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

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Initiatives: Artificial Intelligence; Lead a World-Class D&A Organization

As AI matures and pushes decision making closer to automation, analytics will become invisible to the decision-making experience, and fewer people will need to know about them. This will result in diminishing importance for many business-side data and analytics roles.

Overview

Specific Maverick Caution

This Maverick research contradicts the prevailing wisdom that companies need to prioritize data and analytics (D&A) roles (in particular on the business side) and increase data literacy and user adoption of self-service analytics to drive success with analytics. In the short term (up to 18 months), these roles are needed to help make sense of the chaos created by a growing data volume. In the long term (18 months to five years), transition to applications and managed services with embedded augmented and automated decisions will begin to lighten the load on business-side D&A roles. In fact, as more decisions are augmented and automated via AI, many data and analytics roles will be less important. As Maverick research, this document's findings and advice should be treated with caution.

Maverick Findings

- A "data-driven decision" is the main impact of data and analytics, not the data and analytics themselves.
- The underlying data and analytics for augmented decisions or automated processes are increasingly invisible to most users.
- Organizations often identify "user adoption" and "data literacy" as critical measures of success for data and analytics projects, and with this they prioritize fulfillment of data and analytics roles.
- Trust in AI is growing and so is AI accuracy, and with these developments, AI will become the primary influence in most business decisions.

Maverick Recommendations

Data and analytics leaders in the midst of a digital transformation looking to promote data-driven decisions should ignore data literacy and user adoption of analytics tools and instead:

- Shift their focus to monitoring how decisions are made and leverage prescriptive analytics to augment the decision-making experience in context.
- Deprioritize the fulfillment of data and analytics roles that are focused on consuming data and generating more analytics. Instead, prioritize decision engineering and AI governance roles as well as the data foundation required to support decisions.
- Take an inventory of operational decisions: those made by people, those made by people and machines, and those that have been automated. Prioritize projects with embedded augmented or automated decisions over the propagation of new descriptive analytics dashboards.
- Prioritize expertise in decision engineering and decision intelligence over self-service analytics as the latter will diminish in importance as we transition to decision automation.

Strategic Planning Assumptions

By 2030, the number of traditional descriptive analytics dashboards will decrease by more than 50% in most modern digital businesses.

By 2030, 75% of operational decisions will be made within an AI-enabled application or process.

Maverick Research

Gartner Maverick* research delivers breakthrough, disruptive and sometimes contradictory ideas that challenge conventional thinking. Formed in our research incubator, it is designed to explore alternative opportunities and risks that could influence your strategy.

Analysis

User adoption for self-service analytics tools has stalled between 25% and 30%. Gartner measured this regularly in surveys from 2007 through 2017 (see Figure 1). A more recent survey from 2021 has the average number of employees using analytics and business intelligence tools at 29%, slightly below the average from 2017. Additionally, 68% of chief data and analytics officers surveyed by Gartner in 2021 made data literacy a key element of their data strategies. In a 2022 survey, 24% of respondents ranked increased data literacy for employees within their top five most compelling objectives for 2023.

Although these two measures (user adoption and data literacy) are independent of each other, increasing both together is often seen as an indicator of a successful data-driven organization.

A data-driven organization is one that liberally shares data and analytics assets and leverages them to influence decisions that drive positive business outcomes for all stakeholders, including business, IT, partners and customers.

