2020 Planning Guide for Business Analytics and Artificial Intelligence

Published 7 October 2019 - ID G00401231 - 45 min read

By Analysts Carlton Sapp, Sumit Agarwal, Joseph Antelmi, Soyeb Barot, Daren Brabham, Jason Lewis

Initiatives: Analytics and BI Solutions for Technical Professionals

In 2020, organizations will demand business analytics and AI capabilities everywhere. Data and analytics technical professionals must understand these trends in order to foster innovation, tackle shifting technologies and create enterprise-grade analytics services.

More on This Topic

This is part of an in-depth collection of research. See the collection:

- 2020 Planning Guide Overview: Building Skills for Digital Transformation

Overview

Key Findings

- The rapid transition to an "infrastructure and applications everywhere" philosophy is driving the need for a connected assortment of distributed intelligence and analytics solution patterns. This transition will enable support for a broader, more complex set of analytics requirements.
- New methods for augmenting analytics with automated machine learning and AI-powered business intelligence will transform analytics initiatives, roles, delivery and operating models.
- Compared with data governance, analytics governance will evolve to focus more on the oversight and validation of analytics use cases. However, verification of analytical output will always focus more on the underlying data.
- Data scientists are spending too much time deploying and managing models, and not enough time creating them. This is a big problem for organizations that desperately desire transformational machine learning development.

Recommendations

To deliver an effective analytics and BI program, data and analytics technical professionals should:

- Architect for a portfolio of connected intelligence and analytics outputs by leveraging and combining the generalized architectural patterns outlined in this research, such as streaming analytics integrated with data science and advanced analytics.
- Shift the focus from getting data in and hoping someone uses it, to embedding analytical functionality into existing applications and integrating them into custom product offerings.
- Drive the organization's existing analytics, data preparation and data science initiatives with an augmented analytics strategy that is powered by AI and machine learning.
- Adopt a decentralized analytics governance model to promote collaboration and collective analysis in siloed data environments.

Business Analytics and Artificial Intelligence Trends

Business analytics and artificial intelligence (BA&AI) capabilities have been catalysts for organizations' competitive advantage. They have widely been used to harvest value — such as improved and optimized decisions — out of large quantities of data. Artificial intelligence (AI) and machine learning (ML) are forms of advanced analytics that have accelerated the ability to harvest value from large quantities of data over a broad set of information sources.

In recent years, much debate has been stirred regarding whether AI and ML have a place within traditional analytics and business intelligence (BI) initiatives. While many feel AI and ML have been exaggerated, more and more organizations are finding that they are powerful tools for:

- Getting more human resources involved in data-driven decision making
- Improving the ability to mine larger quantities of data

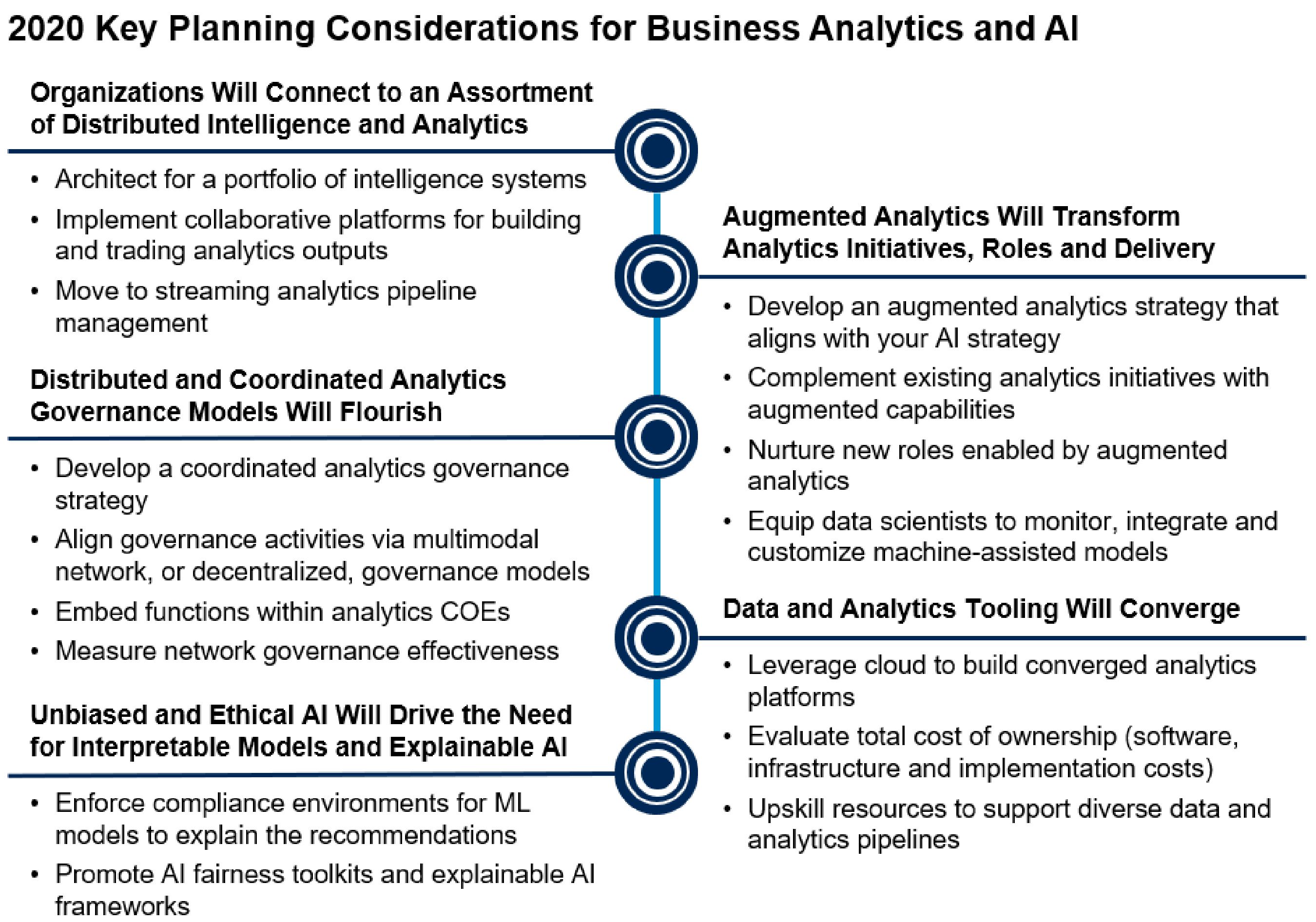
Gartner has long held the position that, if you want to improve the decision-making process or make better decisions in your organization or agency, you need to use analytics and some form of BI and AI. BA&AI is not only about improving performance, but also about accelerating your ability to acquire knowledge.

In fact, thanks to capabilities from AI and ML, advancements in analytics technologies are not trending to replace human resources. Rather, they are accelerating human resources' ability to acquire knowledge and improve productivity. However, more human intervention — coupled with the rapid proliferation of infrastructure and applications with "data everywhere" — means that technical professionals responsible for provisioning analytics must architect for patterns of interconnected sets of analytics outputs.

Therefore, the future of BA&AI will be based on connected intelligence. Connected intelligence is a collection of intelligent and analytical systems related by common management. In connected intelligence, an organization or agency is responsible for multiple analytics systems in multiple phases of development. However, those environments may not be related by common design or data, and they may not necessarily be interconnected operationally.

As a result, the future of BA&AI will be based on trends that focus on connectedness, augmentation, distributed governance and rationalized interpretation of analytics results (see Figure 1).

Figure 1. 2020 Key Planning Considerations for Business Analytics and Artificial Intelligence



Source: Gartner
ID: 401231

Recent trends show that there are three key forces driving the future of BA&AI:

- **Connectedness:** Interconnecting and interoperating various analytics outputs to solve broader, more complex problems
- **Augmentation:** Enhancing the ability to acquire knowledge and improve judgment through AI
- **Knowledge management:** Sharing analytics outputs and contexts

These forces have opened new architectural and design patterns to support the creation of next-generation BA&AI solutions. Table 1 highlights some of the key architectural and design patterns in these new solutions.

Table 1: New Architectural and Design Patterns Enabling Next-Generation BA&AI

Categories Driving the Future of BA&AI	Architectural Pattern	Design Pattern	Value
Connectedness	Graph analytics	Collaboration graph reporting	Knowledge diffusion
Augmentation	Augmented analytics, decision intelligence	Intelligent process automation	Improved automation
Knowledge management	Decision intelligence	Business domain semantic fabric	Improved judgment

Source: Gartner

The new architectural and design patterns outlined in Table 1 come with a shift in practices, operating models and technologies. Therefore, planning considerations for the future of BA&AI must include common management and budgeting, and at least some relationship to mission or business objectives that are resilient to these shifts.

In addition, Gartner clients are at different levels of BA&AI maturity, which is why the planning considerations for 2020 outlined in the research are suitable to different organizational approaches.

New Organizational Approaches

Recent trends show that organizations require more efficient and effective means to develop immersive environments, with different organizational approaches and best practices. Organizations currently develop a vision and ideas for dealing with a variety of BA&AI solutions that look good on paper, but they often have difficulties developing and executing tactical and operational strategies to support the vision.

As a result, in 2020, technical professionals responsible for supporting BA&AI solutions will need to focus on trends affecting organizational approaches, such as:

- Hybrid center of excellence models
- Collaborative operationalization strategies
- New enterprise integration strategies
- Deployment flexibility for diverse BA&AI solutions
- Distributed data management

Data management remains the foundation and enabler of BA&AI. Use of data architectural patterns — such as data marts, data stores or logical data warehouse (LDW) architectures — is still essential to converting and integrating enterprise-specific data and enabling BA&AI. In 2020, however, the focus will shift from collecting and transporting data, to connecting directly to data stored on infrastructure everywhere (see "2020 Planning Guide for Cloud Computing" (https://www.gartner.com/document/code/401229?ref=authbody&refval=3970122)).

The sections below describe the following BA&AI trends, which will broadly affect organizations of many industries, geographies and sizes:

- Organizations will connect to an assortment of distributed intelligence and analytics to support complex decisions.
- Augmented analytics will transform analytics initiatives, roles and delivery.
- Distributed and coordinated governance models will flourish to support the rapid growth of analytics everywhere.
- Data management and analytics technologies will converge and consolidate in support of a more unified platform.
- Unbiased and ethical AI development will advance the need for interpretable models and explainable AI.

The relative importance of each of the trends and its related planning considerations will depend on the maturity of the organization's digital business initiatives, IT-led BA&AI solutions and business-led BA&AI solutions. The Setting Priorities section at the end of this Planning Guide provides additional guidance on how to approach planning:

1. Start building a network of BA&AI solutions
2. Use augmented analytics as a foundational practice
3. Align your governance strategy and operating model with your network of BA&AI solutions

Organizations Will Connect to an Assortment of Distributed Intelligence and Analytics to Support Complex Decisions

Based on Gartner client feedback, BA&AI remains a top concern for business and IT leaders. Analytics is also highly visible in the media because of its impact on business and operational decision making. The diversity of analytics solutions — often in the form of AI and ML — is still increasing, and uncertainty remains about how to effectively manage this diversity and derive value. Smaller analytics projects may have a big fallout, and this risk increases the pressure on analytics teams.

