2025 Edition

Analytical Data Products Report

Wisdom of Crowds' Series

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Definitions

Business Intelligence Defined

Business intelligence (BI) is "knowledge gained through the access and analysis of business information."

Business intelligence tools and technologies include query and reporting, online analytical processing (OLAP), data mining and advanced analytics, end-user tools for ad hoc query and analysis, and dashboards for performance monitoring.

Source: Howard Dresner, *The Performance Management Revolution: Business Results Through Insight and Action* (John Wiley & Sons, 2007)

Analytical Data Product Platforms Defined

Analytical Data Product Platforms are integrated technology environments that include all needed functionality to support multiple analytical or BI use cases, including data engineering, data and analytic governance, self-service BI, AI, data science and machine learning, embedded BI or analytics, cloud support, and agentic AI.

Introduction

In 2025, Dresner Advisory Services celebrates nearly two decades of independent research and leadership in data, analytics, business intelligence, performance management, and related disciplines. This milestone underscores the enduring trust and engagement of our clients and community, who continue to inspire our mission to deliver unbiased, data-driven insights.

This year, we have rebranded this study as the Analytical Data Products Report to better reflect the evolving market and the expanding scope of technologies it encompasses. Now in its 5th annual edition, the report examines a dynamic and increasingly convergent landscape—where organizations weigh the benefits of adopting a single-vendor analytical ecosystem versus assembling a best-of-breed architecture of specialized solutions. As enterprises seek to streamline operations, ensure scalability, and extract greater value from data, this decision has never been more strategic.

Reflecting the rapid advancement of artificial intelligence (AI), we have also introduced agentic AI as a new area of analysis and as a formal criterion in our vendor evaluation framework. Agentic AI represents a pivotal shift toward adaptive, context-aware, and autonomous analytical capabilities that are reshaping how organizations design and deliver data products.

As always, our goal is to help organizations make well-informed choices about their analytics investments. We trust that this report will serve as a valuable guide to navigating the evolving analytical landscape and advancing your journey toward greater intelligence, agility, and performance.

Best.

Howard Dresner

Chief Research Officer

Dresner Advisory Services

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Benefits of the Study

This Dresner Advisory Wisdom of Crowds[®] Analytical Data Products Report provides a wealth of information and analysis, offering value to both consumers and producers of Analytical data product platforms or broader business intelligence technology and services.

Consumer Guide

As an objective source of industry research, the Dresner Advisory Wisdom of Crowds Analytical Data Products Report helps readers to understand how their peers weigh the importance of different aspects of Analytical data product platforms and then leverage and invest in Analytical data product platforms and related technologies.

Using our unique survey system, industry practitioners discover key insights into analytical platforms, which enable:

- Comparisons of current organizational performance to industry norms
- Identification, prioritization, and selection of new initiatives
- Study program success and consider adjustment of existing programs
- Identification and selection of new vendors

Supplier Tool

Vendor licensees use the Dresner Advisory Analytical Data Products Report in several important ways:

External Awareness

- Build awareness for software markets and supplier brands, citing DAS market study trends and vendor performance
- Create lead and demand generation for supplier offerings through association with Dresner Advisory market study brand, findings, webinars, etc.

Internal Planning

- Refine internal product plans and align with market priorities and realities as identified in the Dresner Advisory Analytical Data Products Report.
- Better understand customer priorities, concerns, and issues
- Identify competitive pressures and opportunities

About Howard Dresner and Dresner Advisory Services

The Dresner Advisory Services Analytical Data Products Report was conceived, designed and executed by Dresner Advisory Services, LLC—an independent advisory firm—and Howard Dresner, its president, founder and chief research officer.

Howard Dresner is one of the foremost thought leaders in business intelligence and performance management, having coined the term "business intelligence" in 1989. He

has published two books on the subject, *The Performance Management Revolution – Business Results through Insight and Action* (John Wiley & Sons, November 2007) and *Profiles in Performance – Business Intelligence Journeys and the Roadmap for Change* (John Wiley & Sons, November 2009). He lectures at forums around the world and is often cited by the business and trade press.

Prior to Dresner Advisory Services, Howard served as chief strategy officer at Hyperion Solutions and was a research fellow at Gartner, where he led its business intelligence research practice for 13 years.

Howard has conducted and directed numerous in-depth primary research studies over the past two decades and is an expert in analyzing these markets.

Through the Wisdom of Crowds® Business Intelligence market research reports, we engage with a global community to redefine how research is created and shared. Other research reports include:

- Wisdom of Crowds[®] Flagship BI Market Study
- Agentic Al
- AI, Data Science, and Machine Learning
- Cloud Computing and Business Intelligence
- Data Engineering
- Data and Analytics Governance
- Embedded Business Intelligence
- Generative AI
- Guided Analytics[®]
- Self-Service BI

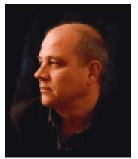
You can find more information about Dresner Advisory Services at www.dresneradvisory.com.

About Jim Ericson

Jim Ericson is a vice president and distinguished analyst with Dresner Advisory Services.

Jim has served as a consultant and journalist who studies end-user management practices and industry trending in the data and information management fields.

From 2004 to 2013, he was the editorial director at Information Management magazine



(formerly *DM Review*), where he created architectures for user and industry coverage for hundreds of contributors across the breadth of the data and information management industry.

As lead writer, he interviewed and profiled more than 100 CIOs, CTOs, and program directors in an annual program called "25 Top Information Managers." His related feature articles earned ASBPE national bronze and multiple Mid-Atlantic region gold and silver awards for Technical Article and for Case History feature writing.

A panelist, interviewer, blogger, community liaison, conference co-chair, and speaker in the data-management community, he also sponsored and co-hosted a weekly podcast in continuous production for more than five years.

Jim's earlier background as senior morning news producer at NBC/Mutual Radio Networks and as managing editor of MSNBC's first Washington, D.C. online news bureau cemented his understanding of fact-finding, topical reporting, and serving broad audiences.

The Dresner Team

About Elizabeth Espinoza

Elizabeth is director of analytics at Dresner Advisory and is responsible for the data preparation, analysis, and creation of charts for Dresner Advisory reports.

About Sherry Fairchok

Sherry is senior editor at Dresner Advisory, ensuring the quality and consistency of all research publications.

About Danielle Guinebertiere

Danielle is vice president of client services at Dresner Advisory. She supports the ongoing research process through her work with executives at companies included in Dresner market reports.

About Michelle Whitson-Lorenzi

Michelle is director of research operations and is responsible for managing software company survey activity and our internal market research data.

Survey Method and Data Collection

As with all our Wisdom of Crowds® market studies, we constructed a survey instrument to collect data and used social media and crowdsourcing techniques to recruit participants.

Data Quality

We carefully scrutinized and verified all respondent entries to ensure that only qualified participants were included in the study.

Executive Summary

- A majority of 52% survey respondents prefers single-vendor integrated platforms; 37% favor best-of-breed (build your own) platforms. Sentiment varies by geography, function, industry and more variables including success with BI, AI use and other technology, leadership, and cultural factors. Chief advantages of both integrated and best-of-breed platforms are illuminating and often intuitive (figs. 5-19).
- Data engineering is very important to critical in organizations and is frequently applied by a majority of respondent organizations today, with multiple applicable use cases, features, and data sources. Deployment favors cloud (figs. 20-29).
- Just 41% of organizations in our survey have established formal data governance organizations; those with governance in place report a diverse mix of structures, reporting, scope, activities, administrative, co-creation and data catalog feature requirements (figs. 30-39).
- Self-service BI is an area of ongoing high attention and criticality. Seventy-three percent report moderate or significantly greater success (figs. 40-41).
- Collaborative BI is on a plateau of sustained and near very important criticality. The top old and new collaborative channels mirror historical findings and include email, virtual and face-to-face meetings, and formal presentations. Interest in features and frameworks varies; Microsoft Teams and SharePoint are the top frameworks (figs. 42-47).
- Guided Analytics[®], an outgrowth of earlier research on data storytelling and related topics, is at a sustained level of important criticality with varied authoring and user feature requirements (figs. 48-50).
- Natural language analytics sees slowly increasing criticality; use remains limited and is not increasing; multiple output requirements are specified (figs. 51-52).
- About half of respondent organizations are using or experimenting with generative AI today, and many have future plans (figs. 53).
- Embedded BI rebounded to all-time high importance and adoption with a mix of objectives, adoptive trends, features, and targeted audiences (figs. 54-60).
- Al, data science, and machine learning involves a mix of users, is of steady high importance, with multiple use cases, scope and scalability, features, neural network, and generative and open-source adoption using many data sources (figs. 61-72).
- Cloud computing importance and adoption continue on a trajectory of high importance, perceived advantages, disadvantages, security requirements, architectures, connectors, licensing, hosting, and provider choices (figs. 73-83).
- Analytical data product vendor ratings are shown in Fig. 84.

Study Demographics

Our 2025 survey base provides a cross-section of data across geographies, functions, organization sizes, and vertical industries. We believe that, unlike other industry research, this supports a more representative sample and better indicator of true market dynamics. We constructed cross-tab analyses using these demographics to identify and illustrate important industry trends.

Geography

Survey respondents represent the span of geographies. North America (including the United States, Canada, and Puerto Rico) accounts for the largest group with 59% of all respondents. EMEA accounts for 22%, Asia Pacific for 16%, and Latin America 4% (fig. 1).

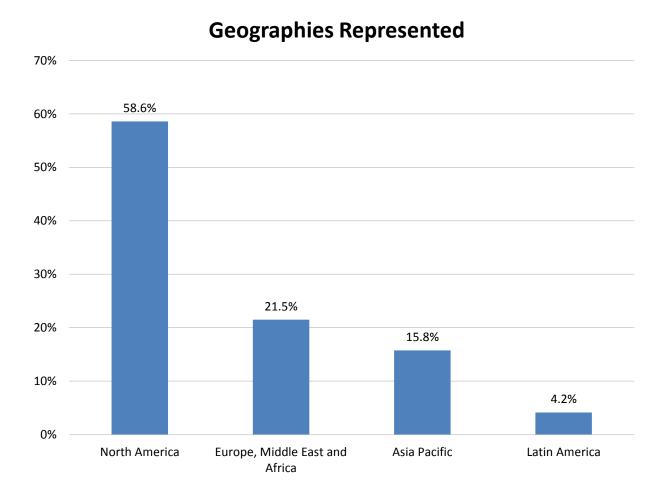


Figure 1 – Geographies represented

Respondent Functions

Finance (29%) and IT (28%) are the functions most represented in our 2025 study (fig. 2). Executive management is the next most represented with 14%, followed by the business intelligence competency center (BICC; 11%).

Tabulating results by respondent function helps us create analyses that represent different perspectives by function.

Functions Represented 35% 29% 28% 30% 25% 20% 14% 15% 11% Business Intelligence | Analytics Completency... Research and Development Resol 10% 4% 3% 5% 3% 1% 1% 0% sales o Marketine

Figure 2 – Functions represented

Vertical Industries

Survey respondents are from a broad range of industries with no individual industry dominating the responses. In 2025, manufacturing (22%) and technology (20%) are most represented, followed by business services (17%) and financial services (11%).

Tabulating results across industries helps us develop analyses that reflect the maturity and direction of different business sectors.

Industries Represented

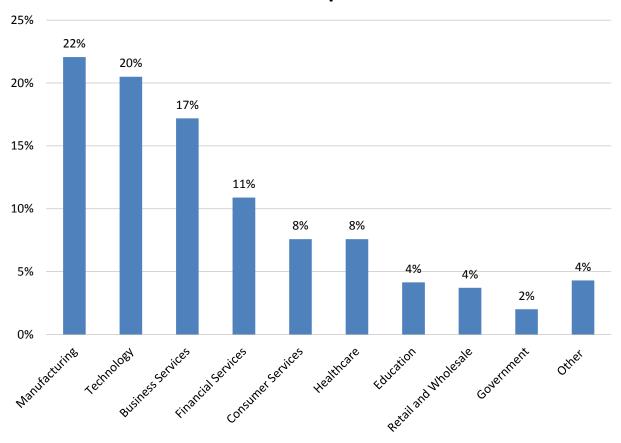


Figure 3 – Industries represented

Organization Size

Survey respondents include a mix of different-sized organizations (measured by global employee head count). Small organizations (1-100 employees) represent 19% of respondents, midsize organizations (101-1,000 employees) account for another 29%, and large organizations (>1,000 employees) account for the remaining 52% (fig. 4).

Tabulating results by organization size reveals important differences in practices, planning, and maturity.

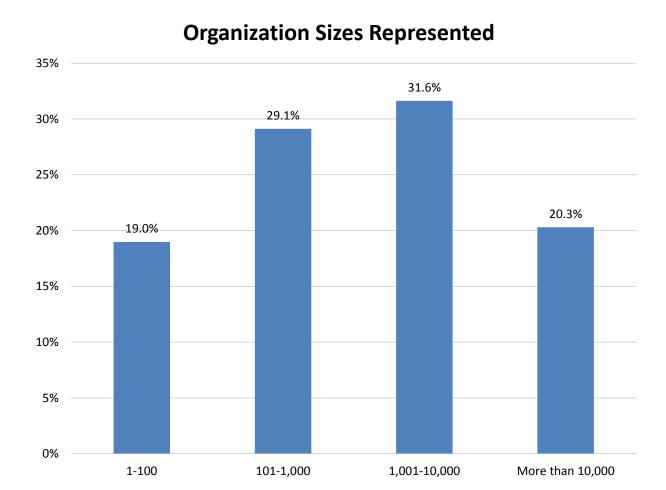


Figure 4 – Organization sizes represented

Analytical Data Product Platforms

The concept of analytical data product platforms is not new. However, as technology advances, these platforms evolve and become more functional and more open, making them more viable than in the past.

For the purposes of this report, we define analytical data product platforms as integrated technology environments that include all needed functionality to support multiple analytical or BI use cases, with the possible exception of analytical data infrastructure (ADI).

Analytical data product platforms include the following capabilities:

- Agentic AI capabilities
- Al, data science and machine learning
- Data engineering (data preparation, data integration, data workflows)
- Cloud-based support, including SaaS
- Data and analytics governance
- Embedded BI and/or analytics
- Self-service (including user governance, guided analytics, collaboration, natural language interface)

Analytical Data Product Platform Preferences 2021-2025

We asked survey respondents, "Do you prefer best-of-breed solutions for analytical data product platform functionality or a complete, integrated platform from a single vendor?" In 2025, as in the prior three years, a majority (52%) choose single-vendor integrated platforms, versus about 37% that favor best-of-breed (build your own) platforms (fig. 5). (In 2025, we also broke out "internal development with open-source components" [11%], which accounts for the gap down in the best-of-breed finding.) The preference for single-vendor platforms has ranged between 52%-55% since 2021. Our global sample has never favored the best-of-breed approach. In every case, unique BI needs and journeys might favor the scalability (and other) benefits of the platform approach versus the customization (and other) benefits found in multiple stand-alone vendors. Nonetheless, all three choices are relevant today. Figures 6-19 give a snapshot of cultural and environmental demographics and drivers of analytical platform use.

Analytical Data Product Platform Preferences 2021-2025

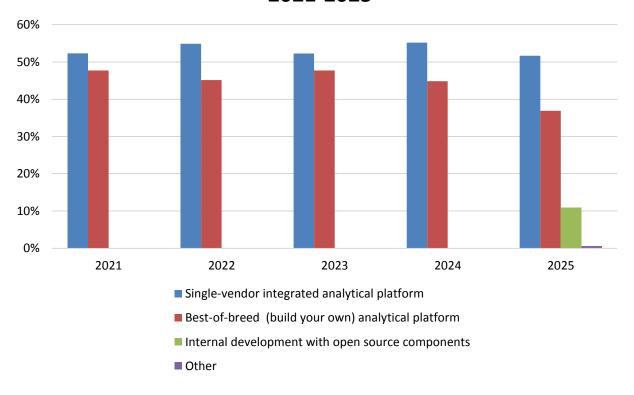


Figure 5 – Analytical data product platform preferences 2021-2025

Analytical Data Product Platform Preferences by Geography

Sentiment toward single-vendor versus best-of-breed analytical data product platforms varies somewhat by geography in 2025 (fig. 6) but reveals distinctions not seen in the global sample (fig. 5). This year, Latin America and EMEA far exceed the mean-value global preference for single-vendor platform preference (65% and 61% respectively versus 52% globally). North America and Asia Pacific respondents weigh in below the global single-vendor 52% preference at 49% and 47% respectively. Newly included "internal development with open-source components" accounts for 10%-12% of responses in any geography. We would expect different regional histories of single-vendor relationships, first-mover instincts, and product availability to color these results.

