan Payments; Yellowfin

Gartner Recommended Reading

Data Storytelling: Analytics Beyond Data Visualizations and Slideshows

Executive Essentials: Master Storytelling to Become More Persuasive and Increase Engagement

Engage and Influence Business Stakeholders Using Data-Enabled Storytelling

Climbing the Slope

Driver-Based Modeling

Analysis By: Clement Christensen

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Driver-based modeling is the identification and quantification of interrelated activities that yield business performance results. Driver-based modeling leverages historical data, but its measurements are not purely historical (descriptive and diagnostic). Rather, when used with predictive or graph analytics — driver-based modeling enables FP&A leaders and teams to contextualize potential business performance results (predictive).

Why This Is Important

FP&A leaders leverage driver-based modeling to measure, predict and contextualize business outcomes. These models incorporate both internal and external operational and financial data to develop deeper, richer and enterprise-aligned insights. Driver-based modeling helps present operationally-aligned, outcome-based stories to decision makers, driving accountability, and avoiding the disadvantages of accounting-based models.

Business Impact

Driver-based modeling includes frameworks of dependent and independent variables to model business outcomes. These models enable FP&A to conduct 'what-if' analysis, explore business assumptions and support self-service environments by showing how operational decisions translate to financial outcomes. Driver-based modeling is also a cornerstone for D&A governance improvements, AI-driven forecasts, and complex scenario modeling.

Drivers

- Increased interest in AI-driven forecasting, graph analytics and improving data environments to support advanced analytics continues to increase mainstream adoption of driver-based modeling.

- Communicating how interrelated business outcomes were achieved and influencing decision makers with insights requires negotiating and defining categories of relevant and actionable value drivers.
- Decision makers continue to ask FP&A to broaden their D&A insights and distinguish real business phenomena from red herrings.
- When markets shift and core business assumptions change, legacy approaches to reporting or forecasting (such as time series or trend analysis) often fall short of business expectations.
- Left unbridled, democratized, self-service analytics may lead to ad hoc, disjointed decision making that impacts business outcomes and financial performance. Driver-based modeling provides a way to create a structure for self-service analytics that is intuitive to end users.
- Digital transformation and market forces are accelerating the need for deeper, richer, more nuanced and connected insights that effectively account for decision, process, outcome interdependencies and spillover effects.
- Developing data-driven cultures requires creating a common language of business drivers and KPIs that improves FP&A leaders' ability to coordinate their team's work and their team's ability to "sell" insights to decision makers.
- FP&A teams often struggle to improve business partnerships and create valuable reports, analysis and insights when their approach is misaligned with business's needs.
- Driver-based modeling establishes a business-oriented foundation for more advanced analytics (such as complex scenario modeling or other AI/DSML modeling) to evolve.
- Improving forecast accuracy often requires triangulation of predictions using multiple approaches to test for sensitivity, validity and relevance. Driver-based models offer alternative forecasting approaches enabling triangulation.

Obstacles

- Driver-based modeling provides flexibility, but requires that the FP&A team have a deep understanding of driver relationships to business outcomes. Extensive alignment between FP&A and business teams is necessary to scope, develop and manage driver models.

- Attempting to develop a driver model at levels of granularity where drivers cease to be valuable or defining drivers at a level that is too broad to be useful. Further, overemphasis on financial drivers (sometimes called “reverse engineering the income statement”) will lower the value of driver-based modeling.
- In reality, not every business unit may need a driver-based model. Where business units are less complex or where drivers (KPIs) are more obvious, driver-based models may not be required.
- Maintaining modeling relevancy in dynamically changing business environments requires a continuous effort by FP&A teams.
- Poor data availability and quality inhibit FP&A’s ability to identify the true drivers behind business outcomes.

User Recommendations

- Create visual, working copies of “driver maps.” Then, offer business outcome owners opportunities to edit the framework.
- Examine enterprise strategies, activities and KPIs that align with decision-maker needs. Do not start by unpacking the P&L or chart of accounts.
- Start driver-based models with “north-star” outcomes. “North-stars” are KPI(s) used by executives or the Board to measure and communicate enterprise value outcomes.
- Leverage your FP&A team’s comparative (knowledge) advantage of strategy, tactics and operations to define the most widely accepted KPIs. Feedback from business outcome owners may come later.
- Refresh driver maps and models periodically to ensure continuing relevance to business and operating realities.
- Implement a variety of analytics, statistics or DSML approaches to define the relevant relationships and interdependencies between drivers and business outcomes.