However, a rising number of smaller, distributed analytics projects are emerging throughout many organizations. This trend is forcing technical professionals to manage multiple analytics systems — in multiple phases of development — in order to support more complex decisions.

Such systems may not be related by common design or data, or be interconnected operationally.

As a result, organizations must shift their focus to connecting to an assortment of intelligence and analytics to support more complex decisions. However, this shift requires planning emphasis in areas that are new or significantly enhanced from previous years of BA&AI planning.

Planning Considerations

To prepare for these trends, data and analytics technical professionals should focus on the following planning priorities in 2020:

- Architect for a portfolio of intelligence and analytics systems
- Implement collaborative platforms for building and trading analytics outputs
- Move to streaming analytics pipeline management

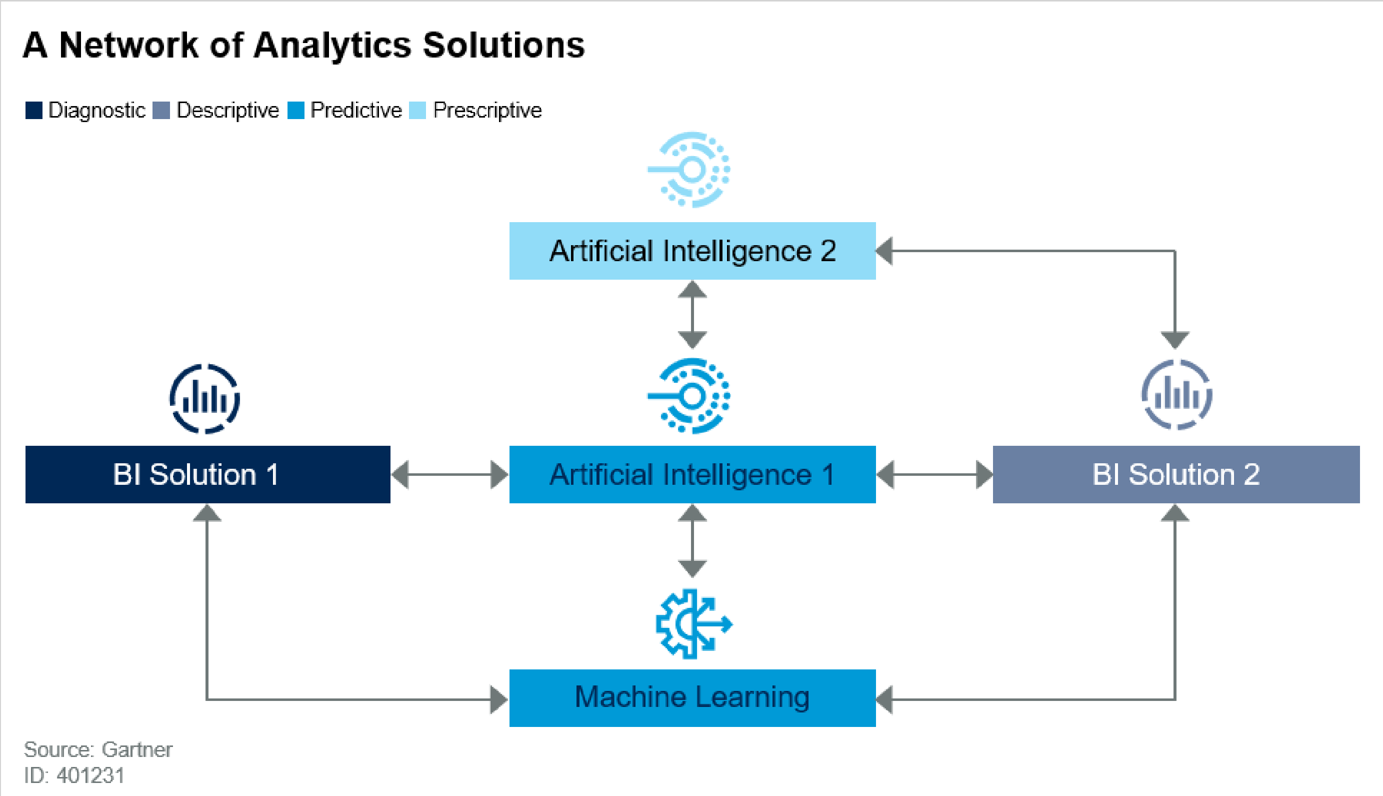
Architect for a Portfolio of Intelligence and Analytics Systems

Architect for an assortment of intelligence and analytics solutions, regardless of where data is stored or where it resides. Data management should remain central to your architecture. However, you must also devote time to the following:

- Specifying how to interconnect different types of analytics solutions (e.g., AI, BI or ML)
- Managing the communications among the solutions

For example, it is common practice to leverage a federated reference model to support different types of BI solutions. However, the federated reference model should be capable of supporting a network of analytics solutions that are linked together to solve a broader objective (see Figure 2). This network includes not only BI solutions sharing information with other BI solutions, but also AI methods informing BI solutions using bidirectional information flows. The link between BI solutions and AI methods is also known as “AI-assisted BI” or “AI-powered BI.”

Figure 2. A Network of Analytics Solutions

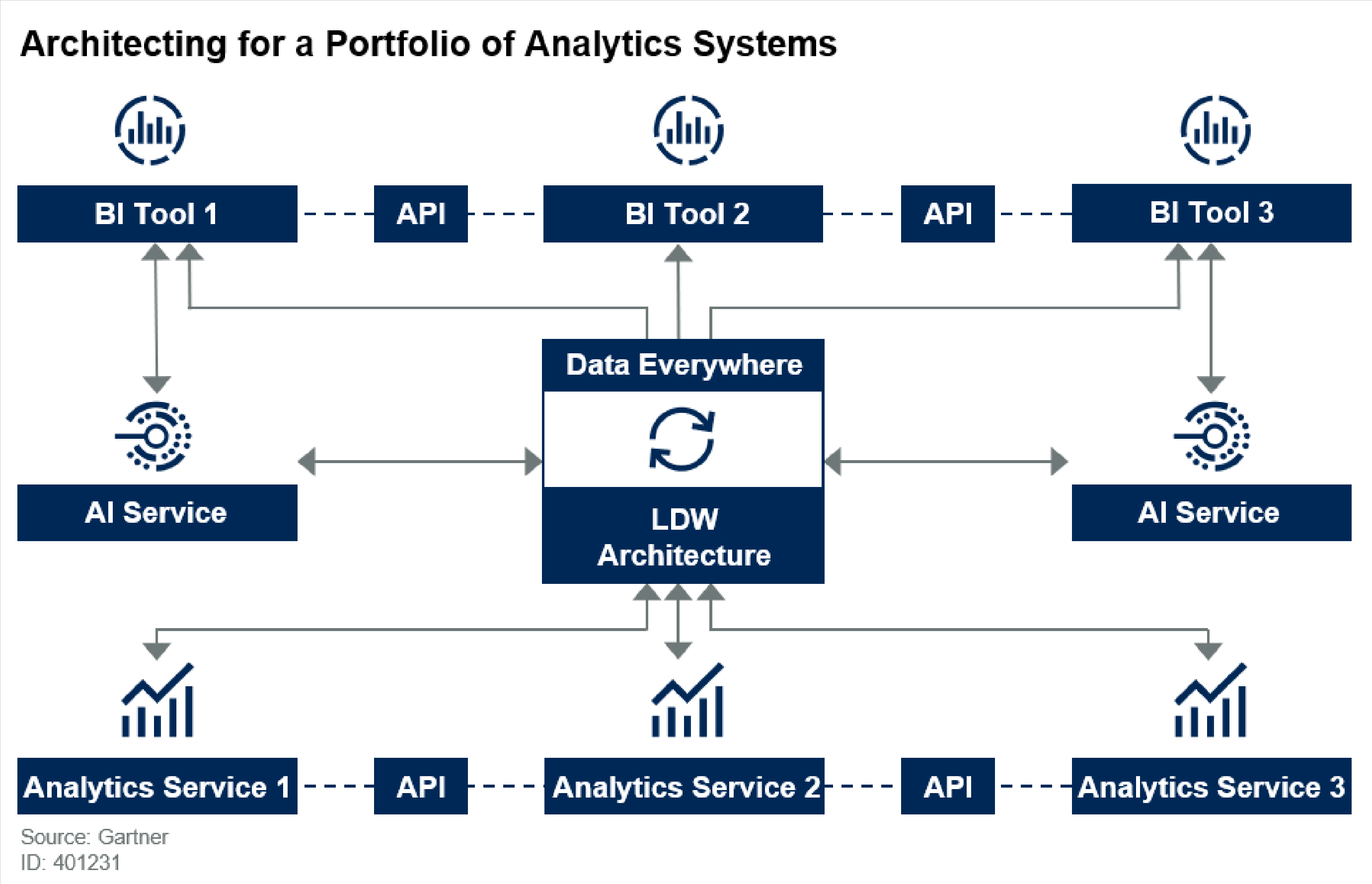


In a portfolio of intelligence and analytics solutions, the architecture is the technical framework that designates:

- The way users will employ the solutions
- The internal and external relationships and dependencies among the constituent solutions
- The end-to-end functionality, data flows and communication among the different solutions

Extend federated implementation models and federated reference architectures for existing analytics systems to include ML capabilities and AI-powered BI. For example, Figure 3 shows a federated BI implementation model updated to include AI and ML services. A federated BI implementation model is a good place to start adding AI-powered services and diverse analytical services that may extend to remote infrastructures or various cloud configurations.

Figure 3. Architecting for a Portfolio of Analytics Systems



For more information, see:

- "Reference Architecture to Enable Real-Time Self-Service Analytics" (https://www.gartner.com/document/code/370032?ref=authbody&refval=3970122)
- "Demystifying the Analytics and BI Space" (https://www.gartner.com/document/code/377817?ref=authbody&refval=3970122)
- "The Evolving Capabilities of Analytics and Business Intelligence Platforms" (https://www.gartner.com/document/code/353081?ref=authbody&refval=3970122)

Implement Collaborative Platforms for Building and Trading Analytics Outputs

Managing and maintaining multiple analytics platforms is a time-consuming process that requires significant overhead, and it doesn't always scale well for technical professionals as new user requirements and technology capabilities emerge. To reduce overhead and gain economies of scale, technical professionals must place more emphasis on unifying analytics platforms and on promoting reuse and sharing of analytics outputs.

Pay specific attention to users who request to share their analytics outputs or findings with other users who leverage different analytics platforms. This is a growing trend because the domain expertise is embedded into the analytics output. Traditionally, users would integrate data first and then apply business logic on that integrated data. In this new paradigm, however, the analysis is performed before any significant integration occurs. The shift from data integration to analytics integration reduces data management overhead. This approach is not ideal in all use cases, and it does not eliminate the need for a solid data integration strategy. However, there is value in embedding domain knowledge into the analysis, and in sharing the output of that analysis with other forms of analysis from various business domains.