Analytical Data Product Platform Preferences by Geography

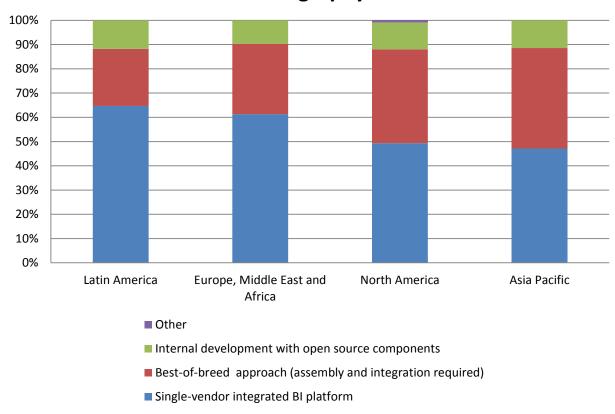


Figure 6 – Analytical data product platform preferences by geography

Analytical Data Product Platform Preferences by Function

Sentiment toward single-vendor versus best-of-breed analytical data product platforms varies by function in 2025 (fig. 7) and by role bucks the overall global distribution seen in fig. 5. This year, single-vendor integrated analytical data product platforms are most preferred by executive management (65%, an audience that might be more attuned to cost and standardization), and sales and marketing (57%, where integrated platforms may be most commonly available). IT (53%) and R&D (50%) respondents are next most likely to prefer the single-vendor approach, but are slightly more agnostic according to need. Respondents in finance, the BICC, and especially operations are more likely to prefer the best-of-breed/open-source approach.

Analytical Data Product Platform Preferences by Function

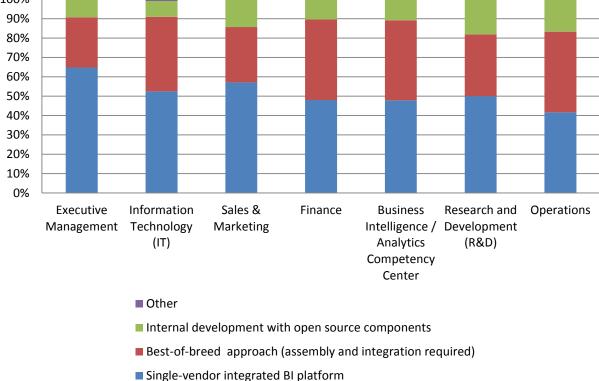


Figure 7 – Analytical data product platform preferences by function

Analytical Data Product Platform Preferences by Industry

Sentiment toward single-vendor versus best-of-breed analytical data product platforms varies irregularly by industry in 2025 (fig. 8). We would already expect these findings to be colored by a legacy of industry-tuned platforms in verticals such as healthcare and manufacturing, or the opposite in distributed supply chain or fragmented industries such as retail and wholesale. This year, education widely leads in its preference for single-vendor platforms (67%), followed by business services (57%), healthcare (54%) and manufacturing (53%). The use of internal development with open-source components is not surprisingly found most often in technology (15%), followed by education (14%), business services (14%) and manufacturing (13%).

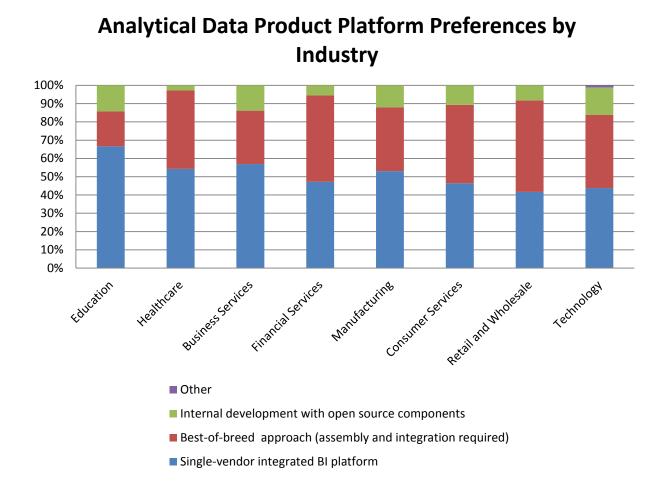


Figure 8 – Analytical data product platform preferences by industry

Analytical Data Product Platform Preferences by Organization Size

Sentiment toward single-vendor versus best-of-breed analytical data product platforms follows an interesting pattern of scale that diverges noticeably among respondent organizations with more than 10,000 employees (fig. 9). In 2025, the preference for single-vendor platforms rises slowly from 51% to 53% to 57% among small, midsize and large organizations before falling to just 41% among the very largest companies. Said another way, only very large organizations clearly prefer the best-of-breed/open-source model over the single platform. In one sense, this might be intuitive, given the expanding catalog of application subjects and the complex, fragmented and distributed nature of the largest organizations made of greater numbers of departments and multiple lines of business. We would expect analytical data product tools and solutions to consolidate and commoditize over time to the extent that enterprise needs and initiatives are met.

Analytical Data Product Platform Preferences by Organization Size

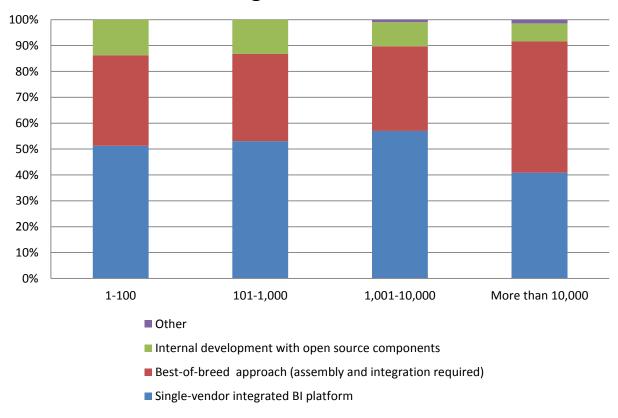


Figure 9 – Analytical data product platform preferences by organization size

Analytical Data Product Platform Preferences by Success with BI

Success with BI shows a clear correlation to the adoption of best-of-breed/open source analytical data product platform adoption in 2025 but comes with a caveat (fig. 10). This year, organizations that say they are completely successful with BI are about 56% likely to choose best-of-breed/open source, and all less-successful organizations are slightly to considerably more likely to choose single-vendor platforms. Most noticeably, somewhat unsuccessful and unsuccessful organizations are just 34%-35% likely to take the best-of-breed/open-source path. This finding might be intuitive for many reasons including more mature BI and IT practices that are capable with multiple tools and analytical processes or a lack of sufficiently capable BI platforms to ensure BI success. Another interesting finding appears to contradict this, however: the use of internal development with open-source components is far more common in somewhat unsuccessful and unsuccessful organizations than in successful ones. In sum, the finding tells us that completely successful BI organizations are most drawn to dedicated best-of-breed data product platforms that require assembly and integration.

Analytical Data Product Platform Preferences by Success with BI

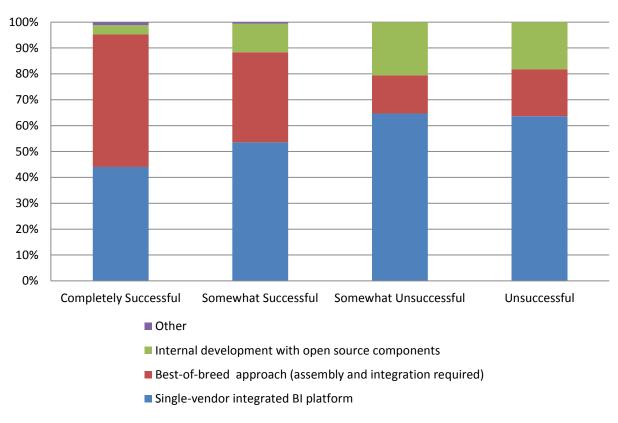


Figure 10 – Analytical platform preferences by success with BI

Analytical Data Product Platform Preferences by BI Budget Plans

Organizations that are increasing their annual BI budgets are most likely (about 57%) to prefer single-vendor integrated BI platforms in 2025 (fig. 11). By comparison, organizations with flat BI budgets are 48% likely to prefer single-vendor integrated platforms, and organizations with decreasing budgets are narrowly (52%) in favor of the single-vendor integrated platform approach. There are many ways to interpret this finding in dimensions of cost, complexity, and functionality.

One conclusion might be that organizations with increasing budgets are initiating or upgrading/consolidating analytical data product platforms with a single-vendor approach. The same thinking might lead us to conclude that organizations that are decreasing budgets might employ multiple legacy systems or unique approaches not consolidated around any single model. It is conventionally the case that integrated platform investments involve lower sunken costs than fragmented ones, though in reality, the mix of cost and utility in any single organization varies.

Analytical Data Product Platform Preferences by BI Budget Plans

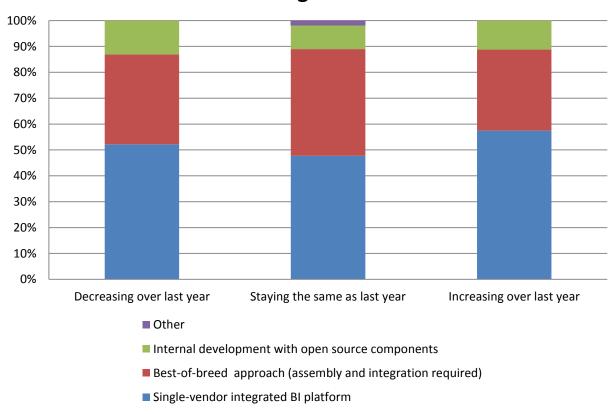


Figure 11 – Analytical data product platform preferences by BI budget plans

Analytical Data Product Platform Preferences by Number of BI Tools in Use

An expected finding in the use of analytical data product platforms is that the increasing fragmentation found in point and best-of-breed and or open-source Analytical data product platforms and solutions results in greater numbers of tools in use (fig. 12). Users of single-vendor integrated analytical data product platforms are 67% likely to report the use of one or two tools, and far less likely to use three to four tools (45%) or five or more tools (30%) in 2025.

Analytical Data Product Platform Preferences by Number of BI Tools in Use

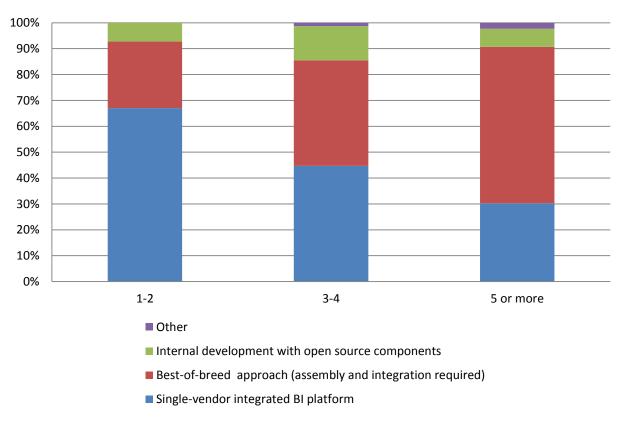


Figure 12 – Analytical data product platform preferences by number of BI tools in use

Analytical Data Product Platform Preferences by Difficulty in Finding Analytic Content

In 2025, the use of single-vendor integrated platforms, best-of-breed and internally developed analytical data product platforms do not correlate clearly to difficulty finding analytic content (fig. 13). Indeed, organizations that express different levels of difficulty all take multiple analytic and data product platform paths. For example, organizations that report it is "relatively easy" finding analytic content are 43% likely to use single-vendor integrated platforms and 45% likely to use the best-of-breed approach that requires assembly and integration. Perhaps more interesting, organizations that find it "difficult" to find analytic content are also most likely (17%) to pursue (or require out of necessity) internal development with open-source components.

Analytical Data Product Platform Preferences by Difficulty Finding Analytic Content

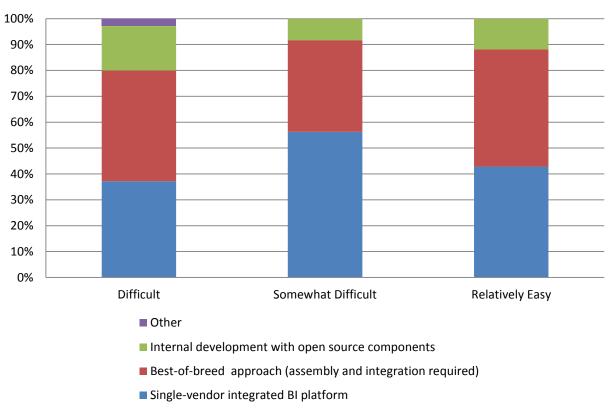


Figure 13 – Analytical data product platform preferences by difficulty finding analytic content

Analytical Data Product Platform Preferences by Data Leadership

Analytical data product platform preferences correlate to data leadership in the form of the presence of a chief data officer (CDO), chief analytics officer (CAO), or other identified data leader (fig. 14). In 2025, data leadership that is currently "in place" coincides more often with the use of best-of-breed (build your own) Analytical data product platforms (52%) versus single-vendor integrated platforms (36%). In contrast, large majorities of organizations with only future plans or no leadership plans report higher use of single-vendor integrated Analytical data product platforms (57% and 62% respectively). One interpretation of this finding is that a technologically minded CAO or CDO is better suited to wrangle and optimize build-your-own solutions and platforms, while organizations attempting to consolidate fragmented infrastructure might resort to the single-vendor approach. Regardless of the presence or absence or data leadership, organizations are 11%-13% likely to pursue internal development with open-source components.

Analytical Data Product Platform Preferences by Data Leadership

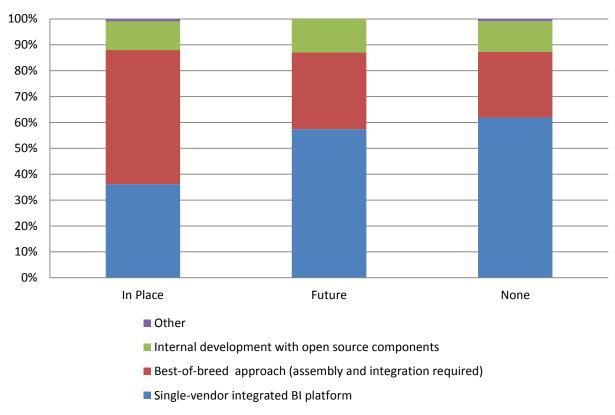


Figure 14 – Analytical data product platform preferences by data leadership

Analytical Data Product Platform Preferences by DSML Adoption

Analytical data product platform preferences correlate to data science and machine learning (DSML) adoption in that organizations more attuned to DSML are less likely to use single-vendor integrated BI platforms (fig. 15). The implication might be that single-vendor platforms are less capable of DSML support, or that DSML-friendly organizations are inherently more involved with best-of-breed approaches where assembly and integration is required. In any case, organizations that use data science and machine learning today are 30% likely to use single-vendor integrated BI platforms, compared to 48%-66% of all occasional, infrequent or non-users of DSML. Once again, the use of internal development with open-source components does not appear to weigh on the adoption or non-adoption of DSML

Analytical Data Product Platform Preferences by DSML Adoption

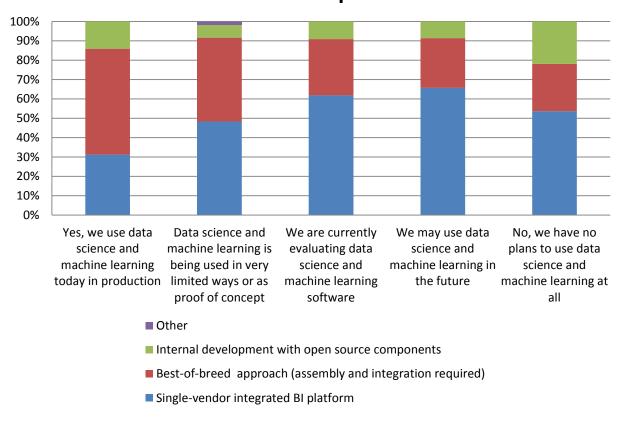


Figure 15 - Analytical data product platform preferences by DSML adoption

Analytical Data Product Platform Preferences by Agentic AI Adoption

Analytical data product platform preferences correlate strongly to agentic artificial intelligence (AI) adoption in that organizations actively pursuing agentic AI are less likely to use single-vendor integrated BI platforms (fig. 16). Again, possible implications might include less flexibility or compatibility with single-vendor integrated platforms or other reasons. In any case, organizations that report having agentic AI in production today are just 26% likely to use single-vendor integrated BI platforms, compared to 45%-60% of all experimental, prospective or non-users of agentic AI. The use of internal development with open-source components does not appear to coincide with the adoption or non-adoption of agentic AI.

Analytical Data Product Platform Preferences by Agentic Al Adoption

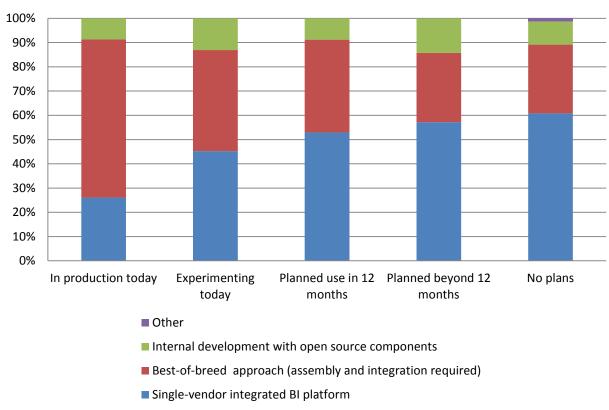


Figure 16 - Analytical data product platform preferences by agentic Al adoption

Analytical Data Product Platform Preferences by Generative AI Adoption

While not quite as strong as the association with DSML or agentic AI (figs. 15-16), analytical data product platform preferences correlate to generative AI adoption in that organizations actively pursuing generative AI are less likely to use single-vendor integrated BI platforms (fig. 17). Yet again, possible implications might include less flexibility or compatibility with single-vendor integrated platforms or another reason. It is also more likely that some generative AI capabilities might be included as features in single-vendor integrated BI platforms. In this case, organizations with generative AI in production today are 39% likely to use single-vendor integrated BI platforms, compared to 48%-65% of all experimental, prospective or non-users of generative AI. The use of internal development with open-source components does not appear to coincide with the adoption or non-adoption of generative AI.