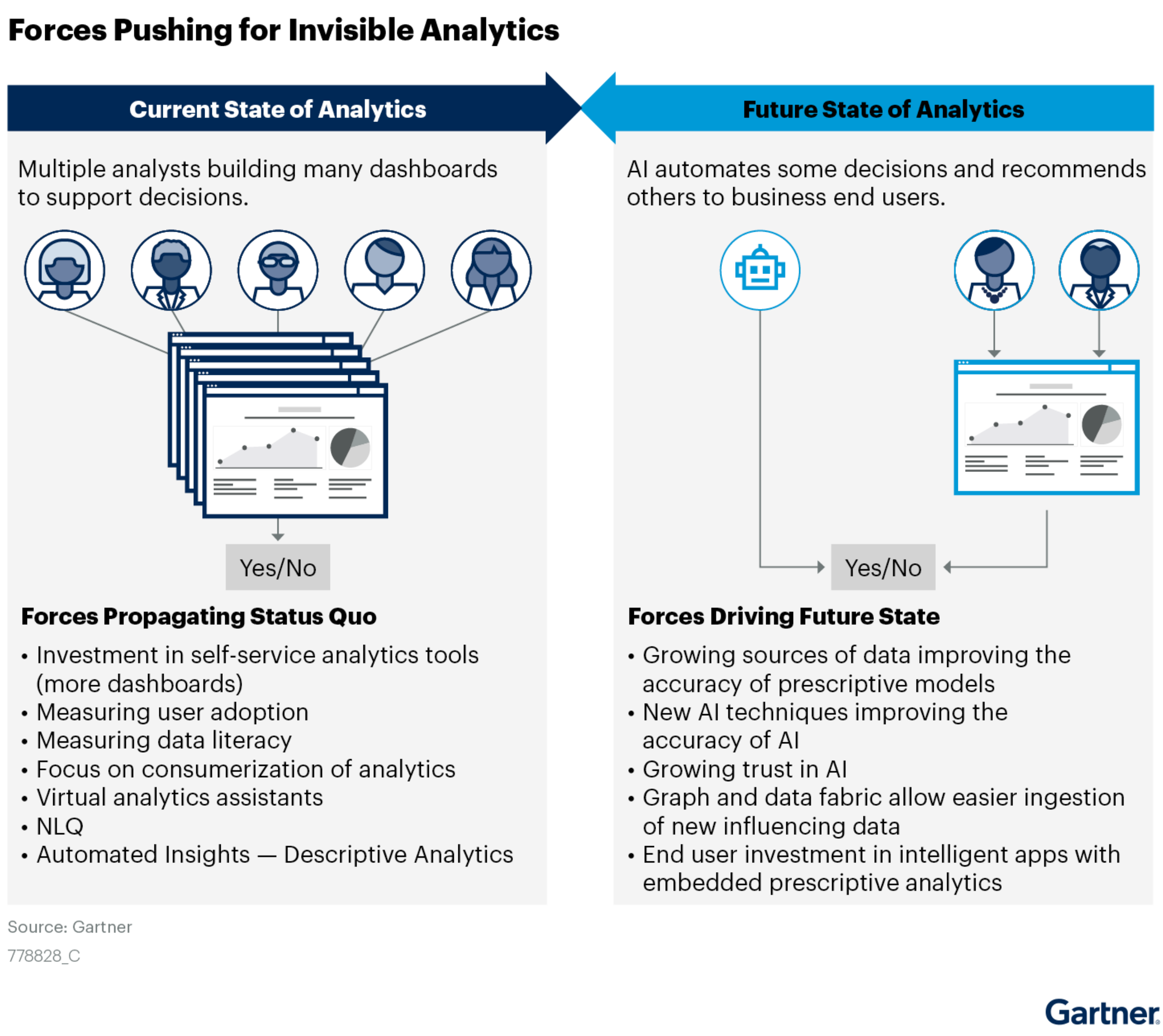
More Data Knowledge and More Analytics

Unbeknownst to many, there are forces that are working against each other in this equation. On one end, organizations are trying to increase the knowledge of operational employees in regard to the value and use cases for data and analytics. This is with the hopes that these employees will be better equipped to interpret data and analytics as they make critical operational decisions. With this, fulfilling D&A roles is often prioritized over others. Additionally, there is growth in augmented features that simplify access and the creation of analytics for nontechnical users (e.g., automated insights, key driver analysis or natural language interfaces for asking analytics questions).

More AI, More Automation, Less Visible Analytics

On the other end of the spectrum, data science teams look to leverage large amounts of data to create machine-learning models that have the ability to predict outcomes and even prescribe a course of action to further good outcomes and avoid bad outcomes. Application leaders in business units are purchasing intelligent applications that have embedded AI for recommendations and automation. These apps often completely resolve the need for analytics in the areas they are automating. An example might be a group of analysts who are working on analyzing market dynamics and competitive pricing to determine the best price for an offering. This exercise might be completely eliminated by an application that automates price optimization as you see in the travel industry for airlines, hotels and rental cars (see Figure 1).