Good practices for implementing collaborative platforms to build and trade analytics outputs include:

- Manage the integration of analytics output — not just the integration of data — by promoting the distinction between the following:
  - Data integration in support of generalized analytics services
  - Analytics integration with embedded domain knowledge in support of broader, more complex decision making

  For example, a financial analyst may share his or her analysis of financial worthiness with an operational analyst evaluating the usage of goods or services provided.

- Build connections between diverse forms of analytics output. For example, provide the capability to seamlessly connect ML predictions to existing BI dashboards.
- Generate an analytics distribution platform that allows users to browse and obtain various forms of analytics outputs to support their decision-making processes.

Move to Streaming Analytics Pipeline Management

> **In a connected intelligence architecture, streaming analytics will become the center of analysis between various analytics solutions.**

The market for streaming analytics (SA) is rapidly growing, due to the increasing need for continuous intelligence, better situational awareness, and faster, more precise business decisions using streams of data (see "Market Guide for Event Stream Processing." (https://www.gartner.com/document/code/367575?ref=authbody&refval=3970122)) Cloud-based SA is a buying trend that is seeing massive growth, and that growth is expected to continue as more data becomes available from sensors and Internet of Things (IoT) endpoints.

Organizations are adopting more cloud-based SA, and therefore, cloud-based SA has become a critical component of data pipeline management. General SA can be a complex and nontrivial undertaking, causing many organizations to forgo investments in real-time SA. However, the complexity has been significantly reduced thanks to the maturity of cloud-based SA services, making them a formidable option for supporting analytics on streams of data (i.e., data in motion).

Good practices for enabling streaming analytics pipeline management include:

- Leveraging stream processing frameworks that support real-time and batch analytics
- Provisioning IoT analytics, from edge to enterprise
- Leveraging cloud service providers and managed infrastructure to support streaming analytics pipelines

For more information, see:

- "Hyperscaling Streaming Analytics: Comparing Stream Analytics in the Cloud With Amazon, IBM and Microsoft" (https://www.gartner.com/document/code/365934?ref=authbody&refval=3970122)
- "Deploying IoT Analytics, From Edge to Enterprise" (https://www.gartner.com/document/code/365936?ref=authbody&refval=3970122)

Augmented Analytics Will Transform Analytics Initiatives, Roles and Delivery

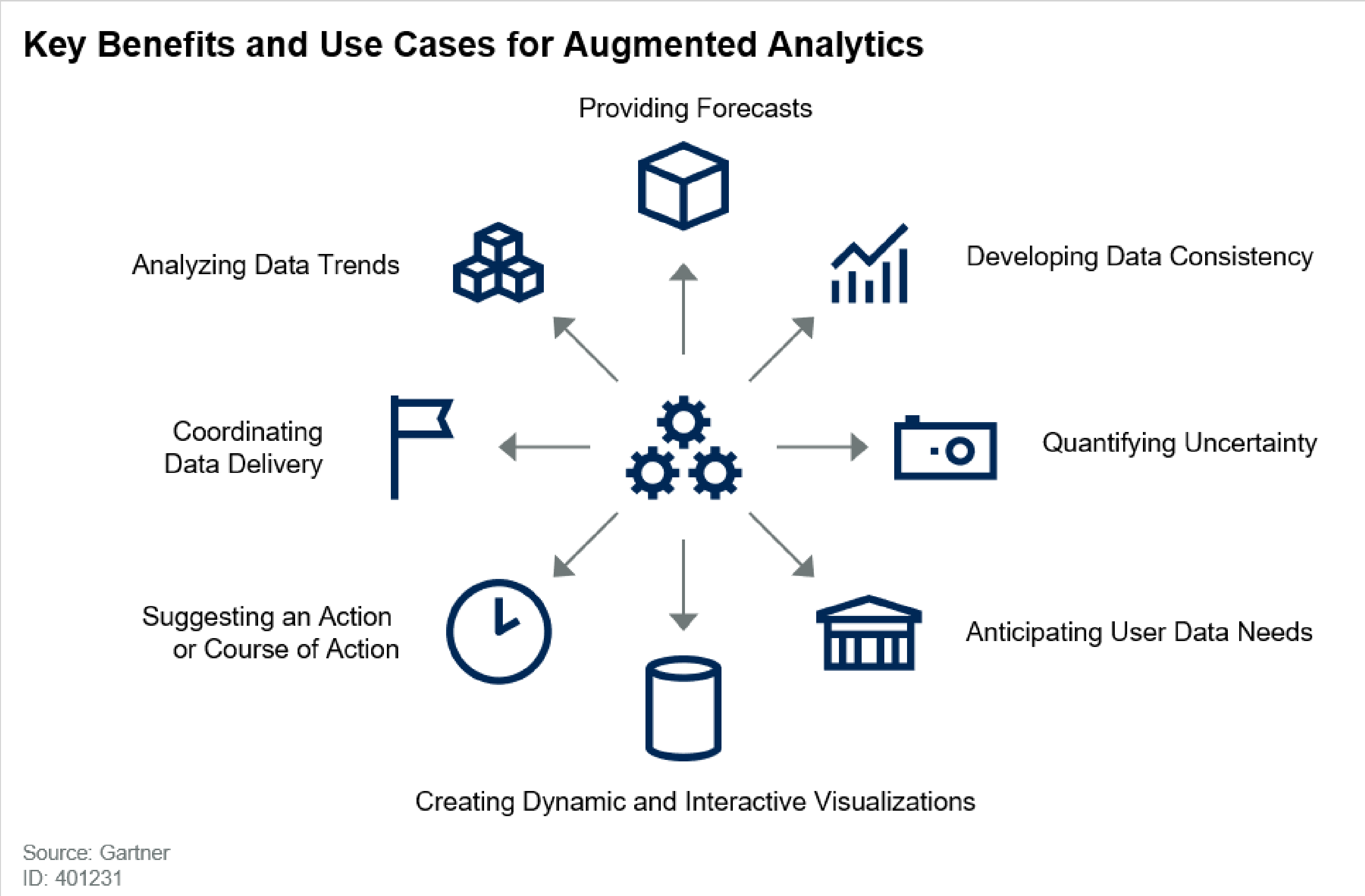
Data and analytics technical professionals have long coped with manual, time-intensive IT processes. Preparing data, authoring analytics content, and training and deploying ML models all require significant time and effort. Challenges are legion:

- Organizations still suffer through extraction, transformation and loading (ETL)/data refresh timelines spanning many hours. A "nightly" refresh is no longer possible if the data refresh takes 18 to 20 hours. This remains a stubborn stumbling block for organizations using traditional ETL processes and tools.
- Tepid self-service analytics adoption has inhibited economies of scale in the analytics authoring process. Technical professionals continue to author BI content on behalf of the organization using modern BI platforms, rather than supporting self-service content authoring on those same modern BI platforms.
- In many organizations, data scientists are spending so much time trying to get their models into production that their leadership, in desperation, has set a simple goal: "Get my data scientists to do more data science and less IT operations."

Augmented analytics has emerged as a discipline and set of product capabilities that promise to replace manual, repetitive and error-prone processes with more automated and intelligent systems. These automated and intelligent systems utilize a combination of ML, other advanced algorithms and humans in the loop to train machines to handle tasks more quickly and efficiently in the analytics space.

Figure 4 summarizes some of the key benefits that can be achieved through augmented analytics.

Figure 4. Key Benefits and Use Cases for Augmented Analytics



Augmented analytics combines ML and AI techniques with other advanced algorithms and statistical functions to transform data management, analytics and BI — as well as many aspects of data science and AI/ML model development and consumption. In doing so, it represents the extension of augmented intelligence. Augmented intelligence uses AI/ML techniques to either supplement humans with new capabilities or assist them with tasks that they know how to complete (but that are difficult, time-consuming or repetitive). Within this context, augmented analytics helps humans discover unknowns and novel insights.

This technology has a revolutionary potential, but it comes with some significant challenges:

- These functions still require domain knowledge and subject matter expertise to ensure that their recommendations align with business problems and goals.
- These functions require humans in the loop to train systems and to ensure that the generated outcomes are valid.

- These functions, which by their nature require large amounts of data, can strain existing governance structures.
- These functions are often misunderstood, leading organizations to put either too much faith in augmented analytics technology or too little.

In order to utilize augmented analytics to its full potential, organizations will have to implement changes to their initiatives, roles and technology.

Planning Considerations

To prepare for these trends, data and analytics technical professionals should focus on the following planning priorities in 2020:

- Develop and adopt an augmented analytics strategy that aligns with your AI strategy
- Complement existing analytics initiatives with augmented capabilities
- Nurture new roles empowered by augmented analytics
- Equip expert and citizen data scientists to monitor, integrate and customize machine-assisted models

Develop and Adopt an Augmented Analytics Strategy That Aligns With Your AI Strategy

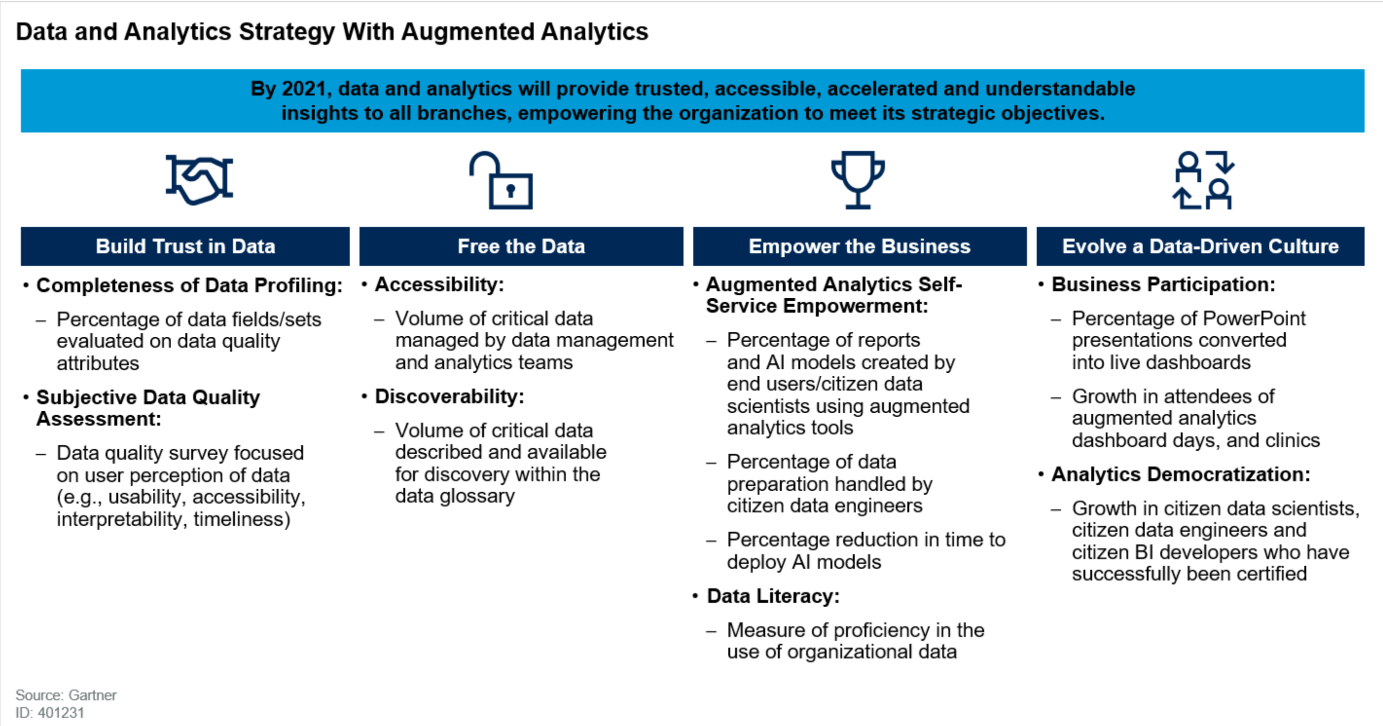
One of the problems with augmented analytics is that it is very technology-driven. As a result, organizations often overlook what exactly they are seeking to achieve. It is therefore imperative that technical professionals develop and adopt principles that go beyond licensing or buying augmented analytics tools.