Analytical Data Product Platform Preferences by Generative Al Adoption

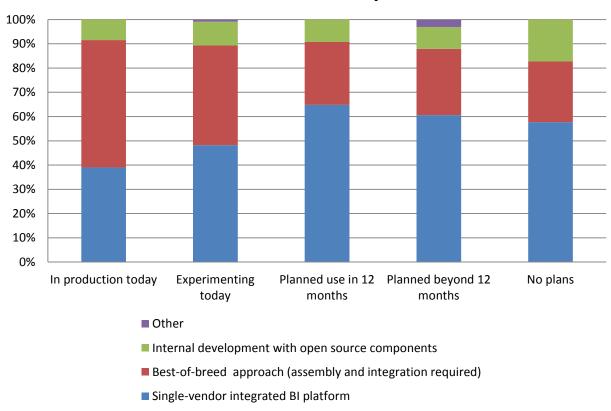


Figure 17 - Analytical data product platform preferences by generative AI adoption

Best-of-Breed Benefits and Limitations

We asked respondents to quantify seven specific advantages/disadvantages associated with the use of best-of-breed analytical data product platforms in 2025 (fig. 18). The results are largely intuitive to organizations that built capabilities from specific preferred products: state-of-the-art functionality, overall flexibility and, interestingly, security are the chief advantages of best of breed while cost reduction, ease of deployment and platform management are the least advantageous or in some cases a split decision. User and data governance falls most in the middle, an indication of a more standalone or fit-to-purpose pursuit not particularly advantageous to best-of-breed or integrated platforms. (We suggest closely comparing and contrasting this page with the following page showing single-vendor integrated analytical platform benefits and limitations.)

Best of Breed Benefits and Limitations

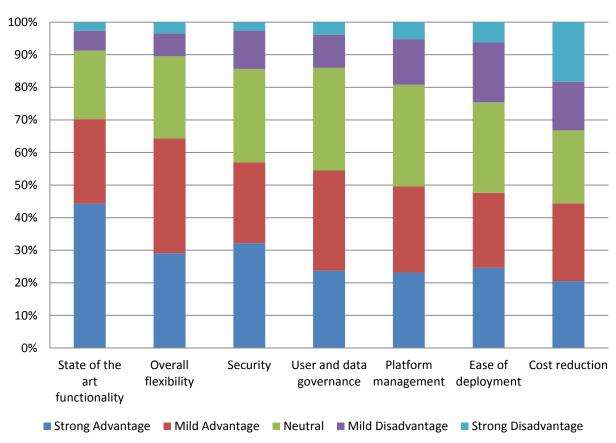


Figure 18 – Best of breed benefits and limitations

Single-Vendor Integrated Platform Benefits and Limitations

We also asked respondents to quantify seven specific advantages/disadvantages associated with the use of single-vendor integrated analytical data product platforms in 2025 (fig. 19). Here, the results contrast with the previous chart (fig. 18) in expected dimensions. In 2025, we find ease of deployment, security, and platform management are the chief advantages of the single-vendor approach. In return, overall flexibility and state-of-the-art functionality are least often cited as advantageous attributes of integrated platforms. Interestingly, cost reduction is seen as less of a benefit than in previous studies, and user and data governance again falls to the middle or undecided category. Side by side, figs. 18-19 amplify conventional thinking in a manifest way. While acknowledging tradeoffs, we also note that the sum of mean benefits is somewhat higher for integrated platforms versus best of breed in 2025, a bit less so than in the previous three years.

Single Vendor Benefits and Limitations

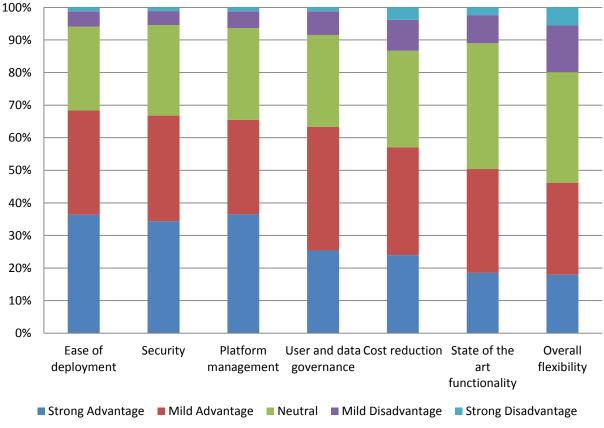


Figure 19 – Single vendor benefits and limitations

Data Engineering

Importance of Data Engineering

We asked respondents about the importance of data engineering. In our 2025 survey, 44% of respondents indicate data engineering is of critical importance (fig. 20) while 37% indicate it is very important. Less than 2% indicate that data engineering is not important.

Importance of Data Engineering

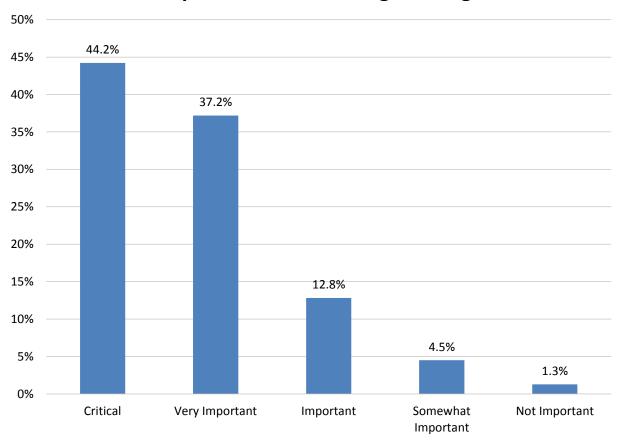


Figure 20 – Importance of data engineering

Use and Plans for Data Engineering

When we asked respondents about their current use and plans for data engineering, 75% said their organizations use data-engineering capabilities today and 20% indicate plans to expand their use. Thirteen percent of respondents indicate plans to use data-engineering tools within the next 12 months (fig. 21). Only 7% have no plans at all to use data-engineering capabilities.

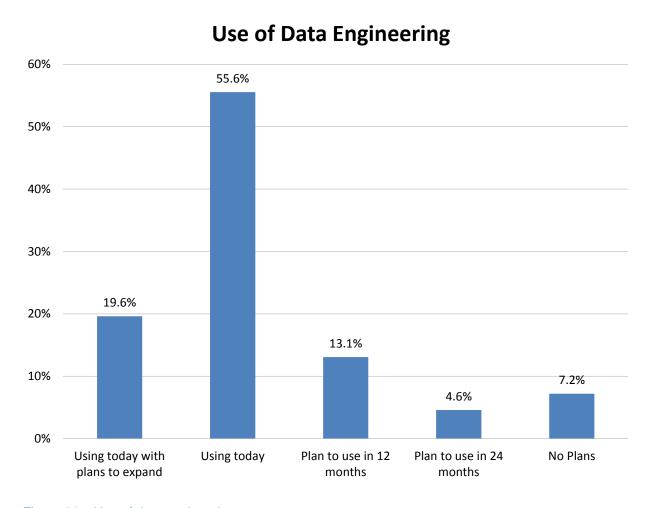


Figure 21 – Use of data engineering

Use Cases for Data Engineering

Data-engineering products are often purchased and used for multiple BI use cases (fig 22). We asked our survey respondents to indicate the estimated percentage of BI use cases for which they purchase and use data engineering products. Thirty-two percent say they employ 60% of their data-engineering capabilities for data integration, cleansing, and transformation workflows for a data warehouse that supports dashboards and reporting. These percentages reflect most organizations' related use of the technology within various BI, analytics, and data science activities.

Data Engineering Use Cases

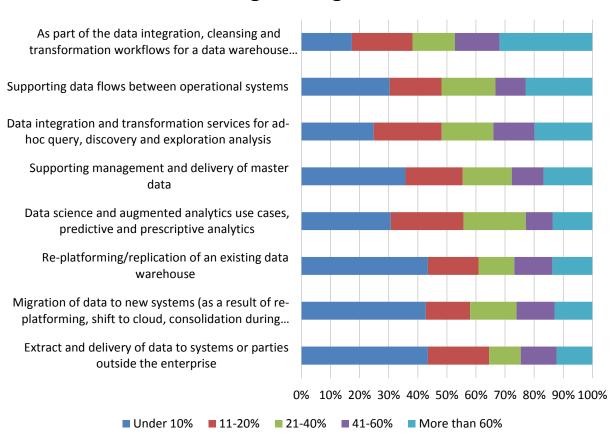


Figure 22 – Data engineering use cases

Data Engineering Features for Data Processing and Transformation

We asked our survey respondents to indicate the importance of the data-engineering features for processing and transforming data listed in fig. 23. We've sorted the 30 top results by the weighted mean of the importance of the features (such as critical, very important, etc.). The top features for data-engineering workflows include the ability to aggregate and group data and ETL and ELT workflows, as well as the management of engineering workflows, such as alerting/job monitoring and execution plan, time-, and event-based schedulers for jobs. Least important is support for Kafka and Apache big data services.

Features for Data Processing and Transformation

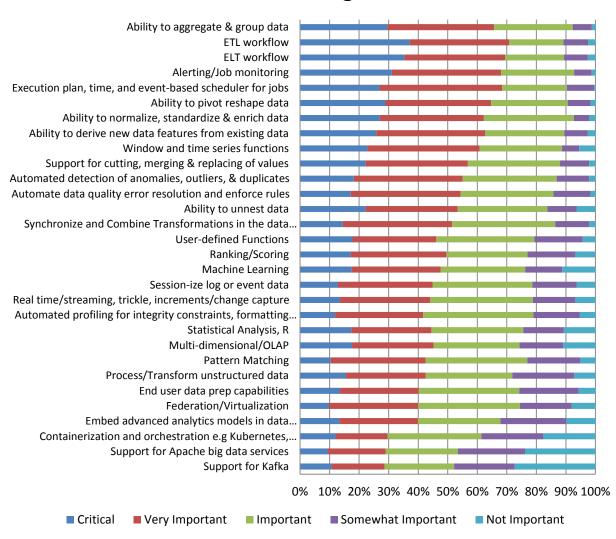


Figure 23 – Features for data processing and transformation

Frequency of Data Engineering

Our survey asked respondents, "How frequently do people in your organization engage in data engineering prior to analysis?" Forty-seven percent of respondents engage in data engineering constantly or frequently (fig. 24). Twenty-two percent use data engineering occasionally, and less than 11% use data engineering rarely or never.

Frequency of Data Engineering

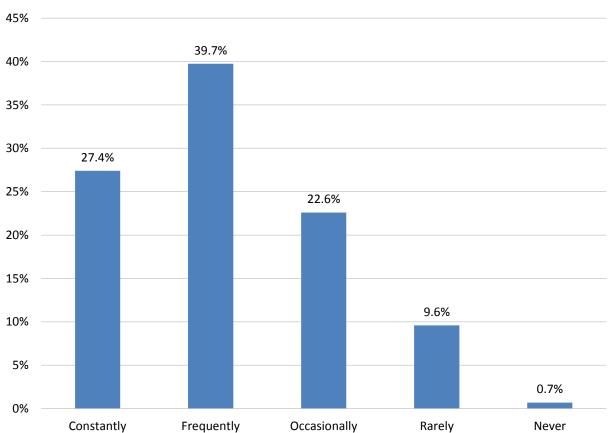


Figure 24 – Frequency of data engineering

Data Engineering Usability

Several trends over 2022-2025 are noticeable in fig. 25. Simple to build/execute data workflow scripts consistently ranks as the most important feature, increasing its score steadily over the years. Features related to automation, such as automated recommendations for data relationships and automated data quality rules, also are becoming increasingly important. Data governance and security features like mask or redact sensitive data and governance capabilities maintain high scores and show growth. Conversely, some features like graphical, drag-and-drop designer have declined slightly in perceived importance. Overall, there is a trend toward greater emphasis on automation, governance, and ease of use in data-engineering tools.

Data Engineering Usability Features 2022-2025

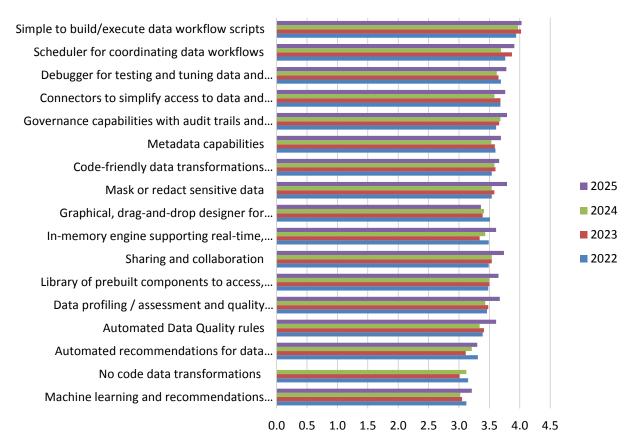


Figure 25 – Data engineering usability features 2022-2025

Frequency of Enrichment with Third-Party Data

We asked our survey respondents about the use and frequency of data enrichment with third-party data as part of data-engineering workflows (fig. 26). Twenty-three percent of respondents say they rarely use third-party data for enrichment of data-engineering processes. Twenty-six percent occasionally enrich their data-engineering workflows with third-party data. Eighteen percent constantly enrich with third-party data and 28% frequently enrich with third-party data. Five percent of organizations never use third-party data for enrichment.

Frequency of Enrichment with Third-Party Data

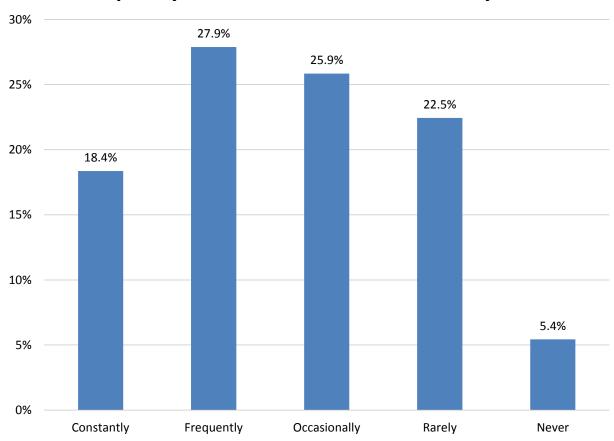


Figure 26 - Frequency of enrichment with third-party data

Data Sources and Targets for Data Engineering

Overall, respondents indicate that relational databases, file systems, and applications are the top data sources and targets for data-engineering workflows (fig. 27). Analytical databases are also a primary target of data-engineering pipelines. Of note is the high score for object stores (e.g., Amazon S3, Google Cloud Storage, Microsoft Azure blob storage), which are an important target for data-engineering workflows but are also frequently used as a source. This is due to their role as an offline storage and staging repository for those workflows.

Data Engineering Sources and Targets

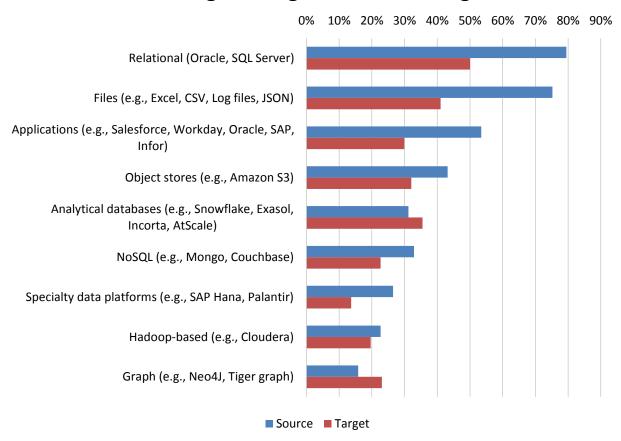


Figure 27 – Data engineering sources and targets

Effectiveness with Current Approach to Data Engineering

There appears to be room for improvement in current approaches to data engineering. Thirty-seven percent of our survey respondents rate their current approach to data engineering as highly effective (fig. 28). Forty-eight percent of our respondents rate their current approach to data engineering as somewhat effective. Fifteen percent of respondents rate their current approach as somewhat or totally ineffective. Data leaders who champion investments in best-practice initiatives can help improve the effectiveness of data-engineering investments.

Current Approach to Data Engineering

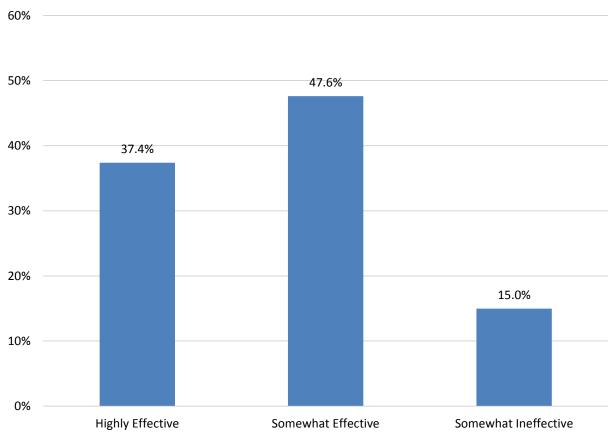


Figure 28 – Current approach to data engineering

Deployment of Data Engineering Capabilities

Fig. 29 shows the distribution of survey responses regarding the importance of data-engineering functionality across different deployment options. The responses are categorized by perceived importance (critical, very important, important, somewhat important, not important) and the deployment options (on premises, public cloud [SaaS], hybrid [on premises and cloud], private cloud). The percentages indicate the proportion of respondents who assigned each level of importance to data-engineering functionality within each deployment option. Private cloud and public cloud are the preferred deployments for data-engineering capabilities.