Gartner Recommended Reading

Driver Mapping: A Cornerstone of Finance Data and Analytics

Business Drivers Unlock the Power of AI Forecasting

Ignition Guide to Developing a Driver-Based Revenue Forecast

Toolkit: Sample Digital Business Model Metric Cascades

Toolkit: Sample Industry Metrics Cascade

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

Finance Data and Analytics Stewardship

Analysis By: Valeria Di Maso

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Early mainstream

Definition:

Finance data and analytics stewardship is the creation, analysis, management and control of finance processes, information and data to enforce governance policies and standards. Information in this context includes finance data, analytics, algorithms, documents, images and metadata — effectively, any and all data assets.

Why This Is Important

Financial planning and analysis (FP&A) leaders can lead stewardship efforts due to their understanding of key financial data and experience as producers and consumers of data. Organizations with established data and analytics (D&A) stewardship practices are better equipped to leverage technology that supports operationalization and automation of governance via AI/machine learning (ML). As FP&A leaders deploy predictive and prescriptive analytics, they must lead enterprisewide data stewardship.

Business Impact

D&A stewardship leads to better governance oversight, accountability and understanding of decision rights relating to D&A across the enterprise and within business areas. This increases the level of business collaboration to engage, facilitate trade-offs, innovate and drive governance to support mission-critical business outcomes. It also leads to better coordination of data governance efforts across the organization.

Drivers

- Most FP&A organizations are deploying advanced analytics, and leaders must recognize that effective D&A governance and advocacy are requisites for success.
- With the emergence of generative AI applications (such as ChatGPT), stewardship is required to ensure proper behavior and trust in how AI is applied in the business.
- Operational support in a day-to-day business context for D&A governance initiatives requires finance data and analytics stewardship.
- Lack of enterprise cohesion in data quality, standards, use and processes lead to decision paralysis and leadership confusion, when data stewardship is missing.
- D&A stewardship's work focuses on problem solving, making it a critical enabler for continuous improvement of strategic D&A programs.

Obstacles

- FP&A leaders have been slow to recognize their responsibility in guiding D&A governance, and have previously thought of this work as solely the domain of IT and chief data officers (CDOs).
- Despite the wider acceptance of information stewardship needs, many organizations have relied on reactive and often heroic efforts of "citizen stewards" to solve data problems. This approach is widespread but insufficient, as it holds back decision making.
- Most organizations are not yet ready to invest the necessary time and money on the right solutions or training their business users to deliver an operational stewardship function. Instead, they are trying to shape D&A stewardship by using a trial-and-error approach before committing to an established discipline.
- Data is power, and it's what gives business unit stakeholders their value to the business. This makes them reluctant to share data with finance.
- Decentralized decision making, based on siloed and shadow data, leads to inefficiencies.

User Recommendations

- Collaborate to create an approach that leverages the existing framework, if stewardship exists in IT.
- Clarify the stewardship process and establish information stewards' reporting lines for consistency with desired business outcomes. IT can execute the instructions and recommendations of stewardship (e.g., data maintenance or policy execution).
- Establish stewardship to guarantee AI's trustworthiness and explainability. .
- Commit to information stewardship that spans multiple business areas, when strategic programs such as MDM or compliance already exist or are underway. Also, identify a lead information steward in finance.
- Build a business case for adopting an enterprise data governance model by demonstrating how it helps deliver on key priorities.
- Ensure to not outsource the work of policy enforcement, due to the lack of context and limited business domain knowledge of the outsourcing partners.

Gartner Recommended Reading

Finance's Role in Enterprise Data Governance: Executive Champion and Lead Steward

Ignition Guide to Creating a Finance Data Governance Policy

Ignition Guide to Building a Data and Analytics Governance Program for Finance

Distilling Data Governance Essentials for FP&A Leaders

Use Value Streams to Create a Common Language for Finance Data Definition Governance

Machine Learning

Analysis By: Shubhangi Vashisth, Peter Krensky

Benefit Rating: Transformational

Market Penetration: 20% to 50% of target audience

Maturity: Mature mainstream

Definition:

Machine learning (ML) is an AI discipline that solves business problems by utilizing statistical models to extract knowledge and patterns from data. The three major approaches that relate to the types of observation provided are supervised learning, where observations contain input/output pairs (also known as "labeled data"); unsupervised learning (where labels are omitted); and reinforcement learning (where evaluations are given of how good or bad a situation is).