The pillars of strategy are well known. A good strategy should align the following:

- Objectives/mission
- Tactics
- Metrics
- Governance
- People
- Process
- Technology

In particular, one aspect that is often missing from an analytics strategy is a set of measurable metrics of success. See Figure 5 for an example of a data and analytics strategy that rolls up with supporting metrics.

Figure 5. Data and Analytics Strategy That Includes Augmented Analytics



When you are building an analytics strategy, it is a good idea to have top-level goals that are supported by the overall architecture. The example in Figure 5 will help your organization prioritize augmented analytics investments, especially in the realm of business empowerment and an evolving, data-driven culture.

Complement Existing Analytics Initiatives With Augmented Capabilities

AI is not meant to work in isolation; instead, analytics will be embedded everywhere. As a result, organizations should look to integrate augmented analytics into existing objectives and processes. For instance, in the Figure 5 example above, the organization emphasized self-service BI, self-service data preparation, and more successful and rapid operationalization of ML models. Such metrics will help organizations prioritize investments in augmented analytics capabilities. Three possible areas of investment include:

- **Augmented data preparation:** Data engineers, data scientists and end users all spend a large portion of their time preparing data for analysis. Augmented data preparation:
  - Delivers capabilities for automatic data profiling, data quality and data harmonization
  - Delivers AI-assisted data modeling, manipulation, enrichment and inference
  - Uses AI/ML techniques to develop metadata and create data catalogs
  - Assists with data integration and database/data lake administration

- **Augmented data science and machine learning (AutoML):** Data scientists and ML architects often struggle to build models that are ready for production. AutoML assists with key steps in the development and maintenance of ML models (see “Augment Data Science Initiatives With AutoML” (https://www.gartner.com/document/code/389992?ref=authbody&refval=3970122)). In this application, AutoML is used to facilitate:
  - Feature engineering and model selection
  - Model operationalization
  - Model explanation
  - Model tuning and management
- **Augmented BA&AI:** End users face challenges when attempting to analyze data quickly and efficiently. Augmented BA&AI provides end users and citizen data scientists with the ability to:
  - Automatically identify, visualize and narrate relevant findings in data
  - Explore data using natural language queries, chatbots and voice
  - Identify correlations, clusters, exceptions and predictions, without having to have a background in data science

Nurture New Roles Empowered by Augmented Analytics

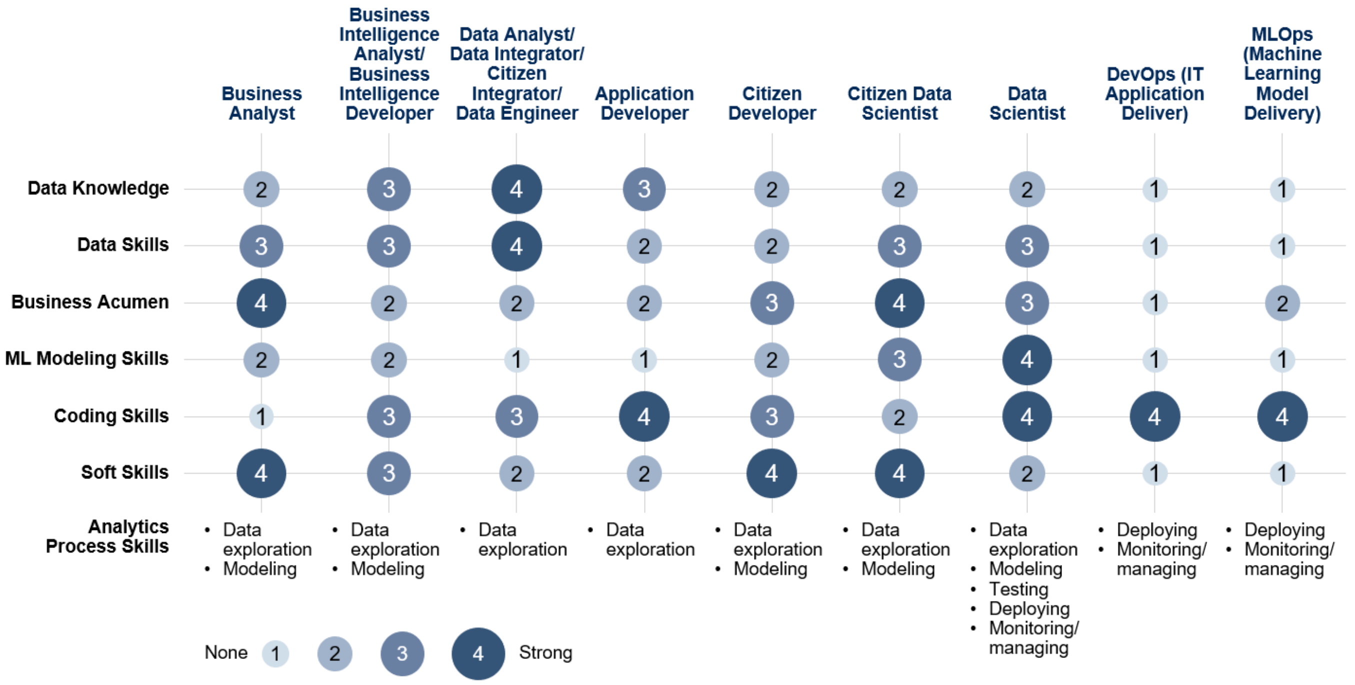
The growing augmented analytics capabilities of many leading BA&AI tools provide fertile ground for organizations hoping to cultivate new roles in advanced analytics. The citizen data scientist role has evolved in recent years, as advanced business analysts have ramped up their coding and ML modeling skills. The citizen data scientist combines:

- A business analyst’s soft skills, business acumen and subject matter expertise in a business domain
- Some introductory and intermediate-level data and technical skills common among expert data scientists

The citizen data scientist is not a specific job title itself. Rather, it exists alongside other well-defined roles in an analytics continuum (see Figure 6). Each role in this continuum owns its own mosaic of core skills.

Figure 6. Continuum of Analytics Roles and Skills

Continuum of Analytics Roles and Skills



Source: Gartner
ID: 401231

Other emerging roles in this continuum include:

- Data engineers, who assist in the preparation and exploration of data for inclusion in analyses
- Application developers, who are keen on integrating ML capabilities into the apps they build for the organization

Organizations are finding that the traditional, typical pathways to professional development are helpful for upskilling analysts into citizen data scientist roles. These include:

- Books, YouTube channels and blogs
- Free and low-cost online training courses
- Peer learning and knowledge sharing
- Face-to-face meet-up groups, online communities and discussion forums
- Formal academic programs, certificates and boot camps

Increasingly, however, the augmented analytics capabilities in BA&AI tools also provide a convenient training ground for analysts to upskill into expanded roles such as data engineers and citizen data scientists. Organizations may already have powerful, modern BA&AI tools in place — as well as a robust cohort of analysts using them to prepare data, author reports and create dashboards. Such organizations should encourage deeper engagement with the more advanced augmented analytics features offered by these tools. This provides a convenient entry point for the citizen data scientist's development.

Equip Expert and Citizen Data Scientists to Monitor, Integrate and Customize Machine-Assisted Models

It is important to build a data architecture that provides your expert data scientists and citizen data scientists with the following:

- Access to the raw data with which to build original models
- The ability to manage machine-assisted models

AI transparency and explainability must be priorities for your augmented analytics investments. These tools should offer multiple ways to visualize the underlying algorithms and datasets, as well as the paths to insight. Select tools that expose, rather than obfuscate, the underlying data. Such exposure can provide:

- A deeper understanding of what models are truly doing with data
- An opportunity for analysts to "learn by doing"
- The foundation for ethical decision making with data

Empower your expert data scientists and citizen data scientists with the ability to monitor and customize machine-assisted models. Develop a plan that involves integrating outsourced, crowdsourced and third-party models, where appropriate, to balance achievement against effort. Operating with black-box models does little to build an always-improving data science team. Maintain control over these processes for maximum effectiveness in the long term. Appropriate governance standards — striking a balance between control and freedom — go a long way toward achieving this objective.

Distributed and Coordinated Governance Models Will Flourish to Support the Rapid Growth of Analytics Everywhere

Traditionally, organizations with a formal information governance strategy tended to follow a command-and-control model designed to achieve compliance with established privacy and regulatory requirements. This approach worked well when IT managed and prepared data for consumption through specific applications and within tightly controlled delivery mechanisms.

However, the demand for AI and self-service analytics has challenged this top-down model. As analytics has become more distributed, coordinating governance across organizational boundaries has become more complex. With the data sources for analytics increasingly residing outside of the analytics group's or the organization's control, it is becoming more important to assert just enough governance over all sources of analytics data to enable new and existing use cases.

Achieving analytics everywhere requires a new distributed and coordinated decision-making framework that supports rapid analytics governance, regardless of organizational and technological boundaries.

Planning Considerations

In 2020, technical professionals can expect even more emphasis on analytics as it is embraced throughout the enterprise. Data-derived insights will supplant experience and intuition, and organizations will eagerly consume analytics from across the enterprise, distributing decision making to individuals newly empowered by that data. To be successful, IT organizations must:

- Develop a coordinated data and analytics governance strategy
- Align governance activities by leveraging multimodal network, or decentralized, governance models
- Embed functions within analytics centers of excellence
- Measure network governance effectiveness

Develop a Coordinated Data and Analytics Governance Strategy

With the rapid adoption of self-service data integration, data science and BA&AI, coordinating a data and analytics governance strategy has become more difficult. A range of factors increase the complexity, including the following:

- Nontechnical users are adopting self-service tools.
- Data consumers may be in different business units or organizations.
- Exploration and discovery may be at odds with security and privacy controls.
- Machine augmentation means that humans aren't involved in automated processes.
- New strategies are required for governing ML models.