Deployment of Data Engineering Capabilities

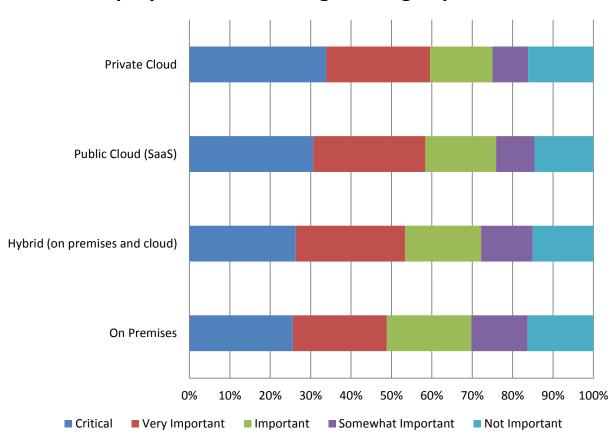


Figure 29 – Deployment of data engineering capabilities

Data and Analytic Governance

Data and Analytic Governance Organization

In 2025, only 41% of organizations surveyed report having any formal governance organization in place (fig. 30). The widespread lack of governance organizations within a persistent majority of organizations is out of step with the broader market's increasing need for more data-driven outcomes. It also shows a failure of alignment with the overall prioritization of governance as an initiative strategic to BI.

Note, however, that the lack of a formal organization for governance does not mean governance is nonexistent. It is likely being performed informally, inconsistently, and incompletely across organizations, and is therefore unlikely to be optimally effective or impactful at an enterprise level.

Governance Organizations

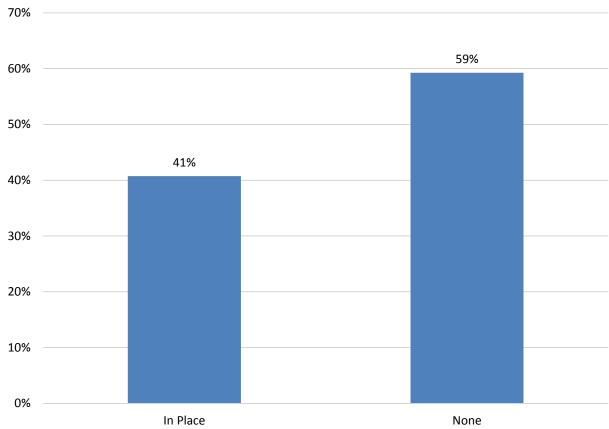


Figure 30 – Governance organizations

Governance Organization Structure

Survey data reporting governance organization structure flows from the minority of respondents reporting the presence of a formal governance organization. The most popular organization structure reported was "distributed team of dedicated roles embedded across the organization" at 36%, more than double any other governance structure included in our survey (fig. 31). The other structure comprised of dedicated governance roles for which we surveyed is "distinct, standalone organization," which at 12% is the lowest level reported.

Despite the apparent shift toward formal governance organizations with dedicated roles (whether distributed or standalone), almost half of respondents report no dedicated formal governance—at 49%, based on the combined categories of "informal, best effort by dedicated individuals with no formal governance responsibilities" (19%), "virtual teams comprised of organization members with secondary responsibilities for governance" (14%), and "none or N/A" (18%).

Governance Organization Structure

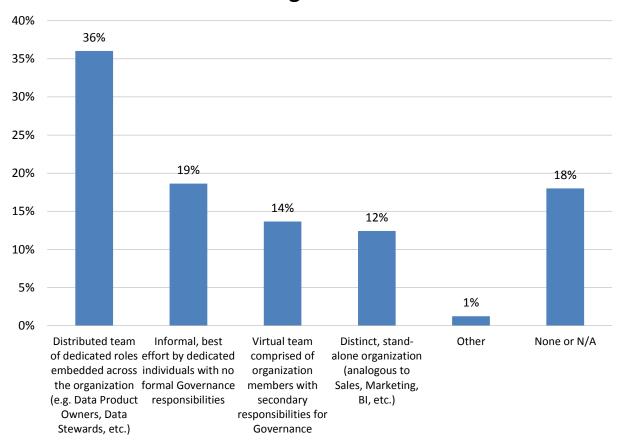


Figure 31 – Governance organization structure

Governance Organization Structure 2024-2025

A year-over-year analysis shows potential for a positive trend toward increasing levels of formal governance roles/responsibilities (fig. 32). Those respondents reporting "none or N/A" mark a substantive downtick from 25% in 2024 to 18% in 2025. While those reporting a "distinct, standalone organization" declined from 17% to 12%, we see an almost 10% increase (from 27% to 36%) for "distributed team of dedicated roles embedded across the organization" (a hybrid structure). "Virtual teams comprised of organization members with secondary responsibilities for governance" also reflected a year-over-year increase from 12% to 14%.

Governance Organization Structure 2024-2025

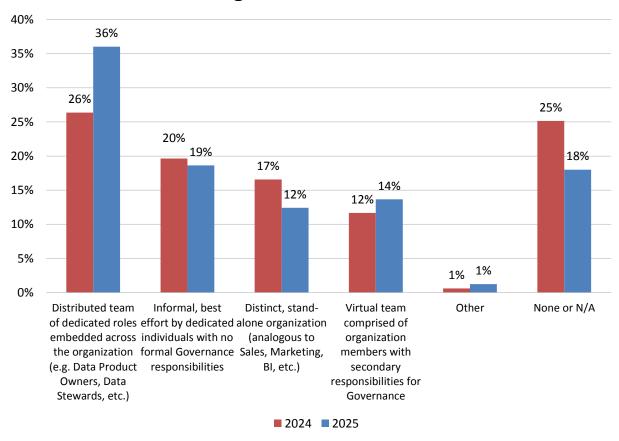


Figure 32 – Governance organization structure 2024-2025

Data Governance Organizational Reporting Structure

In 2025, among respondents reporting they have a formal data governance organization "in place," survey data shows that 45% report into IT, with 27% reporting into the chief data officer (CDO; fig. 33). The balance of distribution in organizational reporting structure sees 10% reporting into the BICC and 6% reporting into finance and "other" functions, respectively. These findings indicate a diverse range of reporting structures for data governance organizations, with the IT and CDO departments being the most common reporting functions.

Data Governance Organizational Reporting Structure

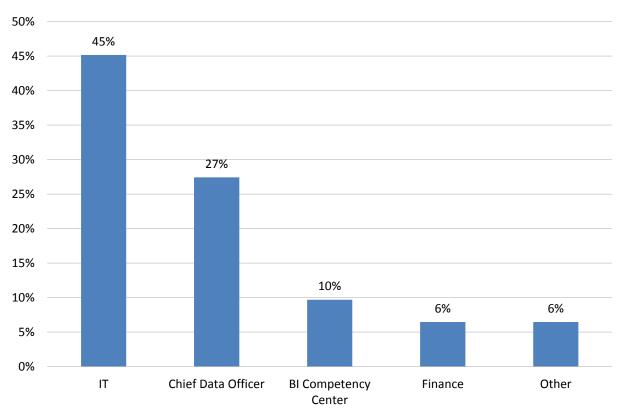


Figure 33 – Data governance organizational reporting structure

2025 Analytical Data Products Report

Data and Analytics Governance Program Scope

Organizations can govern or choose to govern many different types of data and analytic content. Our 2025 survey findings show the most common areas of scope for our respondents' governance programs.

Predictably, most respondents (greater than 50%) reported the top four elements of governance program scope were analytical data, master data, operational data, and analytical reports (fig. 34). The scope encompassed by governance programs rapidly drops off for life cycle management and model management (of any data and analytic elements under governance), analytical charts, anything associated with ML and AI, and cost management of governance (organizational, resources, and/or technology).

We conclude that the survey responses better reflect an earlier time when governance programs focused principally on data and analytical data. While business and mission requirements increase demands on governance programs, with commensurate need to expand the scope of governance (as we discussed in this report's Overview), organizations have been slow to make the necessary changes. Most notably, despite the trend of exceptionally rapid Al adoption, those elements are reported as least under governance.

Data and Analytics Governance Program Scope

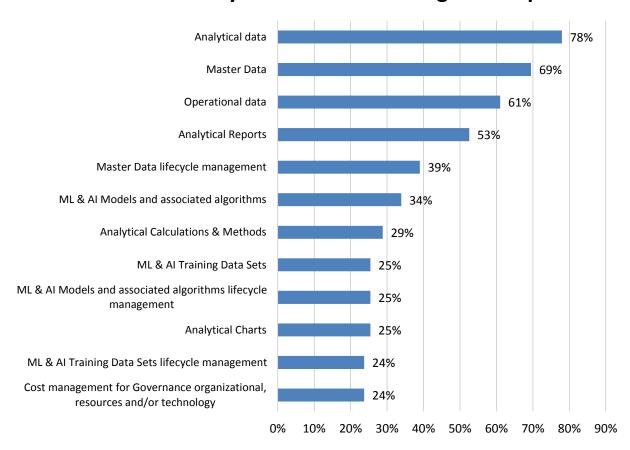


Figure 34 - Data and analytic governance program scope

Data Governance Organization Activities

Our survey data also captures the level of importance for data governance organization activities. For the combined category of "critical," "very important," and "important," seven of 10 activities surveyed are above 90% and all are above 80% (fig. 35). The top activity, data and analytics quality, recorded no other responses. That activity and the second, "controlled access to data appropriate to role," record responses above 50% for "critical," which aligns with other survey contexts in which quality and security are consistently selected as the top two data and analytics priorities.

While all governance organization activities are ranked as important based on the combined category we've described, those focused on life cycle management and cost management rank lower. We believe this reflects the historical focus of legacy data governance programs. We hypothesize that overall priorities will begin to shift as governance programs mature and their scope expands to include additional activities.

Data Governance Organization Activities

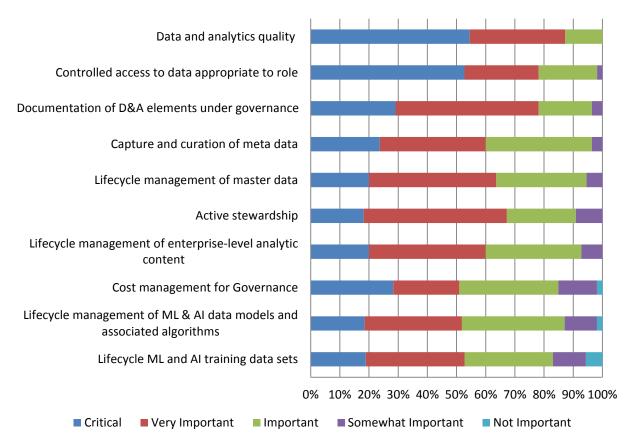


Figure 35 – Data governance organization activities

Data and Analytic Governance Features

In the second year of surveying for the 18 governance features we assess to be integral to enabling and supporting business-focused governance, we observed that for the combined category of "critical," "very important," and "important," every feature exceeded 80% (fig. 36). This reflects the broader market's recognition of these features' relative importance in governing data and analytic elements critical to business and mission requirements. The ranking of the top four governance features is consistent across other Dresner Advisory data and analytic domain surveys, attesting to the persistent and recurring prioritization of security and quality. As all but two governance features exceed 50% for the combined category of "critical" and "very important," we look to the prioritization of "critical" to assess differentiation across the features. As we have observed in other survey data related to this market study, features focused on the more recently identified requirements for governance—life cycle management, cost management, and all associated with machine learning and Al—rank lower than those associated with legacy data governance.

Data and Analytic Governance Feature Requirements

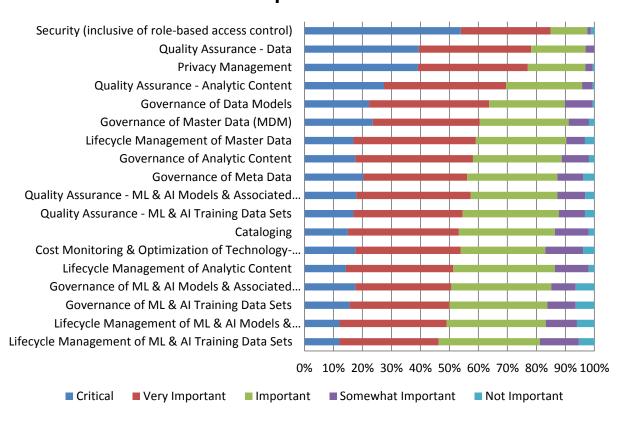


Figure 36 – Data and analytic governance feature requirements

Data and Analytic Administrative Governance Features

As with the data and analytic governance feature requirements already discussed, respondents ranking all but one administrative governance feature requirement ranked above 80% for the combined category of "critical," "very important," and "important" (fig. 37). The top two, "role-based and policy-based access control" and "define levels of access to shared documents, data, analytics, etc.," both ranked above 90%.

The only administrative governance feature requirement that respondents ranked below 80% for the combined category of category of "critical," "very important," and "important" was "check in/out with promote-ability."

Data and Analytic Administrative Governance Feature Requirements

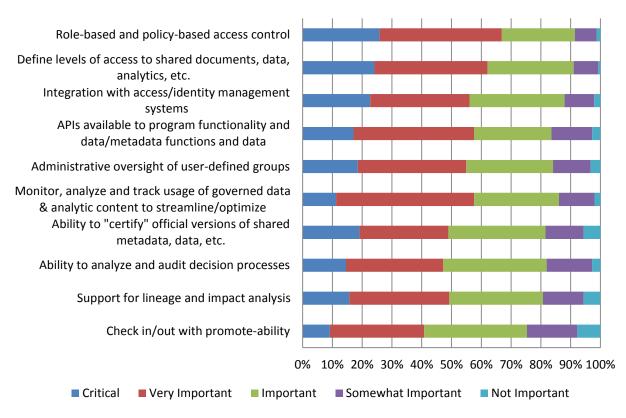


Figure 37 – Data and analytic administrative governance feature requirements

Data and Analytic Collaborative Feature Requirements

We asked respondents to score the importance of 16 "content co-creation and sharing" i.e., collaborative feature requirements in 2025 (fig. 38). This year, at least 63% or far more of our respondents consider all features at least "important." The three top-ranked features (follow governed data and analytic content, search and navigation for content, and annotate data and analytic content) score as either "critical" or "very important" by 55%-56% of respondents. As shown in Fig. 26, importance scores for collaborative feature requirements increased somewhat year over year, a finding echoed by rebounding 2025 importance scores.

Collaborative Feature Requirements

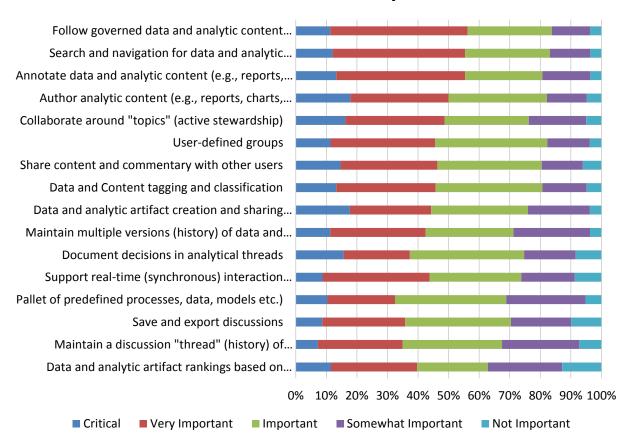


Figure 38 – Collaborative feature requirements

Data Catalog Features for Data and Analytic Governance

While we recognize that cataloging extends beyond governance, catalog capability and functions are integral to an organization's ability to effectively exercise governance of data and analytic content. Therefore, we have opted to include data catalog feature requirements within the context of governance. Respondents confirm this level of importance by rating at greater than 70% every feature requirement for which we surveyed (the combined categories of critical, very important, and important; fig. 39). Five of the eight data catalog feature requirements surveyed exceeded 80% in combined importance. This suggests a systemic change from 2024, when no features exceeded 79% in combined importance, with the majority just exceeding 70%. We believe this reflects increased overall understanding of data catalog features.

Data Catalog Feature Requirements

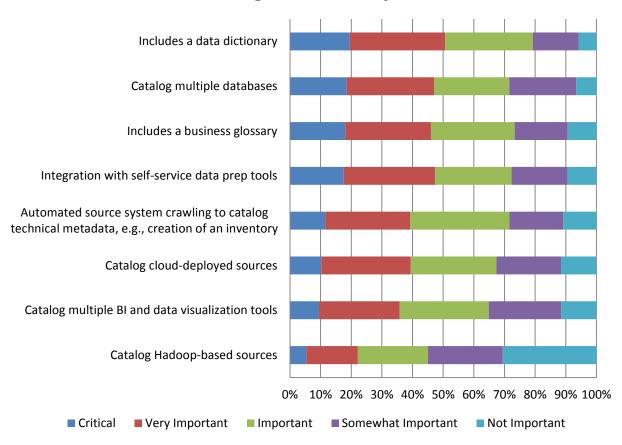


Figure 39 – Data catalog feature requirements

Self-Service BI

End-User Self-Service BI Importance 2017-2025

In 2025, 60% of the sample considers self-service BI "critical" or "very important" (fig. 40), up from 55% in 2024 and 57% in 2023. Weighted-mean importance also increased year over year, from 3.5 to 3.7, just below 2020's all-time high of 3.8. Mean scores are nonetheless within a narrow 3.5-3.8 range for all of the last nine years, a sign of maturing product platform capabilities and expectations met, with criticality steadily well above "important" or approaching "very important."