Figure 1: Forces Pushing for Invisible Analytics

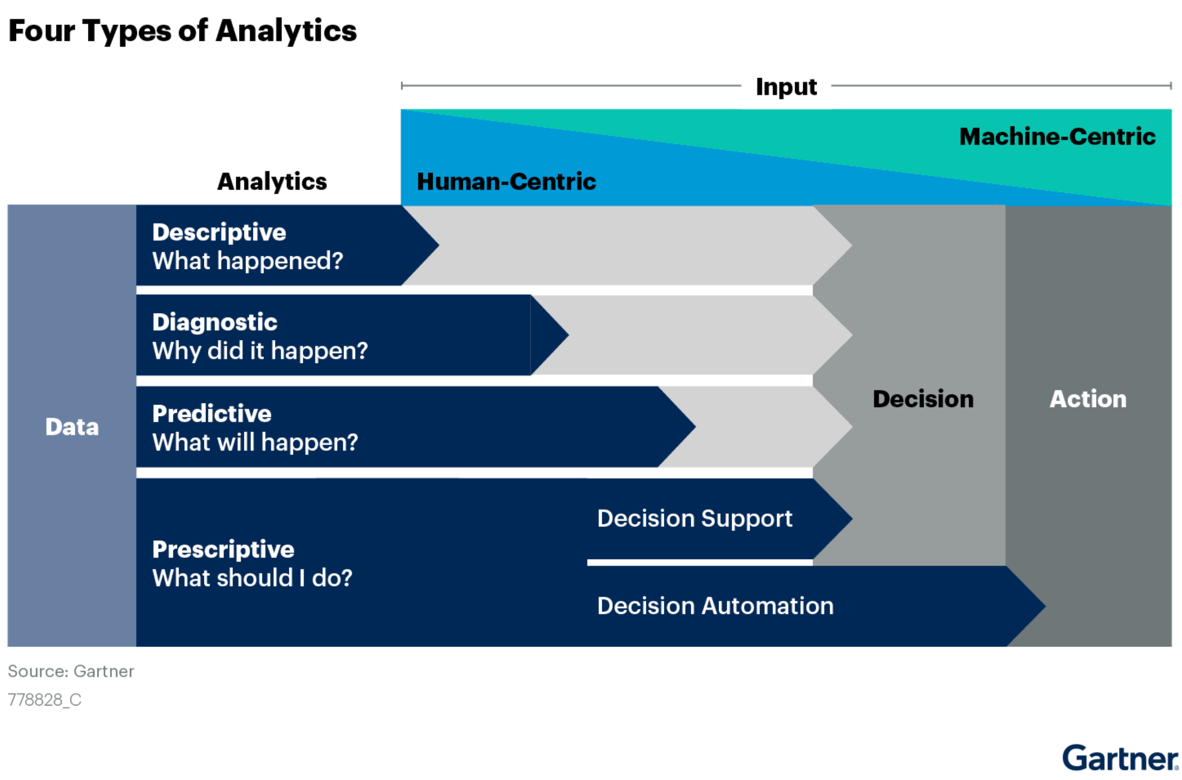


There are forces driving greater data literacy and pushing for more analytics capabilities for more users. On the other end, there are AI projects and applications with embedded AI which are reducing the need for further analytics. Organizations need to understand these opposing forces as they need to be reciprocal and not increase simultaneously. As trust in augmented and automated decisions grows, many business users will need to shift their focus from producing more analytics to augmentation and automation of more decisions via trusted data and AI.

The Chasm — Understanding the Source of the Challenge

There are four types of analytics: descriptive, diagnostic, predictive and prescriptive (see Figure 2).