Policies that address confidentiality and security need to ensure that information is used appropriately and legally; is protected and used only by those who are sanctioned; and is handled in accordance with its value and sensitivity. Typically, these types of policies cover:

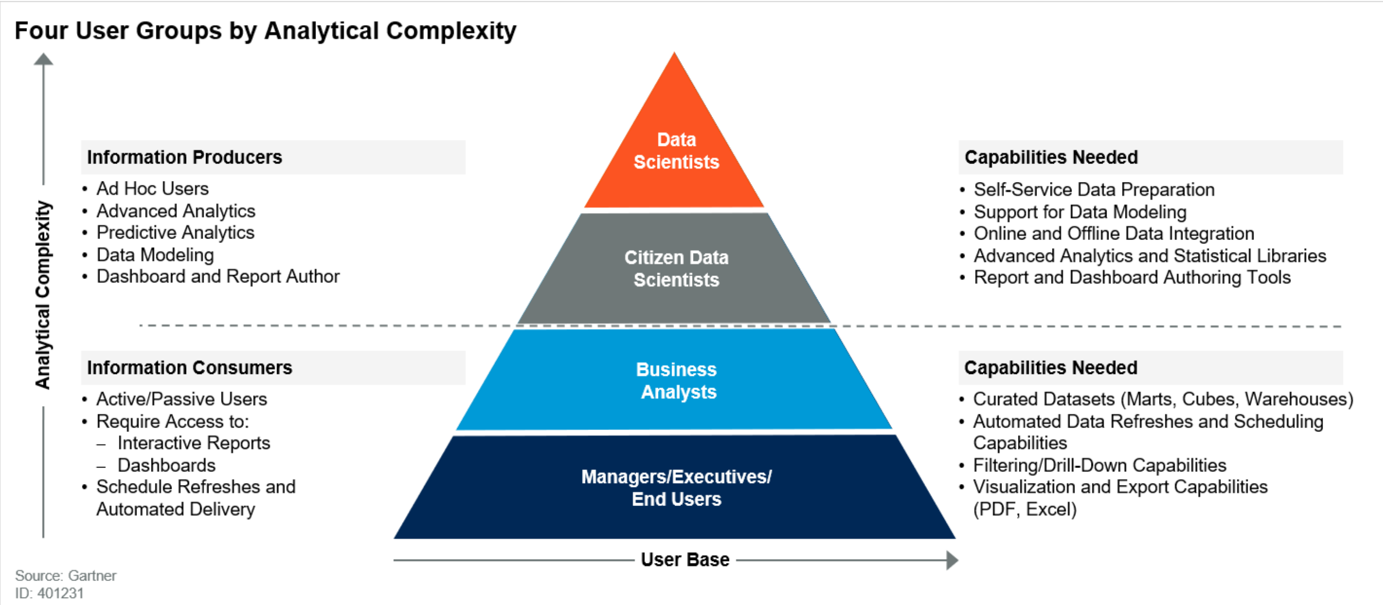
- **Privacy:** Various information assets, particularly those holding personally identifiable information (PII), must be treated with care to avoid exposing sensitive data. Policies for information privacy specify requirements for anonymizing such data.
- **Sensitivity:** Not all information in the enterprise warrants the same level of sensitivity; organizations must treat some categories of information differently from others. Information is categorized in accordance with its sensitivity. This type of policy mandates the need to

make decisions based on the use of information assets, so that the right level of control, access and risk management can be applied.

- **Security:** Access rights to information assets are crucial for minimizing risk. Information security policies focus on who and what can access information. Clear mandates for segregation of duties and the principle of least privilege are included in such policies.

A distributed governance framework must also consider different user categories and the relative complexity of the analytical task (see Figure 7). This segmentation allows the technical professional to extend just enough governance to ensure compliance without hindering the execution. The role of the technical professional is to ensure that security controls extend to tools, data sources and access mechanisms, so that different user groups can accomplish their tasks within the boundaries of governance. (For more information, see "Reference Architecture to Enable Real-Time Self-Service Analytics." (https://www.gartner.com/document/code/370032?ref=authbody&refval=3970122))

Figure 7. Four User Groups by Analytical Complexity



Modern governance practices expedite analytics by removing barriers to exploration and innovation and adapting to the business context. By distributing decision making to skilled workers with data and subject matter expertise, modern governance practices provide users with guidance and context to assist analytics execution within formal governance boundaries. This allows for command and control, as well as trust-based approaches that rely on curation, lineage and certification.

Two key steps that accompany the development of a data and analytics governance strategy are:

- Implementing data curation techniques and tools to support governed self-service analytics
- Deploying machine learning models within the governance framework

Implementing Data Curation Techniques and Tools to Support Governed Self-Service Analytics

Data curation techniques and tools enable business users to discover and analyze data in terms they already understand — i.e., business terms. For example, data catalogs make data more accessible by describing and classifying information in a business-oriented manner. As users search, discover and interact with data, catalogs allow users to further enrich the data by adding their own descriptions and interpretations of it.

Leverage data catalogs to extend governance awareness by classifying and tagging data for self-service consumption. Data catalogs have now become foundational components for self-service analytics and data governance and compliance (see "Building a Comprehensive Data Governance Program." (https://www.gartner.com/document/code/377901?ref=authbody&refval=3970122))

Self-service data preparation and profiling tools provide preprocessing capabilities that empower citizen users to merge data from different sources. Users can then explore, shape, transform, clean and sample that data into curated datasets for self-service data integration, data science and BA&AI. Some data preparation tools embed machine learning to reduce or automate time-consuming tasks (see "Demystifying the Analytics and BI Space" (https://www.gartner.com/document/code/377817?ref=authbody&refval=3970122)). Organizations must incorporate self-service use cases into their governance frameworks. First, they need to account for access to sensitive data sources, as well as the implications of combining nonsensitive data. Then, they need to extend the governance framework by creating sensitive categories of data, such as PII.

Deploying Machine Learning Models Within the Governance Framework

Our clients indicate that they struggle to take data science projects from prototyping to production, and we've provided guidance in "Building a Framework for Managing Effective Machine Learning Workloads." (https://www.gartner.com/document/code/384678?ref=authbody&refval=3970122)

As ML workloads move to production, technical professionals can't afford to neglect business rules pertaining to proper information governance. Part of the continuous monitoring and validation of ML models should be to incorporate adherence to governance frameworks. Data and analytics technical professionals should:

- Incorporate governance rules into each stage of the process: build, train, deploy and monitor
- Catalog data provenance for ML models
- Audit logs and outputs for critical indicators of governance risks

Additionally, data and analytics technical professionals can work with data scientists, developers and engineers to extend governance into automated delivery pipelines by:

- Building and maintaining self-provisionable solution stacks (e.g., preset build environments)

- Identifying standard platforms, networks and hardware that are approved for inclusion as part of any solution stack (e.g., to satisfy architecture quality requirements and security controls)
- Coding desired nonfunctional requirements and controls into environment configuration artifacts, and collectively verifying that artifacts satisfactorily capture requirements
- Creating a build portal so that developers can self-provision infrastructure for a compliant, continuous integration (CI) build environment

Align Governance Activities by Leveraging Multimodal Network, or Decentralized, Governance Models

Network governance models, aka decentralized governance models, coordinate complex activity through an informal social system, rather than through a formal bureaucratic system. Here, we apply this concept to distributed decision making in enterprise information governance. The key characteristics of the network governance model include:

- **Interdependence and collaboration:** Network participants are interdependent and work collaboratively to achieve a desired business outcome.
- **Distributed decision making:** Participants consider governance policies, mandates and accountability for compliance within each business context.
- **Trust-based compliance:** Participants are trusted to comply with the governance framework, and governance is achieved through self-constituted rules and norms.

By evolving the top-down governance model to incorporate the benefits of a network governance approach, organizations will have more agility to adopt augmented analytics and embrace self-service models.

Such an approach is “adaptive” because it allows for different governance styles based on the method that will deliver the required business outcomes in a given context. Gartner observes the following governance styles:

- **Control-based:** Makes decisions according to rules, policies, standards, directives and compliance requirements from regulators. This strategy remains a foundation of, and an anchor for, governance of the enterprise.
- **Outcome-based:** Achieves business outcomes while balancing risk, performance and return on investment within the enterprise guardrails.
- **Agility-based:** Empowers roles and teams with the authority to make distributed or mandated decisions that create value for the business. This strategy relies on people’s competencies, principles, attitudes and ways of working, rather than on authority and rules.

- **Autonomy-based:** Drives value and manages risk from decisions made in real time by people and things. For example, this strategy applies to governing algorithmic machine-to-machine decisions and providing decision support in machine-to-human interactions.

Technical professionals can help their organizations mitigate security and architectural risks by taking the following steps toward adaptive governance:

- **Triage** governance involvement to reduce the governance burden for low-risk initiatives
- **Delegate** governance to improve teams' ability to self-serve
- **Coordinate** governance functions to improve ease and speed of engagement
- **Automate** governance within the build environment

Utilizing a combination of governance styles requires careful coordination and communication between groups, and represents trade-offs. Technical professionals should work with business stakeholders to formulate new adaptive governance models that can extend analytics into emerging self-service use cases.

Embed Functions Within Analytics Centers of Excellence

The insertion of ML-enabled analytics within lines of business has significantly changed traditional BI practices. Data scientists, and even citizen data scientists, use ML platforms to develop and deploy their own AI-based solutions that provide key insights. Most of these platforms support tasks across the entire data and analytics pipeline, thereby supporting the entire ML development life cycle (see "Building a Comprehensive Data Governance Program" (https://www.gartner.com/document/code/377901?ref=authbody&refval=3970122)).

The mandate to deploy AI and ML technologies typically starts at the board level and then filters down the organization, often without identifying business objectives. Technical professionals can help make these deployments more effective by developing the foundational components needed to support AI and ML in the enterprise. For more information, see "Laying the Foundation for Artificial Intelligence and Machine Learning: A Gartner Trend Insight Report." (https://www.gartner.com/document/code/373110?ref=authbody&refval=3970122)

Technical professionals should focus the scarcest skills — those of data scientists — into a center of excellence (COE) in order to achieve critical mass. Data scientists should have dotted-line reporting to lines of business. By being closer to the consumers of analytics, the data scientists can understand requirements better. They will also be in a better position to ensure a smooth handoff of their models.

The COE model balances oversight — i.e., governance, tool selection and management, and methodology — with accountability to the business unit. The COE structure for analytics is well-suited to the needs of the data-driven organization. It prioritizes a centralized strategy, methodology and technology investment while allowing for decentralized execution.

Measure Network Governance Effectiveness

Technical professionals are uniquely positioned to help their organizations identify and remediate performance problems within their information governance programs. Technical professionals deploy the tools and technologies that provide access to data and generate analytical insights. They are often the first line of defense when it comes to identifying security and privacy issues related to data and analytics.

Technical professionals should work with business stakeholders and governance committees to:

- Shortlist the data and analytics key performance indicators (KPIs) and key risk indicators (KRIs) that are most impactful to the business process identified
- Identify and inventory compliance issues arising from self-service use cases
- Analyze and document the current condition and use of data and analytics assets, and their dissonance with the specific needs of business process owners
- Highlight business requirements that don't align with established governance models, and adapt those models to changing circumstances

Data Management and Analytics Technologies Will Converge and Consolidate in Support of a More Unified Platform

AI has introduced a completely new operating paradigm of augmenting humans across all verticals — manufacturing, finance, healthcare, insurance and supply chains. The ultimate goal of leveraging cognitive computing is to build intelligent business systems that simulate human decision making in real time. The best way to achieve that is to embed AI-based systems within business applications, creating a connected intelligence environment and making ML and AI decision making part of the culture and DNA of the organization.