End-User Self-Service Importance 2017-2025

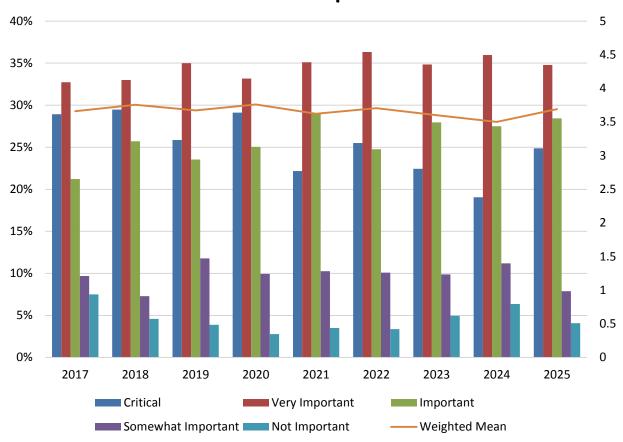


Figure 40 – End-user self-service BI importance 2017-2025

Success in Delivering Self-Service BI 2023-2025

In 2023, we began asking respondents, "Have you delivered self-service business intelligence (BI) in your organization?" In 2025, 32% report they are very successful, compared to 41% that say they are moderately successful, and 6% who report they're unsuccessful (fig. 41). The remaining 22% either have future plans or no plans for enduser self-service BI. Historically, this shows year-over-year improvement among the most successful organizations that offsets lesser successes and slightly weaker future plans.

Success in Delivering Self-Service BI 2023-2025

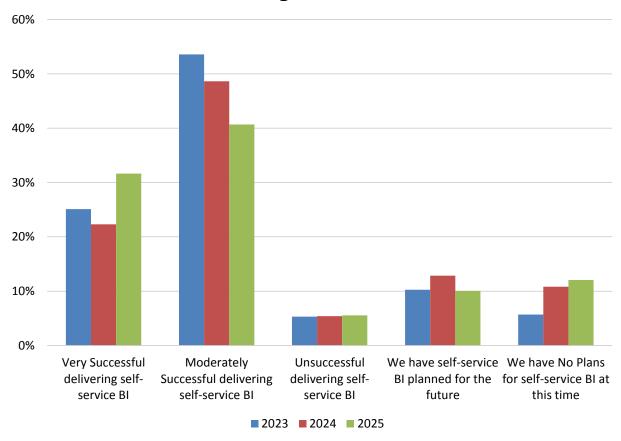


Figure 41 – Success in delivering self-service BI 2023-2025

Methods of Collaboration Today

Collaboration in the process of developing insights and sharing resulting analyses, findings, and decisions is a critical part of BI and is core to self-service. Although all mechanisms for sharing insights are useful, we believe these capabilities within a BI solution offer advantages for collaboration.

Multiple conventional avenues for collaborating with BI are popular and widely used by respondents in 2025, led by email, virtual meetings, face-to-face meetings, and formal presentations (fig. 42). These top four picks (in different order, but identical to the top four methods in our 2024 survey) are at least occasional channel choices for 88%-89% of respondents. About 82% of respondents occasionally use collaborative features built into BI tools. After this, "embedded within other applications," "file-sharing services," and "instant messaging" are at least occasionally used by two-thirds or more of our respondents.

Methods of Collaboration Today

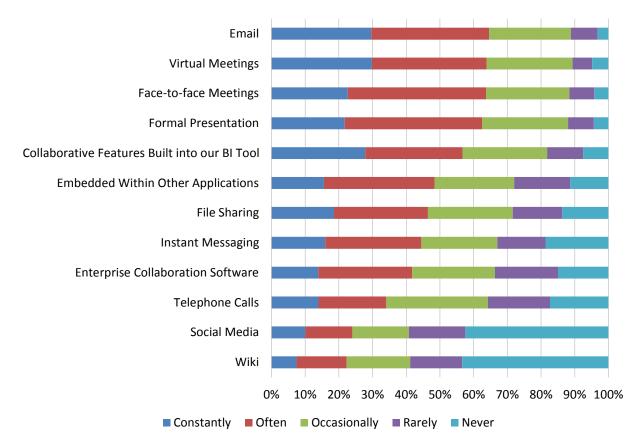


Figure 42 – Methods of collaboration today

Importance of Collaborative BI

A high-level historic view of collaborative BI reveals consistently high relevance at levels frequently approaching the 4.0 mark signifying "very important" (fig. 43). In 2025, the weighted-mean importance stands at 3.7, slightly below the 3.8-3.9 plateau in 2018-2023, and slightly higher than the 3.6 score in 2024. While a one-year deviation can be inconclusive, our 14-year view shows that collaborative BI rose to maturity and consistent importance within distributed workforces and global organizations even before the arrival of COVID-19. In an age of information democracy and governed and ungoverned sharing, 89% of respondents in 2025 say collaborative BI is "important," "very important," or "critical."

Importance of Collaborative BI 2012-2025

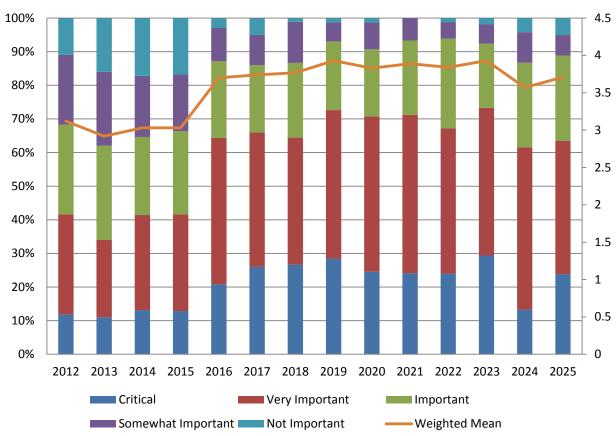


Figure 43 – Importance of collaborative BI 2012-2025

We asked respondents to score the importance of 16 "content co-creation and sharing" i.e., collaborative feature requirements in 2025 (fig. 44). This year, at least 63% or far more of our respondents consider all features at least "important." The three top-ranked features (follow governed data and analytic content, search and navigation for content, and annotate data and analytic content) score as either "critical" or "very important" by 55%-56% of respondents. As shown in Fig. 26, importance scores for collaborative feature requirements increased somewhat year over year, a finding echoed by rebounding 2025 importance scores (fig. 6).

Collaborative Feature Requirements

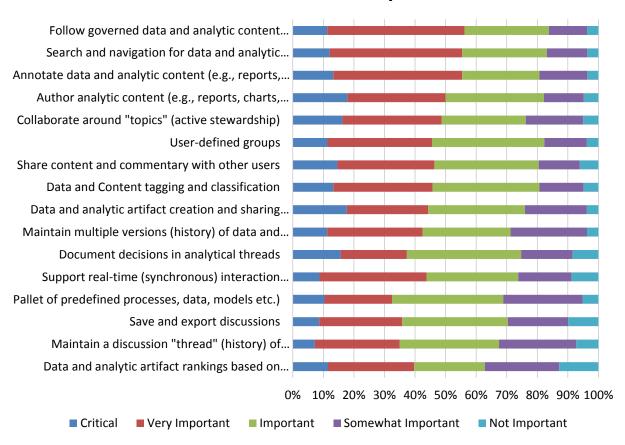


Figure 44 – Collaborative feature requirements

Importance of Integration with Enterprise Collaborative Frameworks 2017-2025

To extend the core collaborative features of a BI tool, organizations may choose to employ enterprise collaborative frameworks to gather more features, scale, or expand scope (fig. 45). Akin to other 2025 collaboration findings, this year's weighted-mean importance of collaboration framework integration reversed a 2024 decline with weighted-mean importance of 3.2, equaling an all-time high seen in 2023. Viewed across nine years of data, the importance of enterprise collaborative frameworks first broke above the 3.0 level of "important" in 2022-2023 and has since held at slightly elevated levels. We note, however, that the weighted-mean importance of enterprise collaborative frameworks is well below the weighted-mean importance of end-user self-service and the overall importance of collaborative BI.

Importance of Integration with Enterprise Collaborative Frameworks 2017-2025

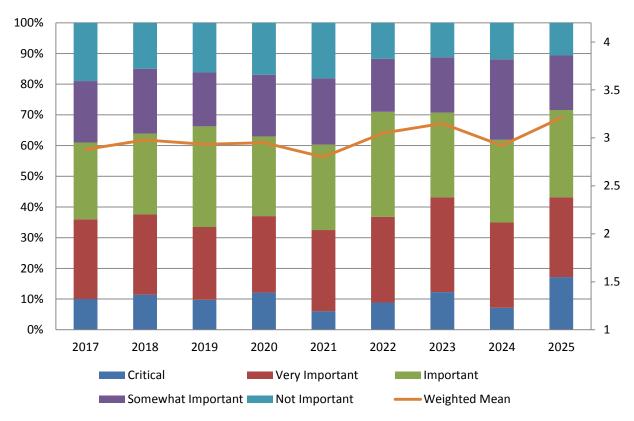


Figure 45 – Importance of integration with enterprise collaborative frameworks 2017-2025

Collaborative BI Features with Enterprise Frameworks 2019-2025

Sentiment toward four collaborative BI features that might be available in enterprise collaborative frameworks is just above, just below, or equal to historic highs in 2025 (fig. 46). Two of these—ability to reference and search BI content; and inclusion of BI objects with other objects—are at new highs this year. All four features score closely in weighted-mean criticality (3.0-3.2), at or just above the level signifying "important." Over the history of our study, slowly growing percentages of respondents find all four features at least "important;" and the narrow range of weighted-mean scores indicate all four remain relevant and important in 2025.

Collaborative BI Features with Enterprise Frameworks 2019-2025

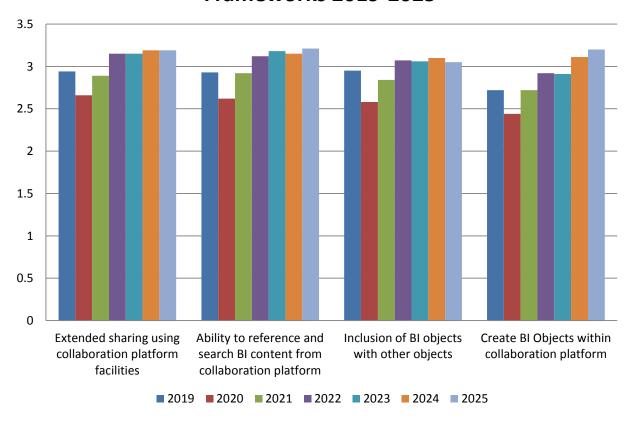


Figure 46 – Collaborative BI features with enterprise frameworks 2019-2025

Enterprise Collaboration Frameworks in Use 2019-2025

In 2025, Microsoft Teams and Microsoft SharePoint remain the two most popular enterprise collaborative frameworks in use by respondents, though the popularity of both fell significantly (by about 10% or more) compared to 2024 (fig. 47). In contrast, some less-popular frameworks gained usage from 2024 to 2025: Jira use increased from 29% to 32%; Google G-Suite rose from 12% to 21%; and Slack rose from 13% to 18%. Lower-ranked Confluence slightly gained users, while Dropbox declined slightly. Well behind, some other enterprise frameworks jockey for attention in 2025, though respondents report almost all have either flat or very minimal use.

Enterprise Collaborative Frameworks in Use 2019-2025

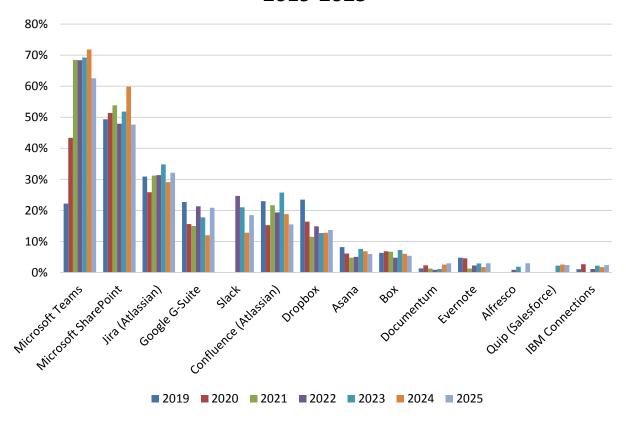


Figure 47 – Enterprise collaborative frameworks in use 2019-2025

Guided Analytics®

In our 2025 study, we included questions to sample the importance of Guided Analytics[®], an outgrowth of our earlier research on data storytelling and related topics. Guided Analytics improves time to insight and action by supporting the creation of connections between related and relevant information and directing and suggesting analytical story flow.

Guided Analytics is at least important to 69% of respondents in 2025, compared to 70% in 2024, and 72% in 2023 (fig. 48). We also observe a decrease in critical responses (10% versus 13% in 2023). Combined scores for "critical" and "very important" remain consistent year –over year (40%). Viewed across five years of data, the topic has hovered near the "important" level with weighted-mean scores of 2.9-3.2.

Importance of Guided Analytics 2021-2025

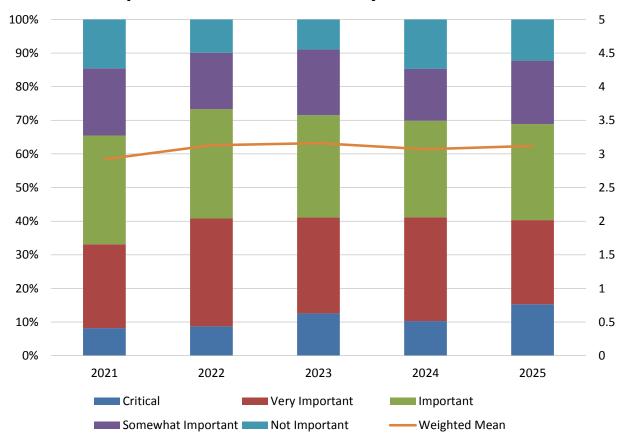


Figure 48 – Importance of Guided Analytics 2021-2025

Guided Analytics Authoring Features

For our 2025 report, we asked respondents to prioritize 11 different Guided Analytics authoring features (fig. 49). This year, as in 2023 and 2024, respondents say flexible, customizable authoring/content creation is the most important feature. Text annotations and author highlighting are the two next-most important features. All 11 features are at least "important" to half or far more of all respondents.

Guided Analytics Authoring Features

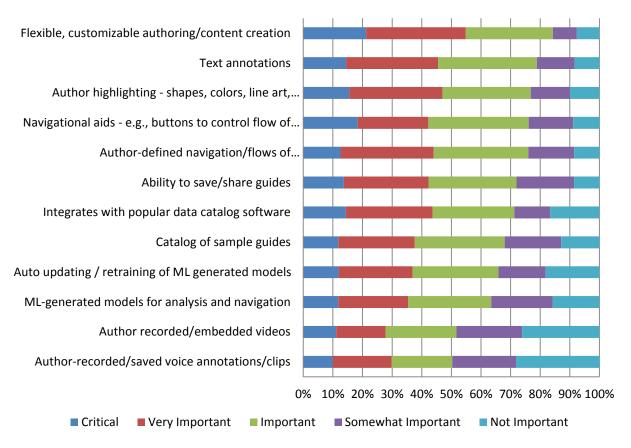


Figure 49 – Guided Analytics authoring features

Guided Analytics User Features

We asked respondents to describe the importance of 12 Guided Analytics user features in 2025 (fig. 50). The top four—user interaction with visual/analytical objects, anomaly identification, search/navigate/recommend, and automated highlighting of objects—are "critical" or "very important" to 40% or more respondents. All 12 features are at least important to 64% or far more respondents. Interestingly, auto generated navigation based on ML models is at the low end of perceived importance in 2025.

Guided Analytics User Features

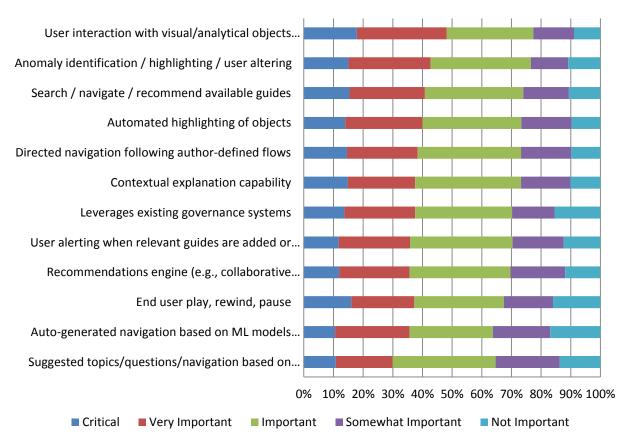


Figure 50 – Guided Analytics user features

Natural Language Analytics

For several years we have asked respondents about the importance of natural language analytics (NLA), which also includes natural language query (NLQ). NLA enables users to speak or type human language requests that are translated into database queries using manipulation language like SQL. To work, these often require the creation and maintenance of lexicons and dictionaries. As NLA becomes more widely required for generative AI, it's likely to continue to grow in importance.