Figure 2: Four Types of Analytics



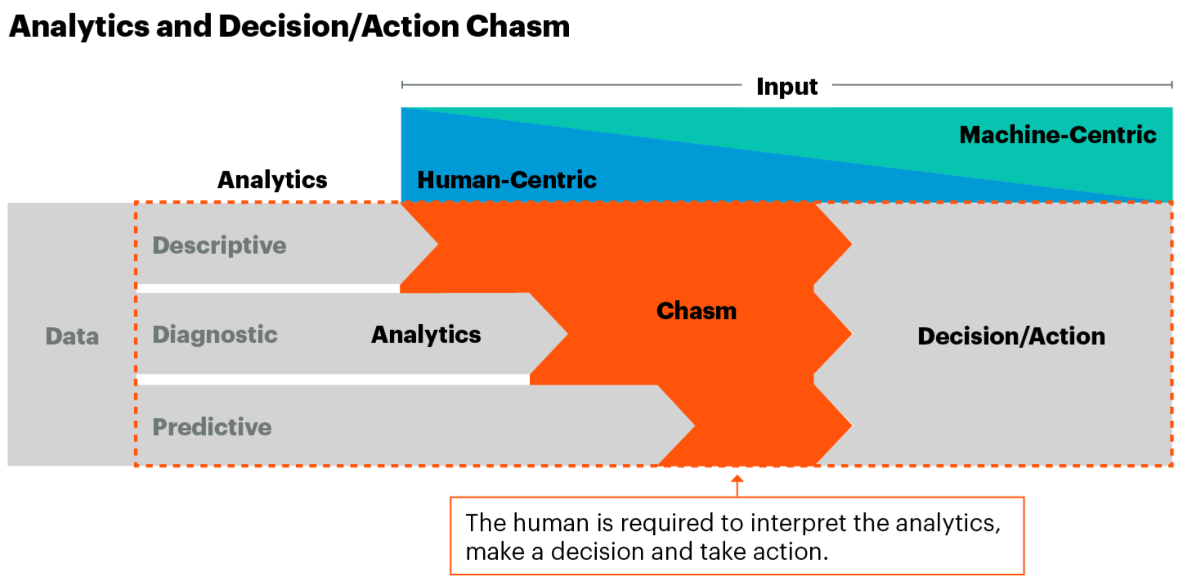
These four types of analytics are often described by what type of information they convey:

- Descriptive — What happened?
- Diagnostic — Why did it happen?
- Predictive — What will happen next?

- Prescriptive — What should I do about it?

One aspect of the chart that is often neglected is the human and machine involvement in decision and action. In each of the first three types of analytics, before a decision is made and an action is taken, there is implied involvement by a human in the process. This human is required to interpret the analytics in order to make an informed decision and take action. The process of "interpretation" is the chasm. The chasm represents the human part of analytics and decision making (see Figure 3).

Figure 3: Analytics and Decision/Action Chasm



Source: Gartner
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According to a Gartner's 2021 Analytics Consumerization-Democratization Survey, descriptive and diagnostic analytics are the most widely used of the four types. [1] Predictive, the third type of analytics, is more forward looking, but it has a similar expectation. The user is trusted to interpret the analytics and blend it with their own experience to make a decision and take an action (or not). This ability to create the analytics and the ability to interpret their meaning and make an informed decision is the impetus around many data and analytics initiatives, including:

1. Filling data and analytics roles

2. Increasing data literacy to improve users' ability to interpret analytics and make decisions

3. The “data-driven” enterprise

4. Consumerization of analytics

5. Training more citizen D&A roles (citizen data scientists, citizen data engineers)

The gap between analytics and decision and action is causing companies to make the assumption that if they improve data literacy and increase user adoption of analytics tools, then they can move closer to being a data-driven company. Another related fact is the lack of clear ROI that comes from these types of analytics. In a Gartner study completed in early 2022, [2] three case studies were randomly selected from 13 vendors in various segments of analytics platform submarkets: only five of 39 stories referenced a specific dollar amount for the ROI. 87% of stories did not demonstrate clear ROI. This does not mean that these types of analytics are not valuable, but it does indicate that it is difficult to quantify the value. It is not easy to cross the chasm and know definitively what the benefits of the analytics were.

Crossing the Chasm from Analytics to Action

Now let’s focus on the bottom of the diagram in Figure 4. Notice there is no chasm. This implies that the analytics and decision-action are connected. Also notice at the top of the diagram the box showing the shift from human-centric decision making to machine-centric decision making. This is demonstrating that the decision is either largely influenced or completely made by a machine (or by AI, to be more precise). This is the force at the other end of the spectrum seen in Figure 1.

At the time of Gartner’s 2021 Analytics Consumerization Survey, prescriptive analytics were only used by 7% of users regularly (over 75% of the time) — by far the least used analytics type. However, evidence shows that this is changing rapidly. Gartner’s 2021 AI in Organizations Survey showed a directional upward usage trend that AI is maturing from 35% usage in 2019 to nearly 50% overall in 2021. [3] To be clear, AI and its most popular technique, machine learning, can be used for many things, including as the foundation of prescriptive analytics.