Why This Is Important

Over the last few years, ML has gained a lot of traction and is entering mainstream adoption because it helps organizations to make better decisions at scale with the data they have. ML aims to eliminate traditional trial-and-error approaches based on static analysis of data, which are often inaccurate and unreliable, by generalizing knowledge from data.

Business Impact

ML drives improvements and new solutions to business problems across a vast array of business, consumer and social scenarios, such as:

- Credit approval automation
- Price optimization
- Customer engagement
- Supply chain optimization
- Predictive maintenance
- Fraud detection

ML impacts can be explicit or implicit. Explicit impacts result from ML initiatives. Implicit impacts result from products and solutions that you use without realizing they incorporate ML.

Drivers

- Augmentation and automation (of parts) of the ML development process has improved productivity of data scientists and enabled citizen data scientists to make ML pervasive across the enterprise.
- Availability of quality, labeled data is driving ML adoption at enterprises.
- Pretrained ML models are increasingly available through cloud service APIs, often focused on specific domains or industries.
- ML education is becoming a standard at many academic institutions, fueling the supply of talent in this space.
- Active research in the area of ML in different industries and domains is driving applicability far and wide.
- Newer learning techniques — such as zero- or few-shot learning — are emerging, reducing the need to have high volumes of quality training data for ML initiatives, thus lowering the barrier to entry.
- New frontiers are being explored, including federated/collaborative, generative adversarial, transfer, adaptive and self-supervised learning — all aiming to broaden ML adoption.

Obstacles

- Conventional engineering approaches are unable to handle the growing volumes of data, advancements in compute infrastructure and associated complexities.
- ML is not the only popular AI initiative to emerge in the last few years. Organizations also rely on other AI techniques, such as rule-based engines, optimization techniques and physical models, to achieve decision augmentation or automation.
- Organizations still struggle to take their ML models into production. MLOps continues to be a hot trend and organizations look to specialized vendors and service providers for support in their journeys of better operationalizing ML models.
- Application of ML is often oversimplified as just model development. Several dependencies that are overlooked — such as data quality, security, legal compliance, ethical and fair use of data, and serving infrastructure — have to be considered in ML initiatives.

User Recommendations

- Assemble a (virtual) team that prioritizes ML use cases, and establish a governance process to progress the most valuable use cases through to production.
- Utilize packaged applications that fit your use-case requirements to derive superb cost-time-risk trade-offs and significantly lower the skills barrier.
- Explicitly manage MLOps and ModelOps for deploying, integrating, monitoring and scaling analytical, ML and AI models.
- Adjust your data management and information governance strategies to enable your ML team. Data is your unique competitive differentiator, and adequate data quality — such as the representativeness of historical data for current market conditions — is critical for the success of ML.

Sample Vendors

Amazon; ClearML; Databricks; Dataiku; Domino Data Lab; Google; H2O.ai; KNIME; Microsoft; MindsDB

Gartner Recommended Reading

Market Guide for Multipersona Data Science and Machine Learning Platforms

Market Guide for DSML Engineering Platforms

How to Improve the Performance of AI Projects

Infographic: Common Layers of Data Science and Machine Learning Activity

Use Gartner's MLOps Framework to Operationalize Machine Learning Projects

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

Appendixes

See the previous Hype Cycle: Hype Cycle for Finance Analytics, 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

Hype Cycle for Finance Analytics, 2022 - 12 July 2022

Hype Cycle for Financial Analytics, 2021 - 25 August 2021

Recommended by the Author

Some documents may not be available as part of your current Gartner subscription.

Understanding Gartner's Hype Cycles

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

Use Artificial Intelligence to Supercharge Your Finance Staff

Infographic: Artificial Intelligence Use-Case Prism for Finance

How Leading Finance Organizations Achieve AI Success

Table 1: Priority Matrix for Finance Analytics, 2023

Benefit	*Years to Mainstream Adoption*			
↓	***Less Than 2 Years*** ↓	***2 - 5 Years*** ↓	***5 - 10 Years*** ↓	***More Than 10 Years*** ↓
Transformational		Augmented DSML Citizen Data Science Data Literacy Decision Intelligence Generative AI Machine Learning	Composable D&A Natural Language Processing	
High	Cloud Analytics Driver-Based Modeling Finance Predictive Analytics Natural Language Query	Augmented Analytics D&A Governance for Finance Data Storytelling for Finance Embedded Analytics Finance Data and Analytics Stewardship MLOps Prescriptive Analytics	Explainable AI Graph Analytics in Finance	
Moderate		Self-Service Analytics	Analytics Catalog Multiexperience UI	
Low				

Source: Gartner (July 2023)

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