The importance of NLA, measured by scores of "critical" importance, has increased from 2023 through 2025, while scores of "not important" have decreased during the same time period (fig. 51).

Natural Language Analytics Importance 2023-2025

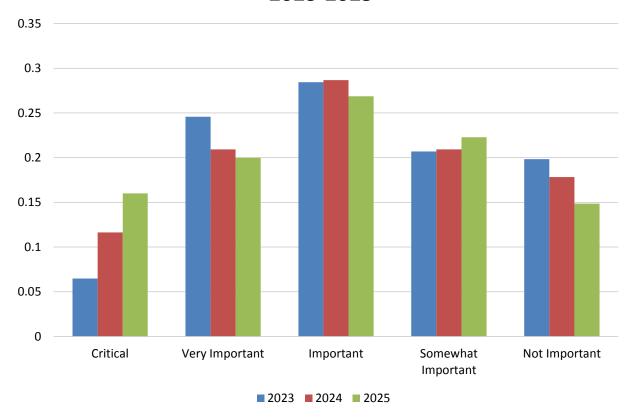


Figure 51 – Natural language analytics importance 2023-2025

Use of Natural Language Analytics 2023-2025

Between 2023 and 2025, adoption of NLA has not changed substantially. While NLA is essential for some specific use cases, the effort typically required to set up and maintain these systems was likely a limiting factor (fig. 52). At no time have more than 28% of respondents been using NLA, while the large balance (greater than 70%) has reported no plans for use. So, while interest in NLA is relatively high, adoption remains below 30%.

Use of Natural Language Analytics 2023-2025

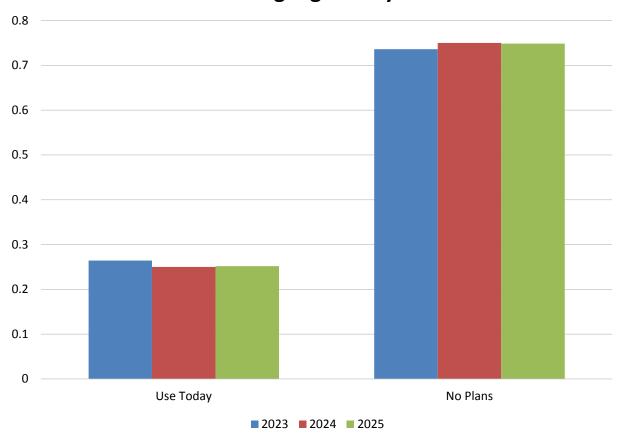


Figure 52 – Use of natural language analytics 2023-2025

Plans Surrounding Generative AI

Fig. 53 shows an abrupt, steep uptake of combined early production use, experimentation, and future plans for generative AI, accounting for nearly three quarters of respondents in 2025. As in 2024, 50% of organizations in 2025 are experimenting or using generative AI in production. We believe this much-faster-than-typical internal adoption curve has been abetted by massive industry investment in multiple iterations of natural language and neural networks, resulting in many free or economical large language models (LLMs) trained on vast arrays of text-based content, commonly used for productivity, coding, or process automation. Later in this report, our industry charts will show that co-pilots and chatbots are near-ubiquitous, used for navigating BI and analytical applications and the Internet at large. Despite early flaws and many gen AI performance questions, just 17% of respondents have no plans for AI activities and just 10% don't know the status of those activities.

Plans Surrounding Generative AI

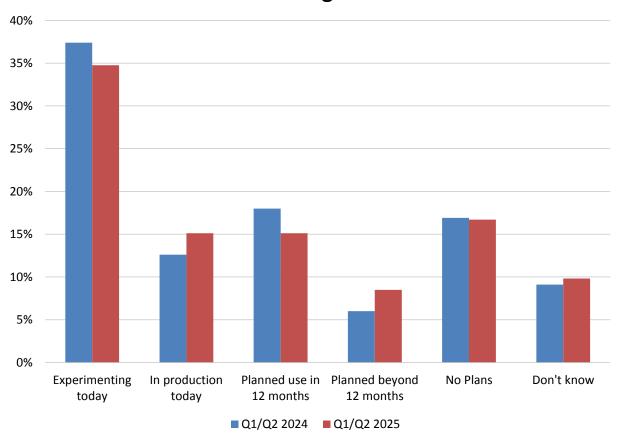


Figure 53 – Plans surrounding generative Al

Embedded Business Intelligence

In our last sample gathered at the end of 2024, importance of embedded BI rebounded sharply to an all-time high level not seen in six years (fig. 54). Weighted-mean criticality is 3.9, near the 4.0 level of "very important," and "critical" scores are at a study-high 31%. Also, combined "critical" and "very important" stand at 73%, equaling the high mark seen in 2018 and far above last year's 61%. Viewed across 12 years the overall importance of embedded BI remains in a range between "important" (weighted mean 3.0) and "very important" (4.0).

Importance of Embedded BI 2013-2024 100% 5 90% 4.5 80% 4 70% 3.5 60% 50% 3 40% 2.5 30% 2 20% 1.5 10% 0% 1 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024 Critical Important Very important Somewhat important Not important Weighted Mean

Figure 54 - Importance of embedded BI 2013-2024

Objectives for Embedded BI

We asked organizations about their 2024 objectives for embedded BI with a choice of nine non-exclusive responses (fig. 54). We see two fundamental top choices: "enhance access to existing reports/analyses" and "provide internal application users with incontext insights and analysis" lead priorities with 30% or greater "critical" scores. "Improve self-service for end users" and "broaden access for internal users" are next most important overall. Along with "provide interface/UI consistent with existing applications," the top five objectives are at least "somewhat important" to 96% or more respondents. As we observed in 2018-2023, in-house enablement clearly remains the theme, compared to lower emphasis on monetization, external users, or cost control.

Objectives for Embedded BI

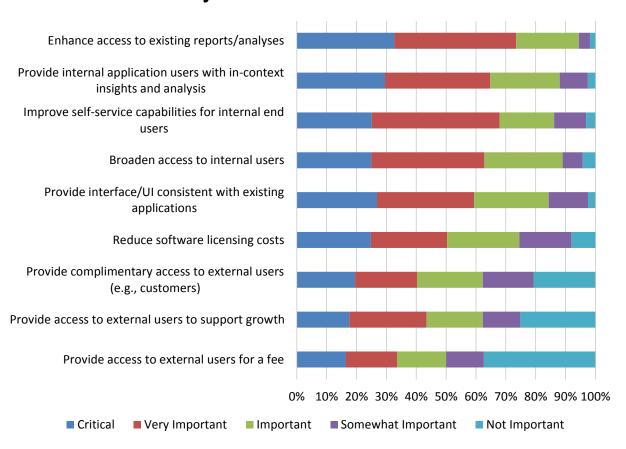


Figure 55 – Objectives for embedded BI

Adoption of Embedded Business Intelligence

Current adoption of embedded BI continued a strong two-year rebound in 2023-2024 that reversed a gradual decline observed over the previous five years (fig. 56). Current use jumped sharply to 57%, compared to 49% in 2023 and 38% in 2022. Future plans were correspondingly somewhat less ambitious than in 2023 and 2022, with slightly lower 12- and 24-month plans, and a mild increase in no plans (from 5% to 7%). As we noted in previous studies, embedded BI is often a tactically applied technology that is still arriving in many organizations. Awareness of embedded technology may account for part of the increase, along with more rigorous expectations for what constitutes embedded BI.

Adoption of Embedded BI 2016-2024

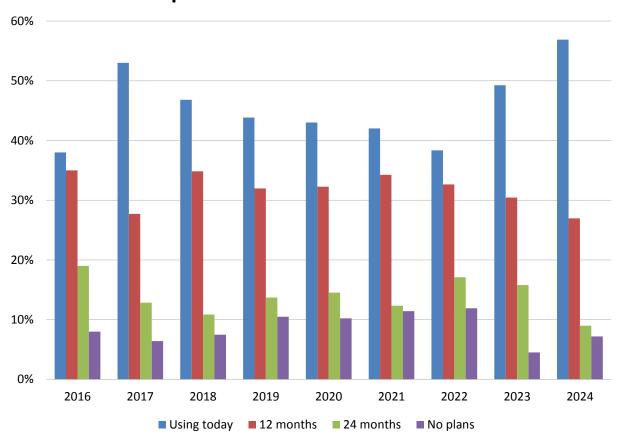


Figure 56 – Adoption of embedded business intelligence 2016-2024

Embedded BI Interface Integration

We asked respondents to describe their interest in 16 embedded BI interface integration features (fig. 57). In 2024, three of the top five features were process-supportive. After top pick "interact with objects," these include scheduled reports and workflow support, which were at least "important" to 92% and 84% of respondents respectively, and collaborative support, which, along with refresh objects/prompts, was at least "important" to 80%. A second tier of only slightly less-important features includes browse/select from catalog of objects, HTML/iframe, re-skinning/customization and open/view objects. Lower priorities include connectors and support for APIs and frameworks. Interestingly, generative AI support interest was in the lower half of integration feature priorities, though still at least "important" to nearly 70% of respondents.

Embedded BI Interface Integration

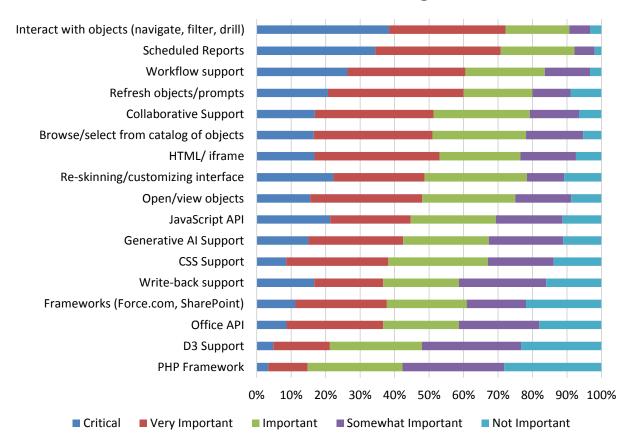


Figure 57 - Embedded BI interface integration

Embedded BI Platform Integration

We asked respondents to prioritize eight embedded BI platform integration features in order of importance to their roles and organizations (fig. 58). The top choice in 2024, single sign-on/security integration, was seen as critical to 43% of respondents and either "critical" or "very important" to 77%. (Not shown, both these findings increased significantly in importance year over year between 2023-2024.) The next most important feature, REST API, is "critical" to 27% and at least "very important" to about 59% of respondents. Interest thereafter drops to a second tier of server-less support, Web services, and run headless/invisibly in the background. Even so, all eight integration features are, at minimum, "important" to more than half or far more respondents.

Embedded BI Platform Integration

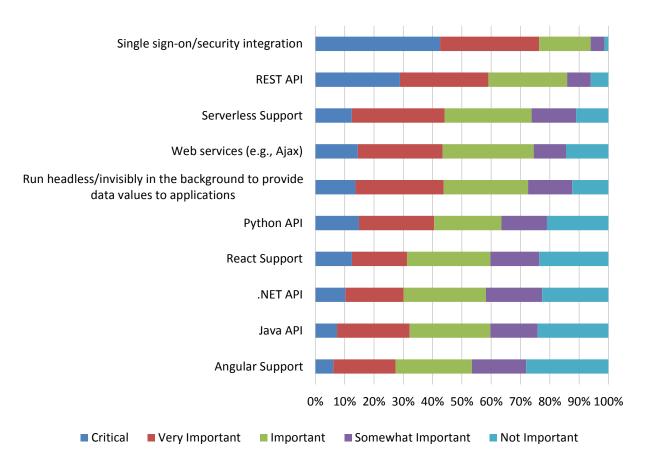


Figure 58 - Embedded BI platform integration

Embedded BI Analytical and User Feature Priorities

We asked respondents to describe the importance of six different embedded BI analytical and user features in 2024 (fig. 59). Data visualization support is the clear top choice, and considered "critical" or "very important" to more than 80% of respondents. Respondents assign less urgency to save and publish BI/analytical objects and apply analytical algorithms, mining, predictive, which are nonetheless at least "important" to 88%-90% of respondents. Three lower priorities, user alerting, modify/create BI/analytical objects and inclusion of user-supplied data for mashups, are all at least "important" to 76%-84% of respondents. As we have seen in earlier studies, basic functionality and information delivery remain the priority over complex manipulation in embedded BI.

Embedded BI Analytical and User Feature Priorities

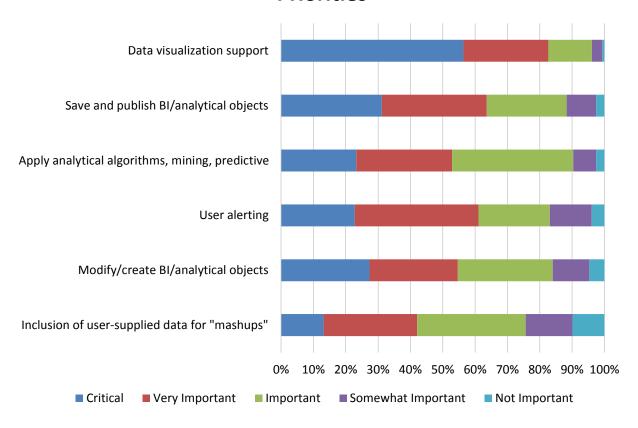


Figure 59 – Embedded BI analytical and user feature priorities

Targeted Applications for Embedded Business Intelligence

We asked respondents to describe interest in 11 specific applications they might target for embedded BI (fig. 60). In 2024, internally developed applications were the top pick, with the highest "critical" (30%) and combined "critical" and "very important" (57%) scores. By weighted mean, Web portals are next most important, followed by ERP applications and financial management applications, all of which are at least "important" to more than 70% of respondents. The top eight application targets, which also include supply chain management/procurement, salesforce management applications, marketing automation applications, and workforce management applications, are at least "important" to 55% or far more respondents. Interestingly, personal productivity applications rank 9th, and call center applications 10th. Electronic medical records rank last, due to industry representation in the overall sample.

Application Targets for Embedded BI

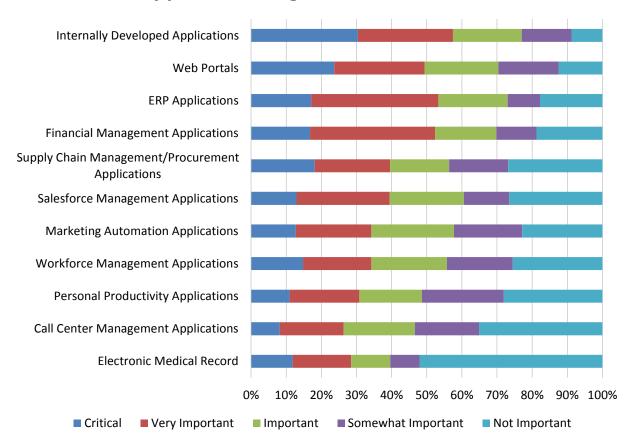


Figure 60 – Application targets for embedded BI

Integration Resources for Embedded Business Intelligence

In 2024 the top three prioritized integration resources for embedded BI were central IT department, business analyst, and data engineer (fig. 61). All three of these top picks were seen as "critical" to 34%-40% of respondents, and at least "important" to 81%-84%. After departmental IT, (critical or very important to 57%), all remaining integration resources with the exception of "customer" were at least "important" to 60%-68% of respondents.

Prioritized Integration Resources for Embedded BI

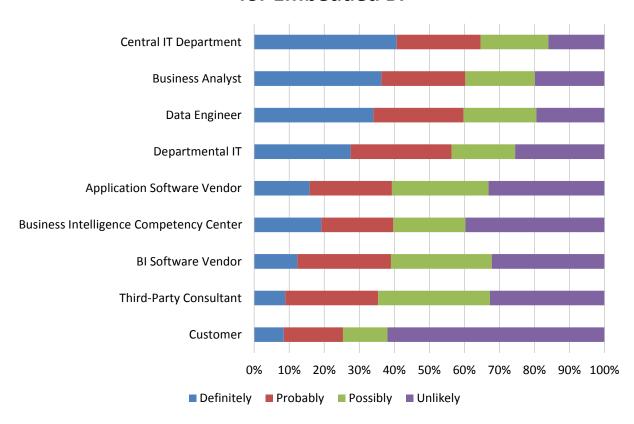


Figure 61 – Prioritized integration resources for embedded BI

AI, Data Science, and Machine Learning

AI, Data Science, and Machine Learning Users

Fig. 62 describes the functional users of AI, data science, and machine learning. We include citizen data scientist, a role that might overlap with other users but generally describes users who can generate models. In 2025, the role of statistician/data scientist is the most likely "constant" or "often" user of AI, data science, and machine learning (63%), followed by BI expert (59%), business analyst (55%), IT staff (48%), and citizen data scientist (45%). Constant use thereafter drops to 33% for marketing analysts and financial analysts, 28% for C-level executives, and 23% for third-party consultants. Overall, the mix of user responses represents a broad mix of deployment and back- and front-office support.