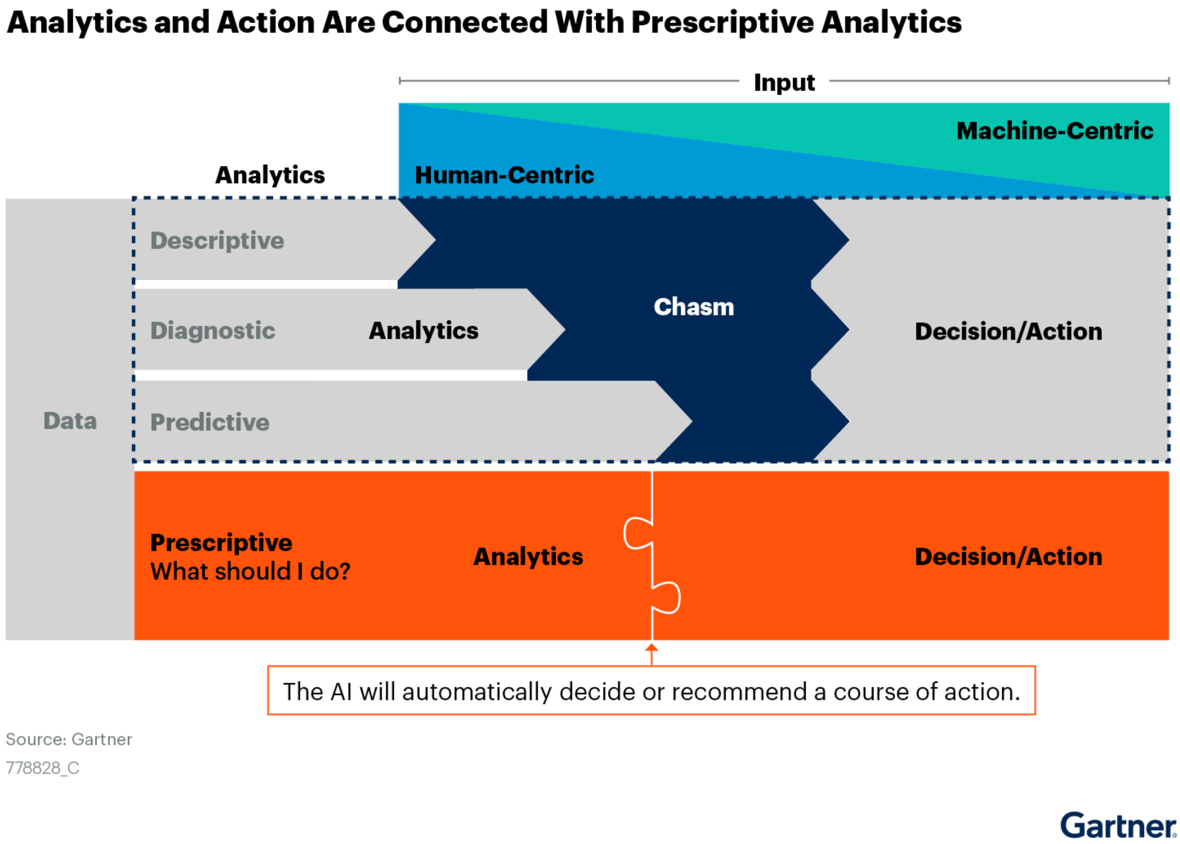
It is also important to point out that there is a relationship between predictive and prescriptive analytics. It should be logical when you think about their purposes which were previously mentioned. Predictive analytics gives the user insight into what will likely happen next. Prescriptive analytics represents a course of action that will influence one of the input factors to that prediction. That is, if the analytics predicts a good outcome, then perhaps the prescription is to do nothing; however, if it predicts a bad outcome, then perhaps you want to influence one of the inputs to the bad outcome to push it in the opposite of the trending direction.

Let's use a customer churn example. A customer support representative is speaking with a client on the phone, and they can see from predictive analytics on their screen that the client has a renewal coming up in two weeks and they have been scored as being at a 90% risk of leaving (churning) and not renewing. Prescriptive analytics on the same screen suggests that offering them a 25% discount will likely change their mind and get them to renew early for another year. This example shows how some analytics types can work in concert.

Additionally, Mordor Intelligence, a research company, in its recent report on predictive and prescriptive analytics showed that investment in these technologies is forecast to grow at a 24% compound annual growth rate (CAGR) through 2028. As a comparison, Gartner's most recent forecast for enterprise software (Forecast: Enterprise Application Software, Worldwide, 2021-2027, 1Q23 Update) shows the CAGR for analytics platforms at 10.1%. This further demonstrates the emergence of interest in prescriptive use cases.