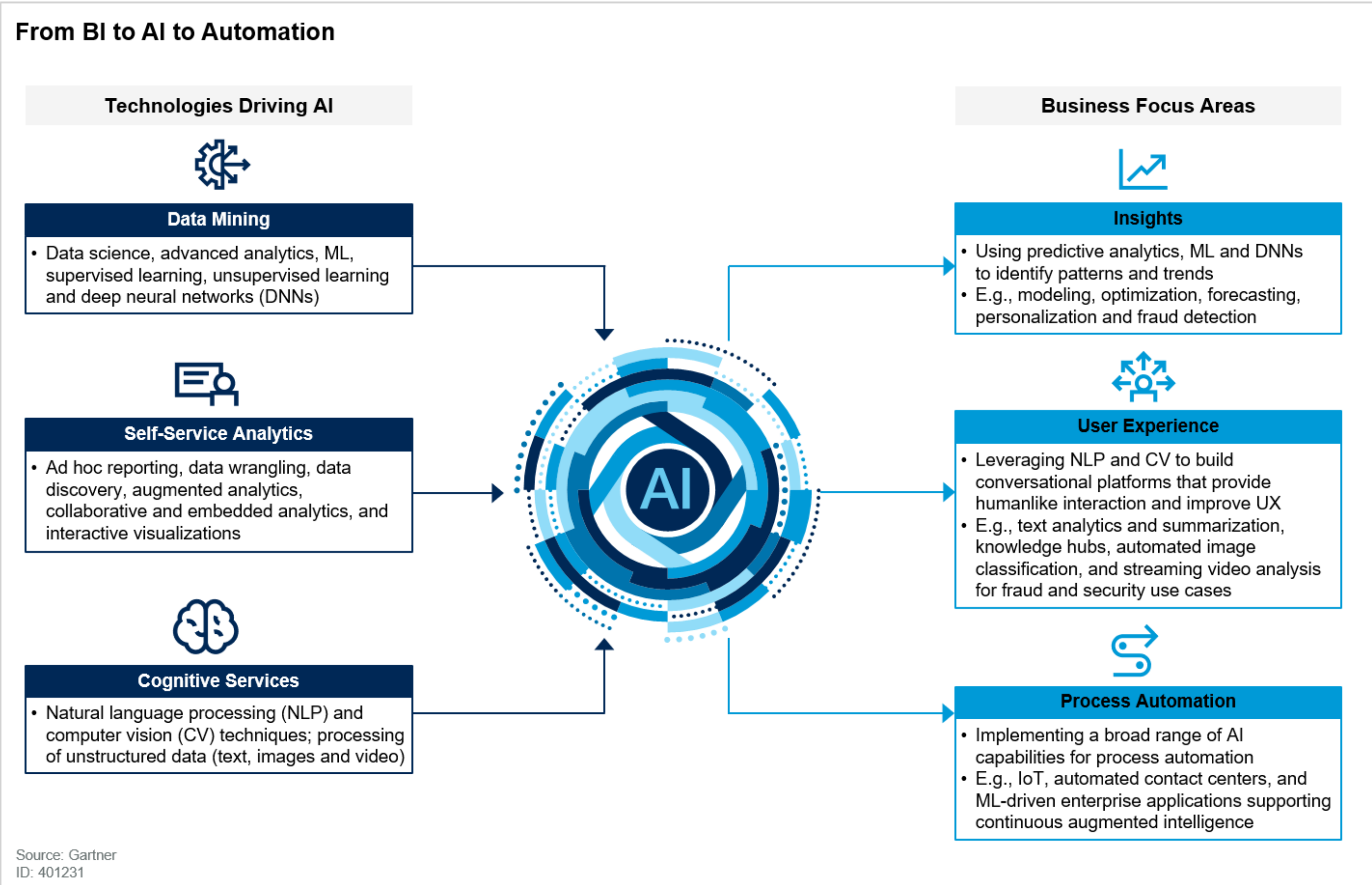
To address business challenges via ML and AI, organizations have deployed a wide range of technologies, which have grown sporadically across various business domains based on adoption and maturity. However, to gain the most business impact, organizations need a strategic vision and a technical implementation strategy. They need to build a consolidation and rationalization strategy that brings together disparate ML and AI implementations and productizes the capabilities for scaling.

> **Today more than ever, the traditional boundaries between data management, analytics, ML, business intelligence and AI are disappearing.**

Organizations have always looked at technologies as a way to drive three key initiatives: gaining insights, improving the user experience and automating processes. This true of AI adoption, which is driving demand for unified platforms that address business use cases. In 2020, the market and vendors will start to build a more unified platform — with data management, advanced analytics, ML and AI as foundational components — and move toward delivering intelligent systems.

To support the business focus areas shown in Figure 8, organizations need to bring together capabilities that facilitate data processing and analysis, such as data mining, self-service analytics and cognitive services. This need is driving the convergence of data and analytics tools.

Figure 8. From Business Intelligence to Artificial Intelligence to Automation



Converging analytics, business intelligence, ML and AI capabilities on a single platform overcomes the challenges caused by using separate systems, and dramatically improves agility and productivity. It also creates opportunities for enhanced, well-integrated applications. Convergence is best achieved by enabling a diversified set of roles — data scientists, citizen data scientists, corporate developers and business users — to utilize a single platform delivering high-performance intelligent systems.

A converged data and analytics platform enables data scientists to operate directly on the original data, wrangle it and share the results directly with business users. Eliminating boundaries between data science and BI domains makes it easier to productize and scale AI-based systems. Many vendors are introducing new features and capabilities to address gaps within incumbent platforms, allowing them to provide end users with new capabilities to scale and manage AI workloads. These changes will deliver benefits such as agility, persistence, low-latency response times and faster retraining of the ML models at the heart of AI-based systems.

You don't have to compromise on gaining the benefits of a modular architecture when you unite best-of-breed services on a general-purpose platform. The advantage of a converged architecture is that the chance of gaining the promised benefits should be higher. For example, having a converged architecture enables everyone on your team to work in a collaborative fashion, improving data quality and categorization and ensuring that your view of your data is accurate and complete. Additionally, by merging data into a centralized repository like an LDW, you can capture a record-by-record-level view of data as it changes, building lineage. The result is gaining a holistic view of your data, instead of worrying about data and analytics silos.

Planning Considerations

In 2020, data and analytics technical professionals can expect even more emphasis on building unified platforms that support analytics, data science and ML, as organizations embrace AI. The expansion from human-centric interaction to machine-driven automation — and building augmented business processes — will have a profound impact on how organizations architect analytics solutions.

Related planning considerations for technical professionals in 2020 include the need to:

- Leverage cloud to build converged analytics platforms
- Evaluate total cost of ownership (TCO), including software, infrastructure and implementation costs
- Upskill existing resources to support diverse data and analytics pipelines

Leverage Cloud to Build Converged Analytic Platforms

Instead of using traditional implementation paradigms in which batch, transactional and streaming analysis are all separated, a converged architecture helps employ all or parts of your data analysis and ML pipeline into a single, scalable platform. A suitable IT infrastructure is a key to successfully preparing the various steps of analytics — collect, transform, analyze, build models and integrate — for the journey to automation. Cloud provides the set of infrastructure services, massive storage and network infrastructure required to scale the architecture, alongside a unified platform to manage the underlying data for sharing, reusability, analysis and retention.

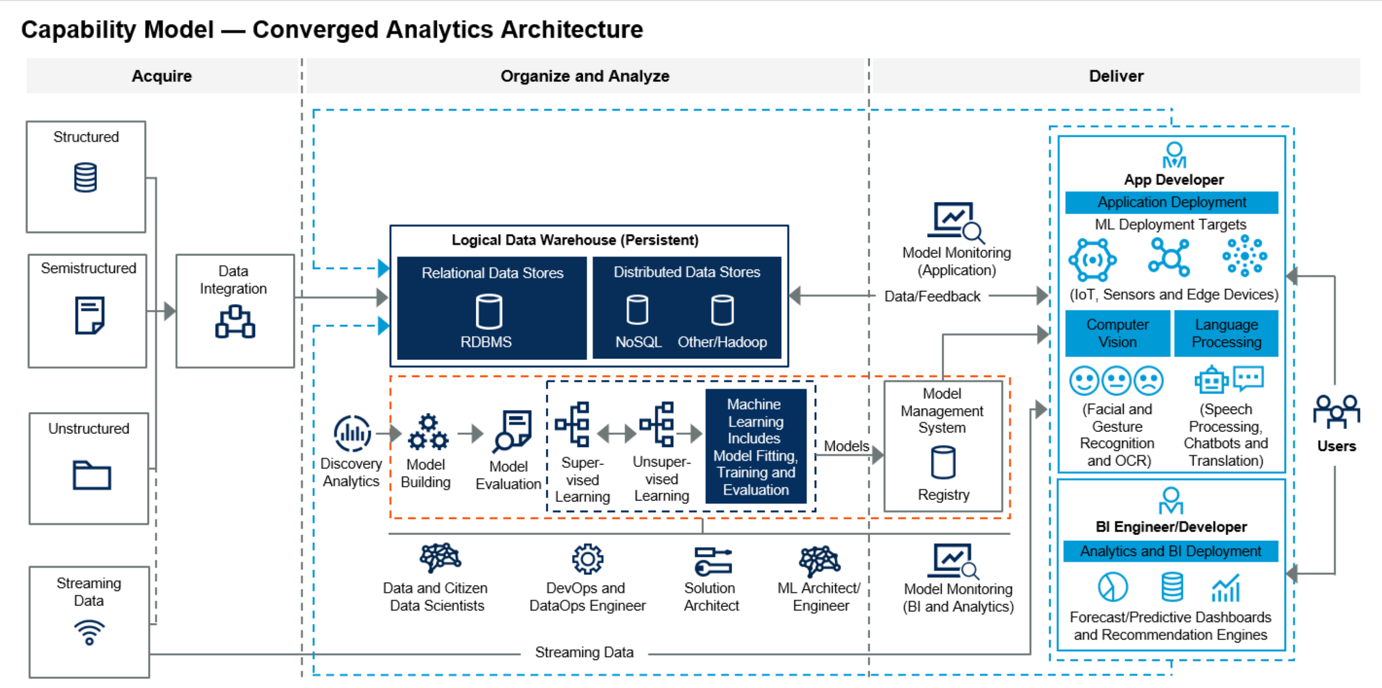
As the data and analytics environment moves into the cloud, it is reasonable to expect the business analytics environment to follow. Data gravity, latency and governance, as well as the use cases supported, are important factors in determining when and how to deploy analytics and extend support for ML and AI into the cloud. Most cloud service providers provide a set of cognitive services and out-of-the-box, use-case-specific AI solutions — such as conversational platforms, IoT platforms and contact centers — that can be excellent drivers. These solutions come with a set of rich API services for flexible integration within your current environment.