AI, Data Science, and Machine Learning Users 100% 90% 80% 70% 60% 50% 40% 30% 20% 10% 0% BI experts Statistician / **Business IT Staff** Citizen Data Marketing **Financial** Third-Party Data **Analysts** Scientists Analysts Analysts **Executives Consultants** Scientists ■ Constantly ■ Often ■ Occasionally ■ Rarely ■ Never

Figure 62 – AI, data science, and machine learning users

Importance of AI, Data Science, and Machine Learning

In our 2025 study, the weighted-mean perceived importance of AI, data science, and machine learning stands at 3.3, below last year's 3.6, and below the historic high of 3.7 in 2022 (fig. 63). This year's score is the lowest reported since 2017, which may indicate better understanding or some burnout from overexposure. Scores of "critical" and "very important" are also lower than in 2022-2024. Nonetheless, a narrow range of 3.3-3.7 held from 2018 to 2025, and the current score is well within one standard deviation for the history of the study. This sustained measure of interest, which has never been close to the level of very important, holds considerable room for future growth amid market interest and capex spending.

Importance of AI, Data Science, and Machine Learning 2014-2025

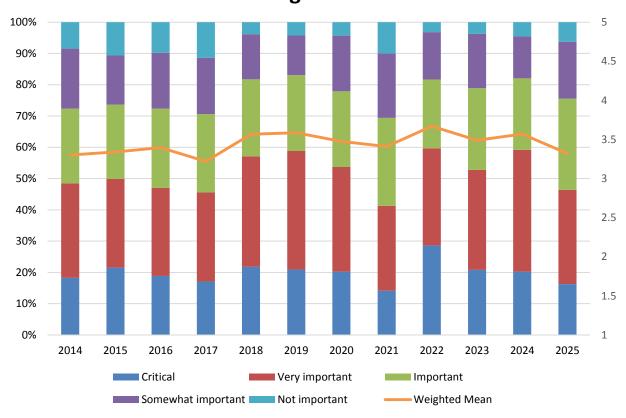


Figure 63 – Importance of AI, data science, and machine learning 2014-2025

Use Cases for AI, Data Science, and Machine Learning

On the much-debated execution end of AI, data science, and machine learning, we asked respondents to describe the relevance of 13 different use cases for the technologies (fig. 64). While current deployment of use cases can still be described as fairly low, we observed a dramatic year-over-year acceleration across all responses from 6%-19% in 2024 to 15%-28% in 2025. The top currently used use cases in 2025 include predictive maintenance (28%), demand forecasting (27%), customer segmentation (26%), and fraud detection (24%). Quality assurance and risk management are also currently in use by more than 20% of respondents. All use cases are targeted for at least 40% use within 12 months, and 12 of 13 use cases are targeted for at least 60% use within 24 months.

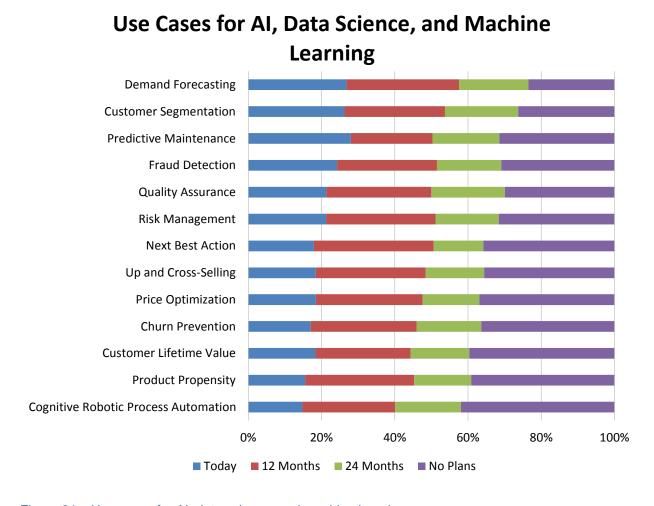


Figure 64 – Use cases for AI, data science, and machine learning

Deployment and Adoption Plans for AI, Data Science, and Machine Learning

Across the last 10 years of our study, we have observed consideration of and actual deployment of AI, data science, and machine learning gain, flatten or decrease slightly, and begin to very mildly rebound in 2025 (fig. 65). (Note: Beginning in 2022, we divided "yes, we use today" into "in production" and "in very limited ways," and combined the weighted mean.) From a 2017 weighted-mean low of 3.0 to a 2021 high of 3.6, 2025 sentiment holds at a rounded level of 3.3, the same as in 2023 and again in 2024. Despite this flattening, sentiment remains above the level of "important" for the last eight years. Those with no plans stand at 15% in 2025 compared to an all-time low of 9% in 2022, possibly indicating some hesitancy or mixed success amid market events. Even so, we expect ongoing momentum in the AI, data science, and machine learning space to bode well for wider adoption as more use cases and solutions become apparent.



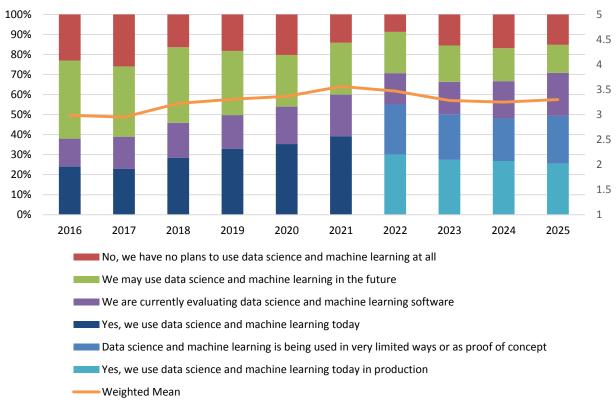


Figure 65 – Deployment of AI, data science, and machine learning 2016-2025

Longevity of AI, Data Science, and Machine Learning 2018-2025

We asked respondents, "How long have AI, data science, and machine learning been in use in your organization?" Across eight years of survey data, longevity is sustained in a rising trend line that includes a varying mix of new adoption and ongoing use of AI, data science, and machine learning (fig. 66). Early use that led to an all-time-high weighted mean in 2022 reversed somewhat in the next two years before resuming an upward trend line in 2025. Most notably, this year the percentage of the most mature AI, data science, and machine learning programs of more than five years reached the record level of 38%. Year over year, startups less than one year held steady at about 14%.

Learning 2018-2025

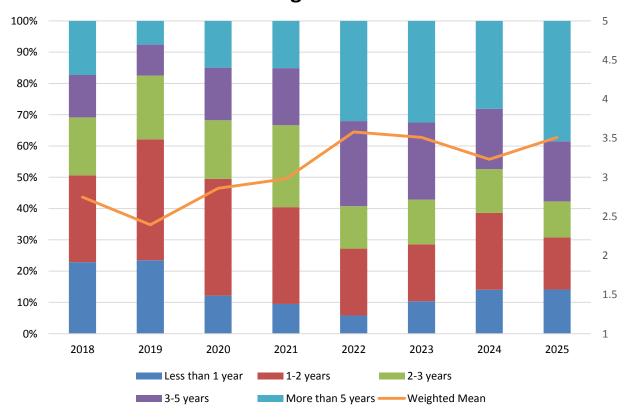


Figure 66 – Longevity of AI, data science, and machine learning 2018-2025

Features for AI, Data Science and Machine Learning

Respondents express significant interest in the full range of feature requirements for AI, data science, and machine learning in 2025. All but two of 23 sampled features are at least important to two-thirds (69%) or far more (up to 79%) respondents this year (fig. 67). The most important among these mostly address traditional statistical methods: outlier detection, model explain-ability, range of regression models, and model management and governance, but also text analytic functions and sentiment analysis.

Features for AI, Data Science, and Machine Learning

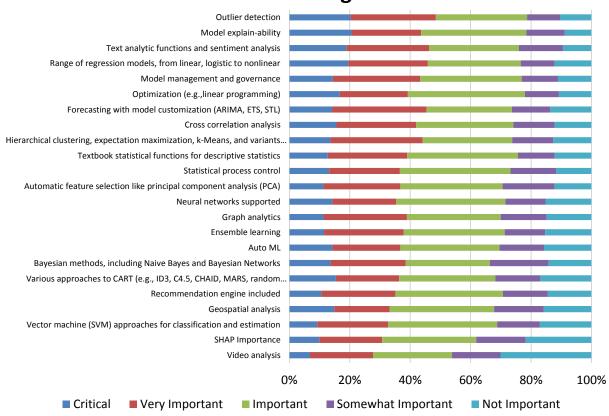


Figure 67 – Features for AI, data science, and machine learning

Usability for AI, Data Science, and Machine Learning

Our study addresses a detailed set of 16 usability benefits that support AI, data science, and machine learning activities and processes. Usability features generally address process or activity simplification and automation. Without exception, respondents give them all significantly high importance scores. All 18 of our 2025 criteria are, at minimum, important to at least 63% and as many as 80% of respondents (fig. 68). The top three features (Python support, low code/no code, and support for easy iteration) are either critical or very important to between 49%-52% of respondents, and at least a dozen other features are critical or very important to about 40%. Half or more of the features sampled are "not important" to only 10% or fewer respondents, and all are at least somewhat important to more than 80% of all respondents.

Usability for AI, Data Science, and Machine Learning

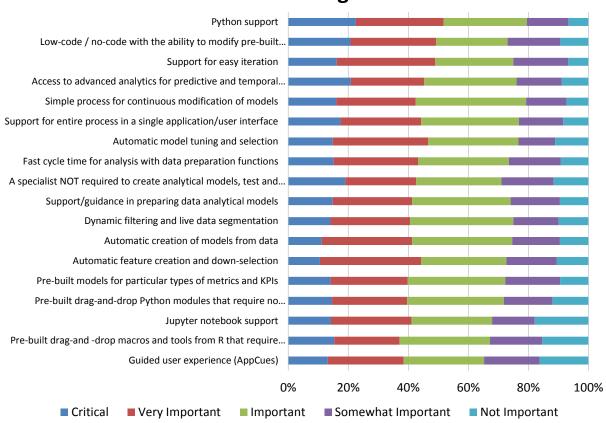


Figure 68 – Usability for AI, data science, and machine learning

Scalability of AI, Data Science and Machine Learning

Our study addresses respondents' interest in a set of scalability technologies and architectures that support AI, data science, and machine learning. All 12 features sampled in 2025 are at least important to at least half and up to more than two-thirds of respondents (fig. 69). This year, as in the last three years, two features—in-database analytics and in-memory analytics—are most important, after which we observe rising year-over-year interest in second-tier features including horizontal scaling, code generation supported, vertical scaling, hybrid/cloud bursting, GPU acceleration, and multi-tenant cloud services.

Scalability for AI, Data Science, and Machine Learning

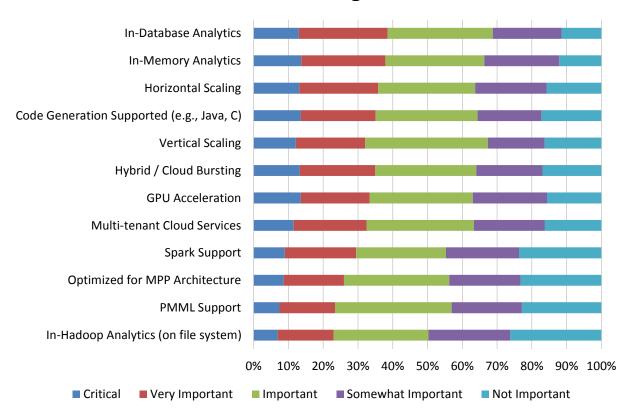


Figure 69 – Scalability for AI, data science, and machine learning

Neural Networks for AI, Data Science, and Machine Learning

We asked organizations to gauge their interest in 11 types or aspects of neural networks in the context of AI, data science, and machine learning (fig. 70). The top five in 2025 are not widely separated in importance and include recursive neural networks, artificial neural networks, transformer networks, feed-forward deep learning, and generative adversarial networks. Each of these five picks is seen as critical or very important by 36%-42% of respondents, and at least important by 66%-71% of respondents. Among the remaining networks, convolutional and recurrent neural networks are most popular. Just 10%-14% of respondents think any are not important.

Neural Networks for AI, Data Science, and Machine Learning

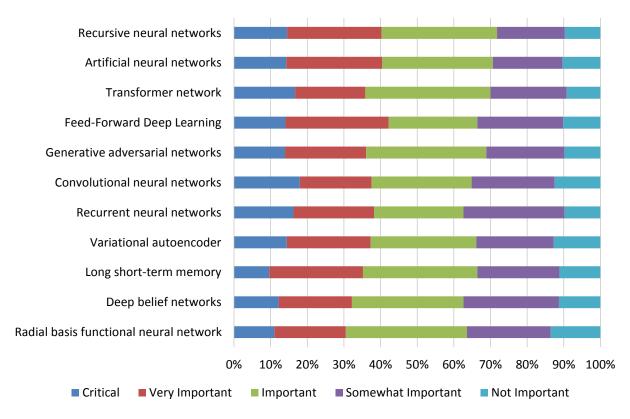


Figure 70 – Neural networks for AI, data science, and machine learning

Data Sources for AI, Data Science, and Machine Learning

We asked organizations to gauge their interest in 33 data sources for AI, data science, and machine learning in 2025. Respondents see all choices within this category as relevant; all but five are at least "important" to 40% or more; and all are at least "somewhat important" to 60% or far more (fig. 71). Top picks Postgres and Amazon S3 are "critical" to 17%-18% of respondents and "critical" or "very important" to more than 40%. Many other technologies of interest represent diverse methods and data management practices.

Data Sources for AI, Data Science, and Machine Learning

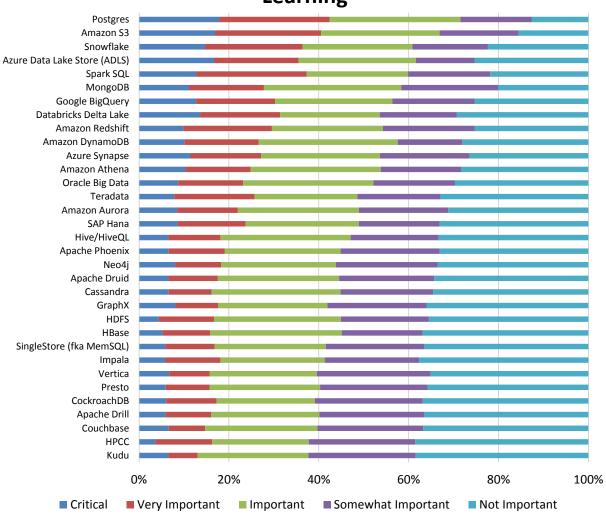


Figure 71 – Data sources for AI, data science, and machine learning

Agentic AI

Outlook for Agentic AI

First introduced by Andrew Ng in March 2024, agentic AI has quickly become one of the most significant emerging AI trends. Ng specifically highlighted the power of agentic workflows—where large language models (LLMs) are embedded into autonomous processes that can act, decide, and adapt with minimal human oversight. This marked a shift from viewing LLMs as simple tools to positioning them as intelligent agents capable of driving business workflows from end to end.

In less than a year, agentic AI has moved from concept to business priority (fig. 72). By early 2025, vendors began releasing solutions, and adoption is accelerating: 10.5% of organizations are actively experimenting or deploying, with another 27% poised to follow. While 58% remain cautious, momentum is building. As early adopters show results, we expect broader adoption across the majority will follow.

Outlook on Agentic Al

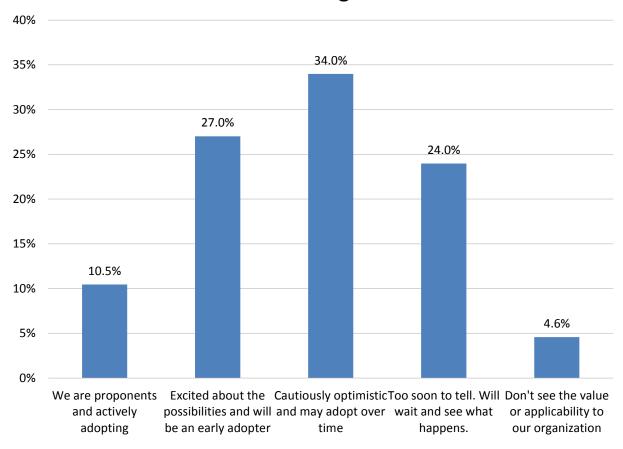


Figure 72 - Outlook on agentic Al

Agentic AI Adoption

Despite growing interest, only 7% of organizations have successfully transitioned from experimentation to production deployment of agentic AI (fig. 73). This figure excludes embedded use cases, illustrating the distinctive adoption path of using vendor-provided functionality in an application or solution context. Although many organizations faced barriers in moving their earlier genAI efforts from experimentation to deployment, the clarity of use cases and stronger value propositions for agentic AI suggest that history may not repeat itself. Encouragingly, 28% of respondents have advanced from excitement to active experimentation, signaling that a meaningful portion of organizations are dedicating resources to validate and scale this innovation. Together, these two groups represent a clear early majority.