Returning to our price optimization example from earlier, when the decision to raise or lower a price is embedded in the system where the action occurs (the purchase of a product), it is easier to identify and measure the benefit of the decision.

Figure 4: Analytics and Action Are Connected With Prescriptive Analytics



The thesis is that as we mature to a world where more analytics will be of the "prescriptive" type. Predictive analytics are focused on one outcome point — the probability that something will occur — when, where and how much. Prescriptive analytics have to be more contextually aware and include decision variables, their constraints and how they affect business outcome. When "prescriptive" analytics are designed correctly in the decision maker experience, organizations will have an easier time measuring the value of the analytics based on the decisions made. Prescriptive analytics have been maturing for a while and are becoming increasingly common. Table 1 shows a few examples:

Table 1: Prescriptive Analytics

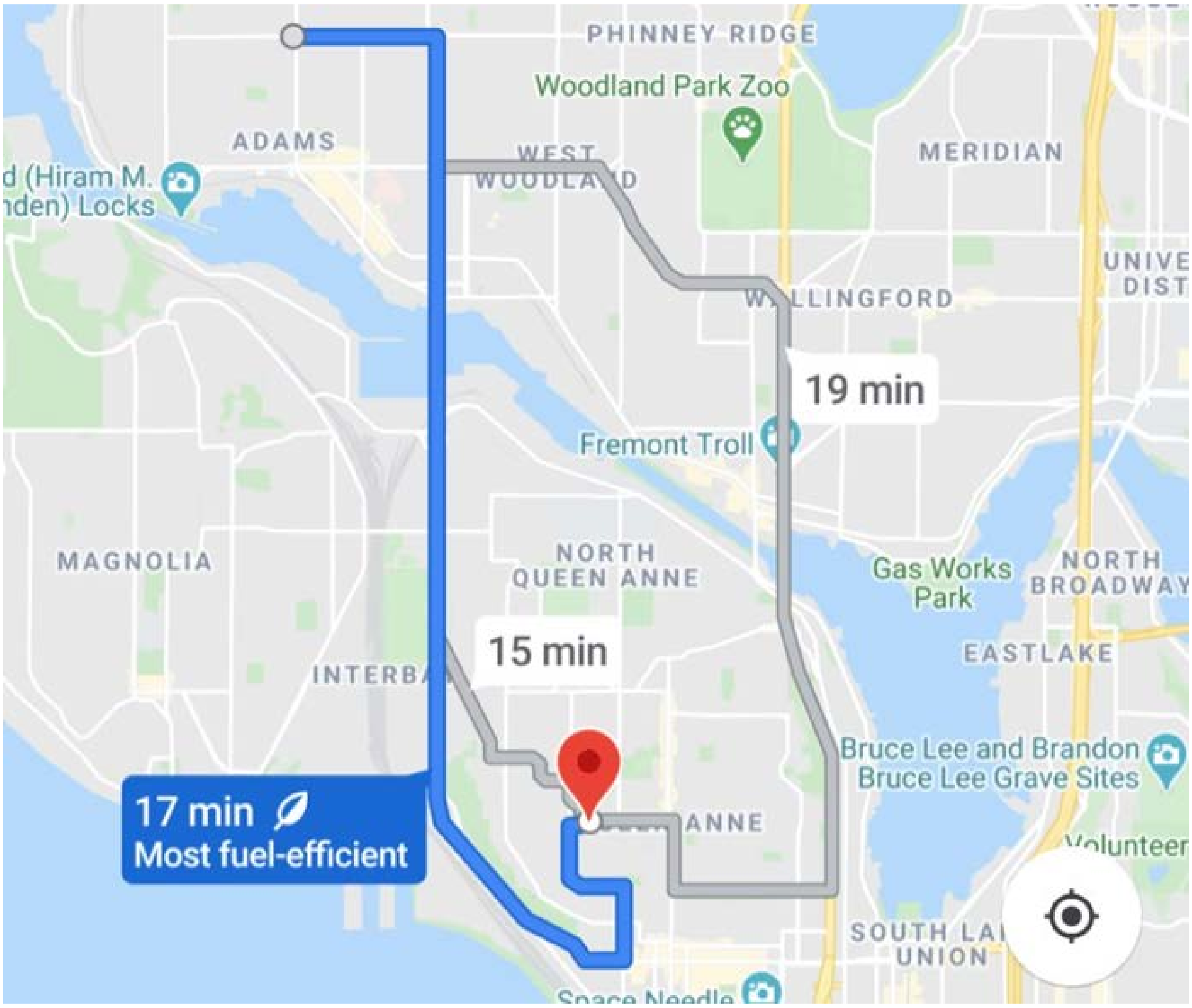
Source	*Prescriptive Analytics Description*
Navigation App	Recommended route change will get you to your location five minutes faster.
Resume Selection	Resumes are filtered by a machine algorithm to find candidates that match requirements.
Predictive Maintenance	ML model monitors IoT sensor data and suggests a convenient time to perform maintenance without causing downtime.
Price Optimization	Pricing systems, like those in the airline industry, fluctuate prices to optimize revenue and utilization based on many factors.
E-commerce	Product recommendations based on knowledge of the shopper and related product affinities for filling the market basket.