Gartner recommends that you build a customized, end-to-end analytics architecture based on the capability model required by your business. In doing so, select specific platform as a service (PaaS) capabilities from the cloud provider, and integrate them with incumbent software as a service (SaaS) solutions. Over time, as capabilities within one converged platform start becoming fundamental, you can port analytical processes from your SaaS provider to a converged, unified analytics platform.

Figure 9 shows an end-to-end analytics and ML architecture, including capabilities you would look for within a converged analytics platform. The goal is twofold:

- Support traditional operational analytics alongside discovery analytics (which drive innovation)
- Build AI-based systems that use predictive, prescriptive and ML techniques as part of the analysis

Figure 9. Converged Analytics Architecture for AI-Based Systems — Capability Model



Source: Gartner
ID: 401231

For more information, see:

- "Solution Path for Implementing a Comprehensive Architecture for Data and Analytics Strategies," (https://www.gartner.com/document/code/351281?ref=authbody&refval=3970122) "A Guidance Framework for Operationalizing Machine Learning for AI" (https://www.gartner.com/document/code/366587?ref=authbody&refval=3970122) and "Reference Architecture to Enable Real-Time Self-Service

Analytics" (https://www.gartner.com/document/code/370032?ref=authbody&refval=3970122) for designing analytics and ML architecture

- "Solution Comparison for Cloud-Based AI Services" (https://www.gartner.com/document/code/377714?ref=authbody&refval=3970122) for building converged analytics platforms in the cloud

Evaluate TCO, Including Software, Infrastructure and Implementation Costs

Data and analytics professionals will need to develop data science, ML and AI capabilities while grappling with the inherent technical challenges of existing implementations. To deliver a seamless experience to end users, a converged data and analytics platform would be most beneficial, since a best-of-breed multivendor architecture poses risk management, cost, license management and integration challenges. Each new capability requires consideration of its capital expenditure (capex) and operating expenditure (opex) costs, alongside its potential benefits and business impact.

The TCO for building a next-generation data and analytics architecture involves the software licenses, compute infrastructure and skill sets required for implementation and operations. Trying to build the platform in-house, or with multiple SaaS components in the public cloud, could incur significant capex in the beginning. However, opex should be lower in the long run, as long as you've estimated the hardware and licensing requirements appropriately.

If you're concerned that the business won't completely buy in to the idea of building a converged data and analytics platform, you could build the architecture using cloud PaaS services. These services generally incur significantly less capex. They are also extensible, depending on the organization's requirements and its adoption of newer technologies. However, as you scale the architecture and usage of data and analytics services, you could see your opex skyrocketing.

In order to maintain acceptable TCO, you need to balance out the capex and opex models by carefully evaluating the anticipated workloads, numbers of users and business use cases. Thinking in advance about how easily workloads can be distributed over different system components can ensure effectiveness of operating cost expenditures, ease of implementation and scalability. The cost model for a cloud-based, converged data and analytics platform is completely different from on-premises chargeback models. Pricing constructs vary considerably among analytics vendors, with several offering cloud services both directly and through major marketplaces. Monthly charges will be impacted by factors such as:

- Data volumes
- Transfer rates
- Processing power
- Service uptime

Use-case evaluations should include the goal of avoiding unexpected costs in the future. Tools are available to help track and manage cloud costs.

For most businesses, however, a pay-as-you-go plan for analytical services is probably the obvious solution. This kind of setup lets the experts run and maintain the environment, so you don't have to hire new employees to do it, and existing employees can focus on their usual tasks. This option keeps your financial forecasts stable and predictable. Overall, keeping your IT efforts going with an opex-heavy converged platform is the new and more flexible approach to keeping those expenses down.

> **A converged platform based on an opex model provides the most flexibility to stay relevant in the quickly transforming technology landscape of data and analytics.**

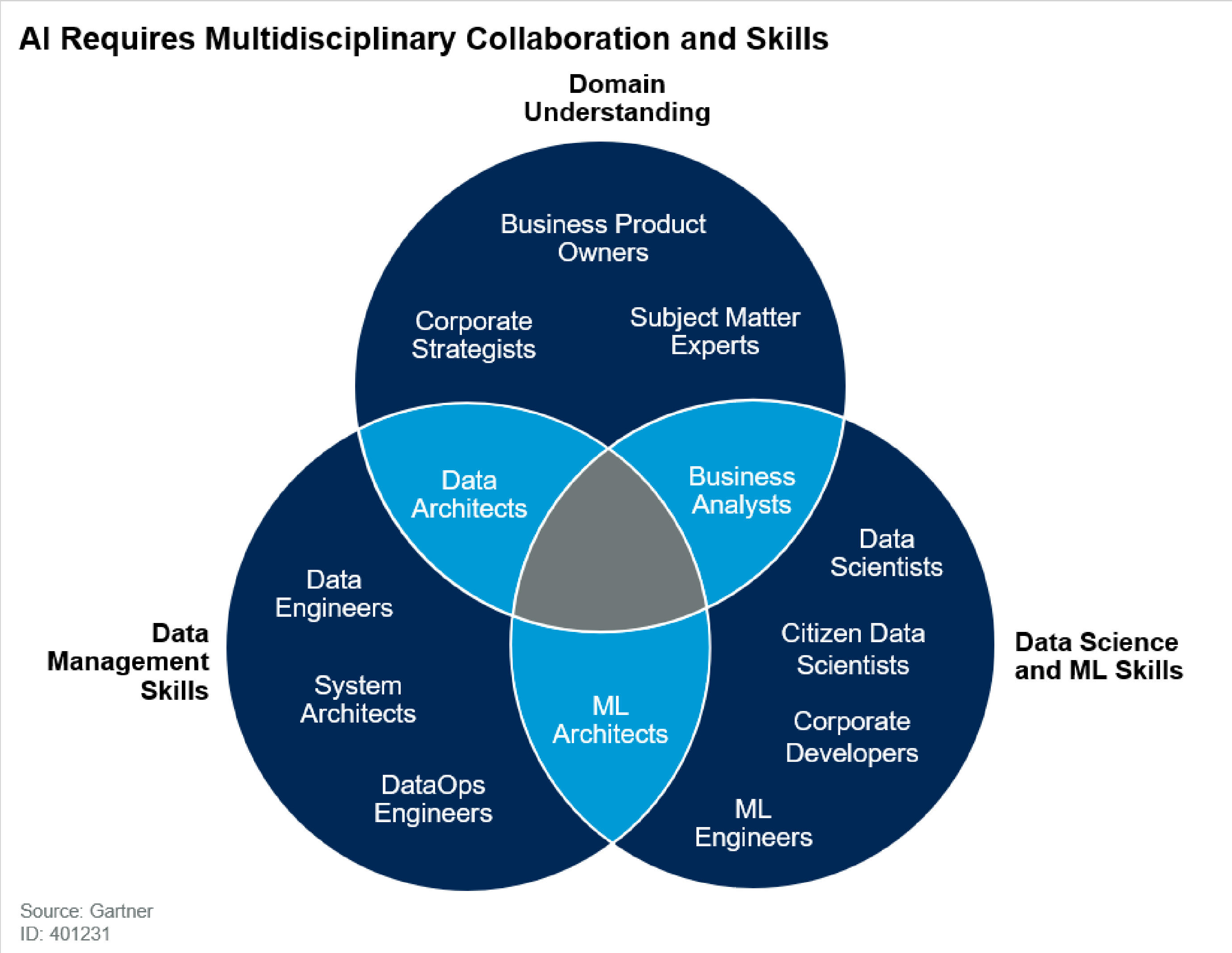
The financial implications of opex versus capex for building a converged data and analytics platform will affect the set of SaaS and cloud PaaS services you select, depending on the phase of implementation. If you want to avoid the difficulties of a capital expenditure, you can opt for public cloud services that use a pay-as-you go model for certain compute-heavy analytical processes. As capabilities mature and adoption increases, in-house IT teams can build a converged data and analytics platform for operational analytics. This way, you combine resources from both private and public clouds to create a hybrid implementation model, offering flexibility and control over the TCO.

Upskill Existing Resources to Support Diverse Data and Analytics Pipelines

To build the next generation of AI-based systems, data and analytics technical professionals will need to guide multidisciplinary teams on the necessary tools and technologies. Creating synergy between AI and data analytics activities — by identifying commonalities in data, tools, technologies and use cases — will be crucial to scaling the architecture. People with skills from varied areas of expertise — including data management, analysis, statistics, platform engineering and application development — will need to work collaboratively to build an advanced analytics and ML platform for continuous delivery.

A converged data and analytics platform can bring together a diversified set of individuals using one collaborative platform, enabling shared data management capabilities among data and analytics teams, with significant overlap and reusability of common data sources (see Figure 10). This environment will allow organizations to leverage common data exploration, visualization and data science capabilities. Such capabilities can help build lineage and capture valuable metadata, enabling organizations to progress toward decision augmentation and process automation.

Figure 10. Multidisciplinary Skills in a Converged Analytics Platform



DataOps and MLOps are key to building an agile delivery pipeline, in order to bring together the required skill sets to productize advanced analytics initiatives. For more information on the emerging roles and skill sets required to support future converged data and analytics platforms, see:

- "Introduce the Machine Learning Architect — An Emerging Technical Professional Role in AI Initiatives" (https://www.gartner.com/document/code/384355?ref=authbody&refval=3970122)
- "Operationalizing Big Data Workloads" (https://www.gartner.com/document/code/360371?ref=authbody&refval=3970122) (see the What Is DataOps? section)
- "Staffing Data Science Teams: Map Capabilities to Key Roles" (https://www.gartner.com/document/code/355635?ref=authbody&refval=3970122)
- "A Guidance Framework for Operationalizing Machine Learning for AI" (https://www.gartner.com/document/code/366587?ref=authbody&refval=3970122) (see the Technical Team section)

Unbiased and Ethical AI Development Will Advance the Need for Interpretable Models and Explainable AI

AI provides the promise of innovative, effective and efficient business and technical solutions. However, AI models are often considered black-box solutions due to their lack of transparency. As AI usage becomes more widespread and technology matures, end users and practitioners are increasingly looking for explanations behind AI-assisted decisions. With a statistical model, it's easy to trace through the data flow, understand the factors that influence the decision making, and compare various "what-if" scenarios. By contrast, AI and ML get opaque as the models become more complex and potentially more accurate.