Source: Gartner (May 2023)

As Trust in AI and Data Increases, Analytics Become More Invisible

Analytics, especially detailed analytics behind the recommendations coming from a machine-learning model, are often invisible to the end user. Think of the navigation example above: When the navigation app says there is now a faster route that will save you time, do you stop to ask it to give you all of the underlying analytics that went into the calculation? No. Instead, you select it and move on. (See Figure 5.) There is a tremendous amount of analytics included “behind the scenes” in this example — distance calculations, real-time feeds of actual traffic conditions, crowdsourced conditions and forecasts of what conditions will be later in the journey — that created the route update recommendation, but you don’t care about that. You only care about getting to your destination faster. You may look at this as a nonbusiness issue, but this is commonplace for delivery and transportation businesses everywhere. This is an example of prescriptive analytics where a human can decide to follow or ignore and where the underlying analytics have become invisible. This is exactly what will happen in many applications that use prescriptive analytics to augment or automate decisions.

Figure 5: Google Maps Showing the Timing for Multiple Routes



Another place where analytics have become invisible is in resume selection. Human resources departments used to comb through hundreds of resumes looking for the right person to fill a role. They would often do this to create a shortlist of candidates. Today, using machine learning, thousands of resumes can be scanned in seconds to find an appropriate shortlist. And, as before, the underlying analytics of the selection have become invisible to most people.

Another aspect of this phenomenon is that while AI is being leveraged to recommend or make decisions, it is also being leveraged on the data side of the equation to augment and automate data quality and integration. In fact, Gartner's most recent AI in Organizations Survey showed that organizations that automatically budget for AI as a part of every project are 2.3 times (or 130%) more likely to reach "strategic" levels of AI maturity.

This is important because the human in the middle making the decision is being squeezed out of data and analytics roles from both ends. The gap between data and analytics is shrinking, just as the gap between analytics and action is shrinking. Thus, D&A roles face imminent deprioritization.

The good news is that humans will be needed to monitor and validate the decisions being made by machines. There will be a decreased need for citizen data engineers and business analysts, but the need for decision engineers and AI governance roles will increase.

What Is Happening, What Will Happen and How Will It Change D&A Roles?

Rule-based decision management tools have been around for a long time. Rule-based systems have specific deterministic guidance that helps to automate certain decisions. For example, you might have an inventory system at a retailer that provides a reorder recommendation when the inventory of any item gets below two units. The purchaser at the retailer can follow the recommendation or decide not to sell the item anymore. These simpler deterministic systems are used to automate many frontline processes already. Another positive characteristic of these systems is that they are more easily explainable because of the deterministic rules (e.g., decision trees).

However, with the growth of data and advancements in AI techniques, we are seeing the growth of more intelligent applications that have recommendations and automation based on probabilistic machine-learning models. These models are sometimes called "black boxes" as their recommendations cannot always be explained. This means that recommendations are being made with a high degree of accuracy but are not necessarily always correct. Price optimization applications in the travel industry are an example of this. Airlines trust that the application's determined price for an airline ticket is the best choice to maximize the revenue opportunity for the airline. While there may be users who monitor this activity, advanced analytics behind the fluctuating price is invisible to most users.

The fact is, future AI-decision-driven organizations will need to leverage and deploy both methods of decision making inside of applications and processes.

- Rule-based decision systems — Top-down approaches using heuristics, rules, knowledge graphs and so forth.

- AI- and ML-based intelligent applications — Bottom-up neural network and AI approaches along with requisite tools in a composite assembly to create well-rounded decisions that use the best capabilities of a machine (processing large volumes of data, classifying categories, and identifying hidden patterns) alongside heuristics and rules.

These types of prescriptive applications are being created by in-house data science teams and are being built and sold by managed service providers. Some of the applications being offered by the service providers have many advantages for the end user and will drive down the need for certain D&A roles.

We started this research with the premise that data and analytics roles will no longer be a priority as analytics become more invisible. While we expect that this is true, we also expect to see the emergence of new roles that will be required. Some of these roles are:

- **Decision engineers —** This role has already been mentioned in Gartner research. Decision engineers support decision-making processes to ensure the most optimal decisions are made. They have a deep understanding of how effective decision-making processes work, and they also provide human and social perspectives. Decision engineers proactively come up with better ways of making optimal decisions, using various techniques and automation. They will have increasing responsibility for understanding the data used to train AI models and the levers that need to be tweaked to drive business outcomes that align with a company's strategic goals.

- **Decision stewards —** Decision stewards might be a new kind of business analyst. Similar to business analysts, they will have business domain expertise in a slightly more technical package. They will use tools to monitor augmented and automated decision-making systems. They will monitor performance, seek out methods for continuous learning and improving model performance, and protect the organization against potentially harmful outcomes.

- **AI governance roles —** AI governance is not a new concept; however, these roles will become significantly more important as more decisions are made by AI. In many cases today, AI governance roles appear in companies with greater AI maturity. In the future, they will need to be foundational to an AI-decision-driven enterprise. There can be several iterations of roles in this area, including those that look to mitigate risks related to government regulations and compliance. AI governance roles will be responsible for basic standards for building and deploying AI. Establish AI-specific standards to cut bias. Collaborate with legal and compliance counterparts to identify laws and regulations that AI initiatives must comply with.

- **Decision systems intermediary —** A decision systems intermediary is not an individual role but an intermediary role played by a provider. As an analogy, the ability to do comparison shopping for just about anything became easier with e-commerce. In the travel industry, intermediaries like Expedia popped up and made it easy for travelers to find competing prices for flights, hotels and rental cars. Kayak took that one step further by being the intermediary of intermediaries. Expect the same thing to happen as companies and vendors mature in this new world. An intermediary of managed service providers will offer up the best prescriptive managed services by price or performance, depending on your needs.

Evidence

[1] **Gartner's 2021 Analytics Consumerization-Democratization Survey** was conducted online between 3 November and 15 November 2021 to understand the anticipated shift from the current paradigm of modern BI (visual-based discovery and self-service) to augmented analytics consumers (natural language query, data storytelling, automated insights, and natural language generation) and the importance of ease of use as a major barrier/enabler to this shift. In total, 62 Research Circle Members participated, 61 from Gartner's ITL Research Circle, 1 from Gartner's CSS Research Circle and 59 were from an external sample. Qualified participants were actively involved in analytics and business intelligence (ABI) within their organization. ABI professionals from North America (45%), EMEA Region (44%), Asia Pacific (4%) and Latin America (7%) responded to the survey. The survey was developed collaboratively by a team of Gartner analysts and was reviewed, tested, and administered by Gartner's Research Data Analytics team.

[2] The results presented are based on the research conducted by the Gartner Secondary Research Services (SRS) team, which reviewed a sample of 39 case studies from 13 global analytics platform companies. For analysis, three most recent case studies for each vendor were examined to identify the ones that referenced a specific dollar amount for the return on investment.

[3] **2021 Gartner AI in Organizations Survey.** This survey was conducted to understand the keys to successful AI implementations and the barriers to the operationalization of AI. The research was conducted online from October through December 2021 among 699 respondents from organizations in the U.S., Germany and the U.K. Quotas were established for company size and for industries to ensure a good representation across the sample. Organizations were required to have developed AI or intended to deploy AI within the next three years. Respondents were required to be part of the organization's corporate leadership or report into corporate leadership roles, and have a high level of involvement with at least one AI initiative. Respondents were also required to have one of the following roles when related to AI in their organizations. determine AI business objectives, measure the value derived from AI initiatives or manage AI initiatives development and implementation. The survey was developed collaboratively by a team of Gartner analysts and Gartner's Research Data, Analytics and Tools team. *Disclaimer: Results of this survey do not represent global findings or the market as a whole, but reflect the sentiments of the respondents and companies surveyed.*

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Emerging Tech: Venture Capital Growth Insights for Decision Intelligence Platforms

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Source: Gartner (May 2023)