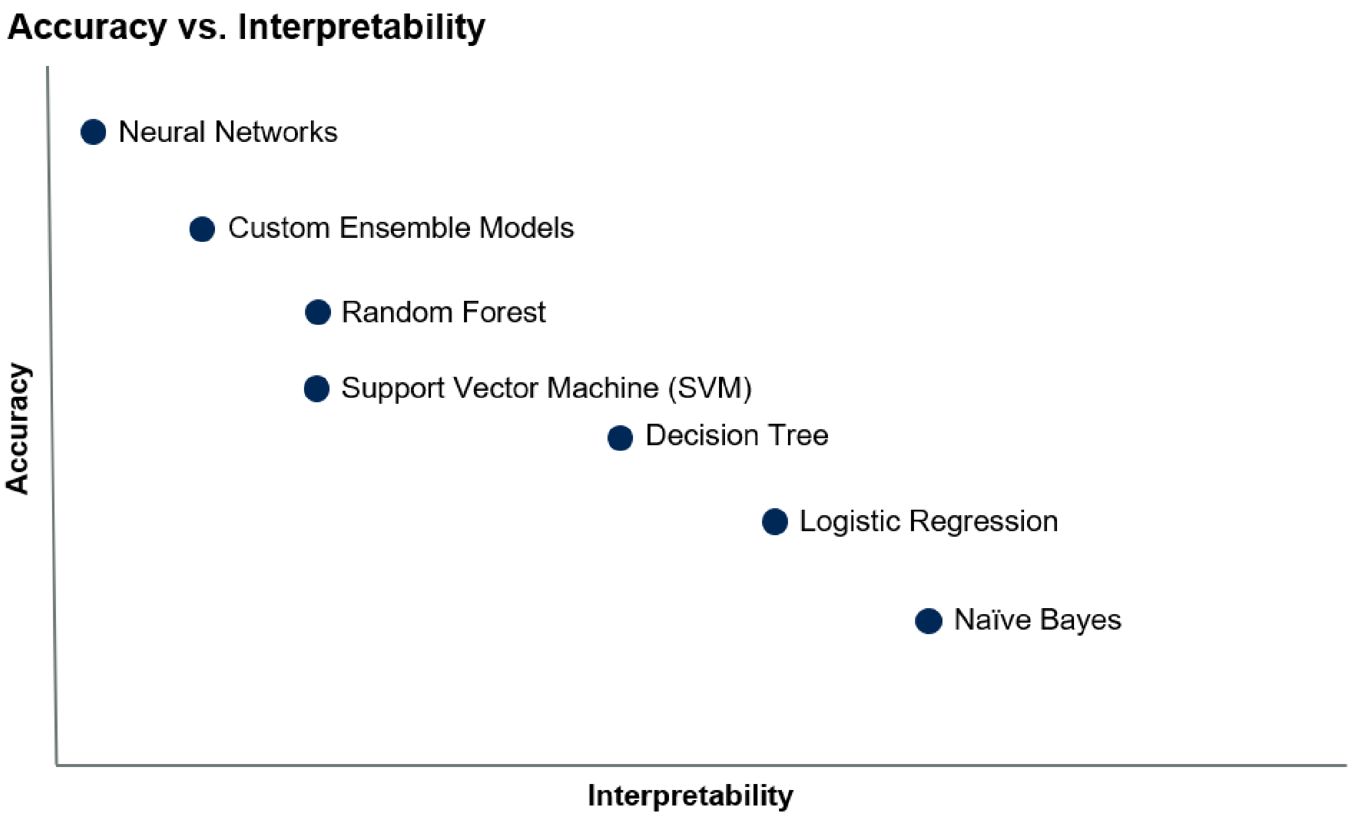
Currently, insurance agents and loan counsellors can generate several what-if scenarios to provide various price quotations to the customer, because they have a good understanding of the factors influencing the pricing. They expect a similar understanding when rule-based models or statistical models are replaced by AI models. Credit models often include applicants' race, gender and income, along with other sensitive personal and financial information. These variables create the potential of unwanted algorithmic bias. For example, in credit applications, single mothers may be deemed a higher risk than single fathers.

In order for organizations to trust that AI models are free of such unwanted bias, they need an explanation of the features that determine a particular prediction. They may also require the ability to compare outcomes by changing some of the input values. For example, changing the applicant's gender should not change any of the model outcomes. However, a change in income or assets should impact the approval or rejection of a loan application.

At the same time, there is a trade-off between model accuracy and interpretability (see Figure 11). Models based on simpler algorithms — such as linear regression, logistic regression or decision tree — are most commonly used. The weights in a linear model, or the splits in a decision tree, provide interpretability of the model. However, models using advanced algorithms (such as random forest or neural networks) — or ensemble models combining multiple models or neural networks — provide higher accuracy but cannot be interpreted this way. They require a more model-agnostic interpretability to provide explanations for specific predictions.

> **The challenge for technology and business professionals is that an AI model trust equation needs both elements — prediction accuracy and explanation of such predictions.**

Figure 11. Accuracy vs. Interpretability Trade-Off



Source: Gartner
ID: 401231

Planning Considerations

Together with business owners, technical professionals — including data scientists, ML engineers and ML architects — need to consider the trade-offs between accuracy and interpretability as they look to balance business outcomes with regulatory requirements and customer expectations. Planning considerations for 2020 should include the following actions:

- Enforce compliance and regulatory environments for ML models to explain the recommendations
- Promote AI fairness toolkits and explainable AI frameworks

Enforce Compliance and Regulatory Environments for ML Models to Explain the Recommendations

Adoption of ML models for business decision making is increasing across several industries, such as financial services, healthcare and human resources. In addition, use of advanced techniques, such as facial recognition and generative adversarial networks (GANs), is growing too. These factors have raised several regulatory compliance, privacy and ethics challenges.

AI is being used in the criminal justice system to identify repeat offenders. The U.S. Fair Housing Act, the Health Insurance Portability and Accountability Act (HIPAA), the EU's GDPR and, most recently, the proposed Algorithmic Accountability Act (AAA) are some of the regulations seeking to protect customer privacy and prevent discrimination. GDPR provides the affected customer with the right to an explanation of an algorithmic decision. The AAA proposes similar provisions.

While the regulations are ensuring a cautious approach to using AI for business decisions, AI technologies and products need more transparency in the prediction process. Marketing campaigns also fall within the scope of these regulations. A marketing campaign for preapproved credit also needs to comply with fair-lending rules. Identifying bias that causes discrimination against customers is a critical requirement within industries impacted by such regulations.

The models need to do more than just provide information about the features creating the bias. The model training and execution should also resolve the bias, either by performing the appropriate feature engineering, adjusting the training data or reviewing model predictions for bias. For unbiased, ethical and explainable AI solutions, organizations will need to include product and platform evaluation requirements — as well as process oversight — into model algorithm selections and training data.

Promote AI Fairness Toolkits and Explainable AI Frameworks

Open source has continually lowered the barrier to entry for developers while providing innovative solutions. Such solutions have provided the foundations for several leading technology platforms, including the following:

- Local Interpretable Model-Agnostic Explanations (LIME) provides a model-agnostic framework for local interpretation of specific predictions. LIME is used by several commercial data science and machine learning platforms.
- SHapley Additive exPlanations (SHAP) is based on Shapley values, a technique used in game theory to determine how much each player in a collaborative game has contributed to its success. It connects game theory with local explanations.
- IBM AI Explainability 360, IBM AI Fairness 360 and Microsoft InterpretML are toolkits that provide several open-source algorithms to identify and mitigate bias in training data (which is often the cause of model bias), and to provide model explainability.

BA&AI professionals should combine packages and algorithms like these to develop unbiased and explainable AI models.

Setting Priorities

Most organizations do not have the time and budget to follow every suggested planning consideration, and Gartner clients occupy a wide spectrum of analytics maturity levels and capabilities. Not all industries, geographies and organizational sizes will have the same analytics initiatives. However, the following guidance focuses heavily on operations and management.

Data and analytics technical professionals must focus on:

- **Provisioning analytics in addition to provisioning data:** Analytics consumers are struggling to consume data fast enough to drive critical decisions. While delivering data for self-service initiatives remains effective, delivering analytics solutions accelerates users' ability to add data as a part of the decision-making process. As a result, more focus should be put on provisioning analytics on behalf of consumers to enable greater usability and performance.

- **Interconnecting analytics solutions as a part of an overall integration strategy:** Integrating data should be viewed as a lower-order integration approach, while integrating analytics outputs should be viewed as a higher-order integration strategy. Integrating analytics outputs provides the ability to address broader, more complex decision processes.

- **Augmenting analytics with AI and ML:** Organizations need to develop an augmented analytics strategy that describes how new capabilities from AI and ML will enhance human output and deliver faster results.

- **Creating distributed analytics governance models:** Governance is moving beyond simply overseeing data. There should be more emphasis on analytics governance frameworks that span the services of a larger, more distributed number of people. Analytics governance models should also govern for unbiased and ethical artificial intelligence.

Document Revision History

2019 Planning Guide for Data and Analytics - 5 October 2018 (https://www.gartner.com/document/code/361501?ref=dochist)

2018 Planning Guide for Data and Analytics - 29 September 2017 (https://www.gartner.com/document/code/331851?ref=dochist)

2017 Planning Guide for Data and Analytics - 13 October 2016 (https://www.gartner.com/document/code/311517?ref=dochist)

2016 Planning Guide for Data Management and Analytics - 2 October 2015 (https://www.gartner.com/document/code/290775?ref=dochist)

Recommended by the Authors

Reference Architecture to Enable Real-Time Self-Service Analytics (https://www.gartner.com/document/3947274?ref=authbottomrec&refval=3970122)

Demystifying the Analytics and BI Space (https://www.gartner.com/document/3905775?ref=authbottomrec&refval=3970122)

The Evolving Capabilities of Analytics and Business Intelligence Platforms (https://www.gartner.com/document/3872599?ref=authbottomrec&refval=3970122)

Building a Comprehensive Data Governance Program (https://www.gartner.com/document/3956689?ref=authbottomrec&refval=3970122)

Augment Data Science Initiatives With AutoML (https://www.gartner.com/document/3956845?ref=authbottomrec&refval=3970122)

Using Augmented Analytics to Boost A&BI (https://www.gartner.com/document/3956850?ref=authbottomrec&refval=3970122)

Building a Framework for Managing Effective Machine Learning Workloads (https://www.gartner.com/document/3906757?ref=authbottomrec&refval=3970122)

A Guidance Framework for Operationalizing Machine Learning for AI (https://www.gartner.com/document/3891986?ref=authbottomrec&refval=3970122)

Solution Comparison for Cloud-Based AI Services (https://www.gartner.com/document/3923891?ref=authbottomrec&refval=3970122)

Introduce the Machine Learning Architect — An Emerging Technical Professional Role in AI Initiatives (https://www.gartner.com/document/3920367?ref=authbottomrec&refval=3970122)

Recommended For You

Control Bias and Eliminate Blind Spots in Machine Learning and Artificial Intelligence (https://www.gartner.com/document/3889586?ref=algobottomrec&refval=3970122)

Enabling Data Quality for Machine Learning and Artificial Intelligence (https://www.gartner.com/document/3887790?ref=algobottomrec&refval=3970122)

Maverick* Research: Gen AI — Artificial Intelligence Empowers a Generation of Radical Thinkers (https://www.gartner.com/document/3803511?ref=algobottomrec&refval=3970122)

Maverick* Research: Artificial Intelligence Will Make Us Dumber Unless We Can Teach It to Teach Us Back (https://www.gartner.com/document/3891508?ref=algobottomrec&refval=3970122)

Evaluation Criteria for Analytics and Business Intelligence Platforms (https://www.gartner.com/document/3890122?ref=algobottomrec&refval=3970122)

on Independence and Objectivity."