Agentic AI Adoption

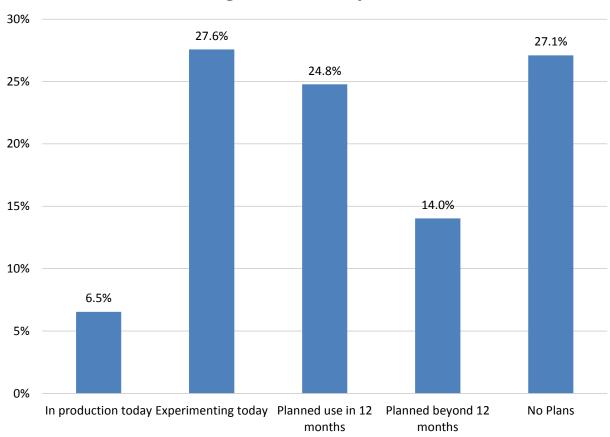


Figure 73 - Agentic Al adoption

Agentic AI Priorities

Where do organizations see the greatest opportunities for agentic AI? Is agentic AI primarily about enhancing productivity, enabling business transformation, or elevating customer experience and decision making? Survey results indicate that it is, in fact, about all of these opportunities (fig. 74). When asked to rate the importance of potential benefits, respondents most often consider improving customer experience and personalization to be critical, followed closely by improved decision making and gains in productivity and efficiency. Interestingly, respondents least often view market and business expansion as critical, suggesting that while agentic AI holds transformational promise, most organizations initially will use it to enhance existing operations rather than drive new growth.

Agentic AI Priorities

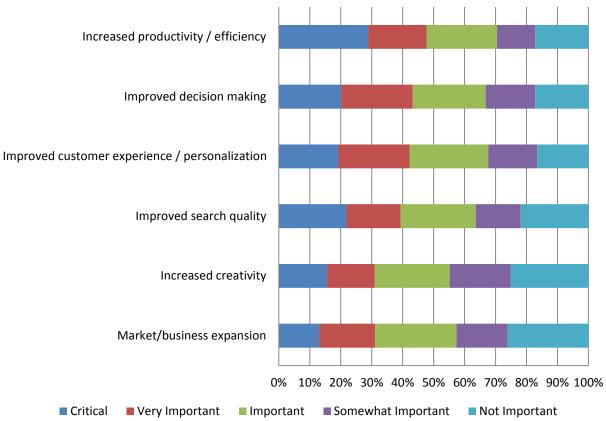


Figure 74 - Agentic AI priorities

Agentic AI Obstacles

Risks have unquestionably muted the production rollout of genAI, and many of these same concerns apply to agentic AI, which is built on similar foundational technologies (fig. 75). Data security and privacy emerge most often as critical issues, cited by 42% of respondents. While other concerns such as response quality and accuracy, implementation costs, talent shortages, and regulatory compliance rank lower individually, they collectively represent substantial barriers. When aggregated, issues related to data security, privacy, legal and regulatory compliance, ethics, and bias form a formidable cluster of risk factors—clearly indicating that trust and governance remain top priorities for scaling AI adoption.

Agentic AI Obstacles

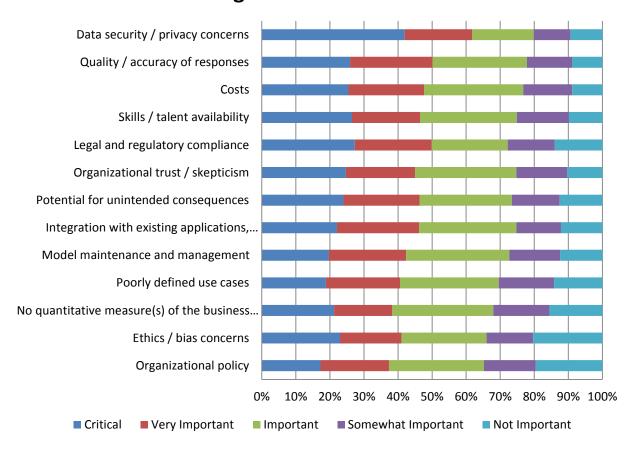


Figure 75 - Agentic AI obstacles

Agentic AI Data Sources

When it comes to driving effective agentic AI outcomes, respondents most often (30%) identify CRM data as critical, underscoring the importance of customer insights in enabling intelligent automation and personalized engagement (fig. 76). This is followed next most often by finance and accounting data (27%), which provides the foundation for risk management, forecasting, and compliance-driven automation. Product data also ranks highly (26%), supporting everything from supply chain optimization to product life cycle management. Together, these data domains reflect the breadth of information required to unlock the full potential of agentic AI across diverse business functions.

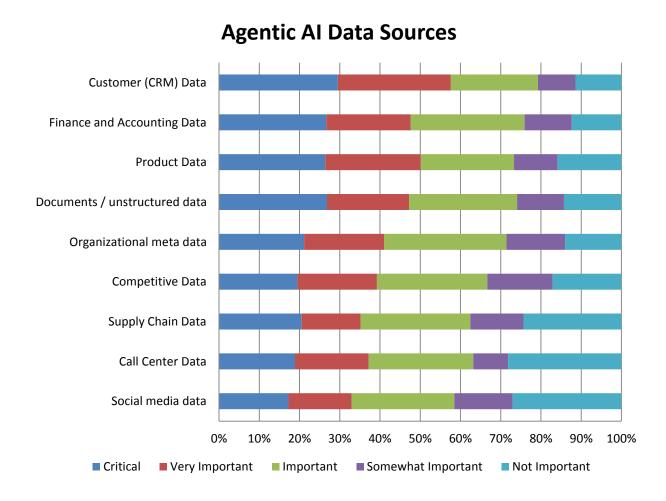


Figure 76 – Agentic AI data sources

Cloud Computing

Perceived Cloud Advantages and Disadvantages

In 2025, we asked survey participants to describe 14 different attributes of cloud computing individually as an advantage, a disadvantage, or neutral (neither an advantage nor disadvantage; fig. 77). This year, scalability is the most important advantage according to 77% of respondents. A second tier consisting of administration, reliability, ease of use, access and availability, control, and availability is scored an advantage by 65%-67% of respondents. All 14 features are considered advantages by between 51% and 62% of respondents. In contrast, cost/ROI and customization ability are the most likely to be seen as disadvantages, by 20% and 18%, respectively. Nearly all these findings are remarkably consistent with early and historical perceptions of cloud software and services, with elasticity and simplicity seen as most important, and customization, control and risk as the most likely caveats. As adoption and scale grows, cost has now come to the forefront as a top reported concern.

Cloud Advantages and Disadvantages

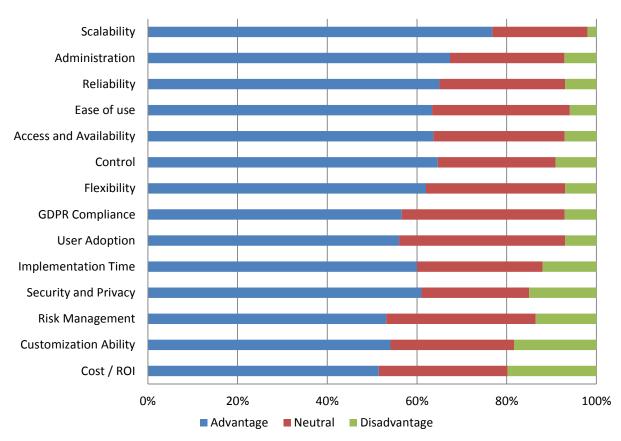


Figure 77 – Cloud advantages and disadvantages

Importance of Cloud Business Intelligence 2012-2025

In 2025, cloud Bl/analytics importance stands at a weighted-mean value of 3.8, far above the 3.0 value signifying "important" and close to the 4.0 threshold that signifies "very important" (fig. 78). This value is equal to the weighted mean seen in 2024 and just below the all-time high 3.9 value reported in 2023. In the longer term, the last two years represent a pause in sentiment that runs counter to the upward trajectory we've seen since our first study in 2012, and particularly in light of the strong upward trend emerging in 2018. By another measure, combined 2025 "critical" and "very important" scores declined slightly year over year, though scores of at least "important" maintain a stable weighted mean importance near an all-time high. Thus, as cloud and SaaS become commonplace and better understood, and as implementations mature, they still remain front-burner priorities.

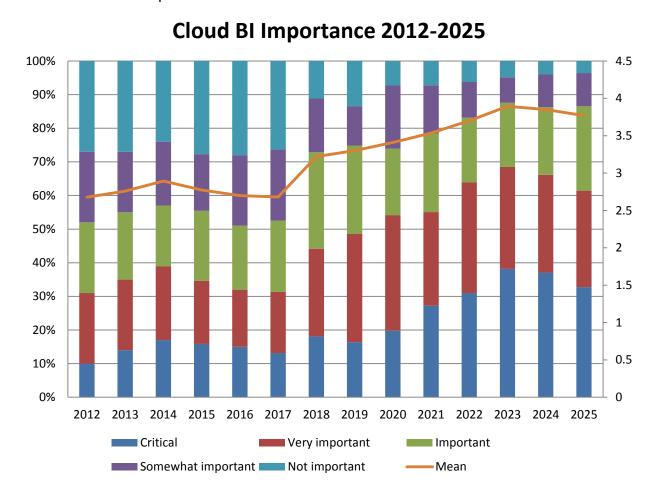


Figure 78 – Cloud BI importance 2012-2025

Current and Future Plans for Cloud Business Intelligence

Current use and future plans for cloud BI/analytics in 2025 continue a four-year trend of near all-time-high adoption (fig. 79). This year, combined current users and evaluators are an all-time high of 75%. Current users alone are flat year over year at 56%, down slightly from a 2022 high of 61%. Across 10 years of data, it's apparent that current use has more than doubled from about one-quarter of respondents in 2016 to more than half in 2025. But about 15% of respondents still report no plans for cloud BI/analytics.

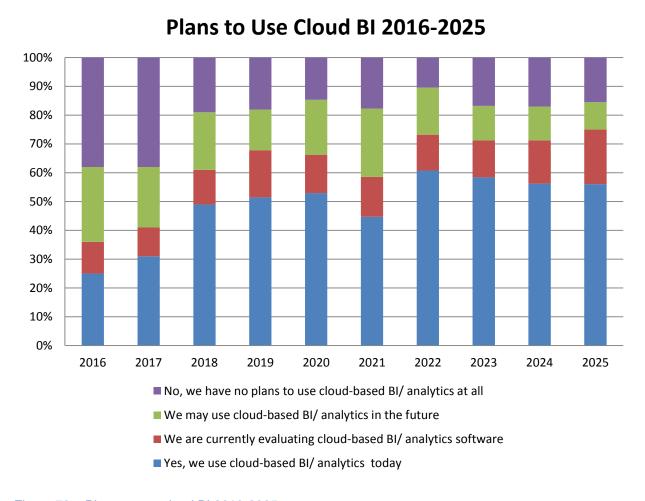


Figure 79 – Plans to use cloud BI 2016-2025

Cloud Based BI Percentage 2024-2025

Beginning in 2024, we asked respondents, "What percentage of your BI/analytical solutions are cloud-based today?" (fig. 80). Responses in 2025 indicated a wide variety of experiences, without suggesting any consensus that would enable us to identify a linear year-over-year trend. Rather, overall sentiment appears to be flat or slightly increasing among the most insistent adopters. In this regard, the percentage of 81% or greater cloud BI use grew from 21% to 28% in 2025. Lower-level use in the 21%-40% quintile also increased, while mid-level users in the ranges of 41%-60% and 61%-80% declined somewhat in 2025. This finding indicates that each organization's cloud migration journey is unique to its culture and strategy, and is subject to constraints arising from organization size, industry, and company age.

Cloud-Based BI by Percentage 2024-2025

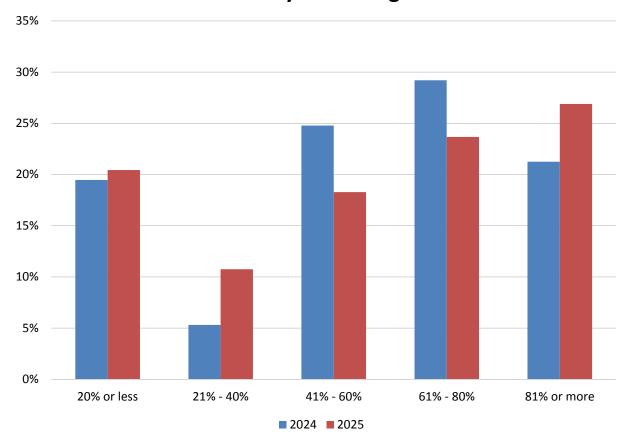


Figure 80 - Cloud-based BI by percentage 2024-2025

Cloud BI Feature Requirements

We asked respondents to describe the importance of 34 cloud BI feature requirements in 2025 (fig. 81). This year, just as it did last year, data quality stands out as the leading feature, with 69% scoring it at least "very important" and 87% scoring it at least "important." Data visualization is close behind and of near equal importance, at 63% and 84%, respectively. This year, the top 11 responses are at least important to 80% or many more respondents (including BI stalwarts such as dashboards, data governance, and several other mostly traditional BI capabilities). All 34 requirements are at least important to half or many more respondents.

Cloud BI Feature Requirements

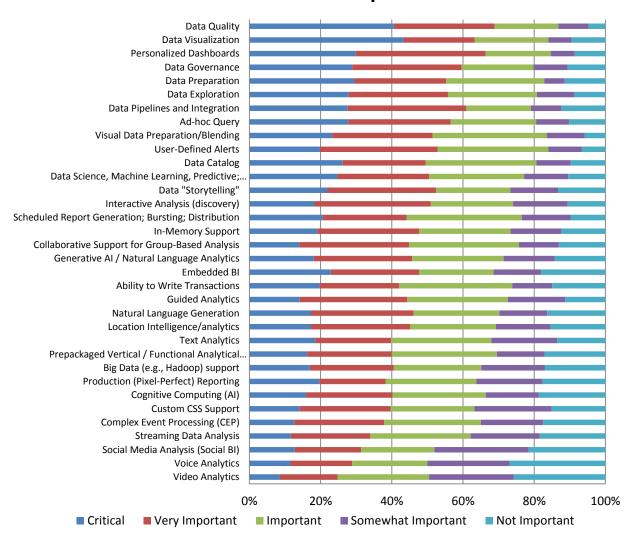


Figure 81 – Cloud BI feature requirements

Cloud BI Architectural Requirements

We asked respondents to describe the importance of 18 cloud BI architectural requirements in 2025 (fig. 82). This year we find very strong interest in the full range of these requirements, led by relational database support, cloud application connections, cloud database connectors, connectors to on-premises applications, multidimensional database support, automatic upgrades, RESTful/Web services, and multitenancy, all of which receive 49%-64% combined "critical" and "very important" scores. A second tier of requirements, led by real-time query to third-party cloud, open client connector, and load balancing across multiple nodes receives 47%-48% combined "critical" and "very important" scores. All 18 features are at least "important" to 63%-84% of respondents.

Cloud BI Architectural Requirements

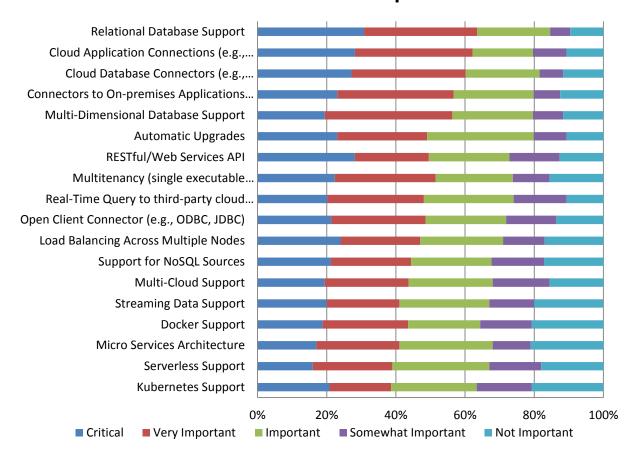


Figure 82 – Cloud BI architectural requirements

Cloud Business Intelligence Security

We asked respondents to describe which specific industry standards for cloud BI security they require from their cloud BI/analytics provider (fig. 83). From a list of 22 specifications, plus "other," only one-third or fewer chose a requirement for any particular standard (a finding we expect is related to respondent duties and is specific to particular industries or functions). GDPR and ISO 27001 are the two standards most commonly recognized by respondents (33% and 32%, respectively). HIPAA and ISO 27018 are the next most frequently expected, not including the "other" response, which 26% gave.

Cloud BI Security Requirements

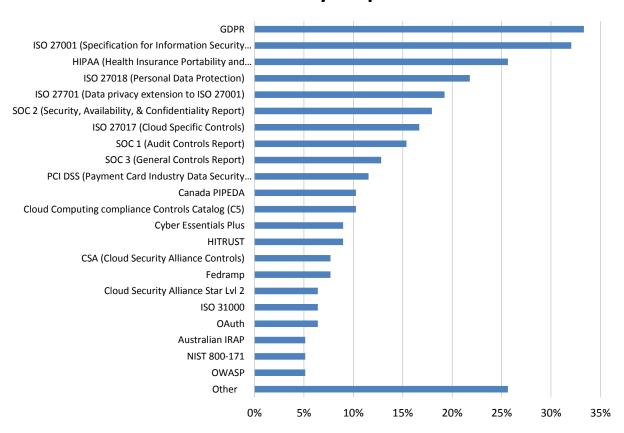


Figure 83 – Cloud BI security requirements

Third-Party Cloud Application Data Connectors

Respondents were asked to check off on a list of 48 cloud application data connectors they would like their cloud BI application to accommodate (fig. 84). The most-specified connector is Microsoft Teams (51%), followed by Google Analytics (33%) and Microsoft OneDrive (33%). Salesforce and GitHub are next-most specified at 29% and 28%, respectively. Fewer than 25% of respondents report interest in the remaining connectors. The 23 lowest-ranked connectors are requested by fewer than 10% of respondents.

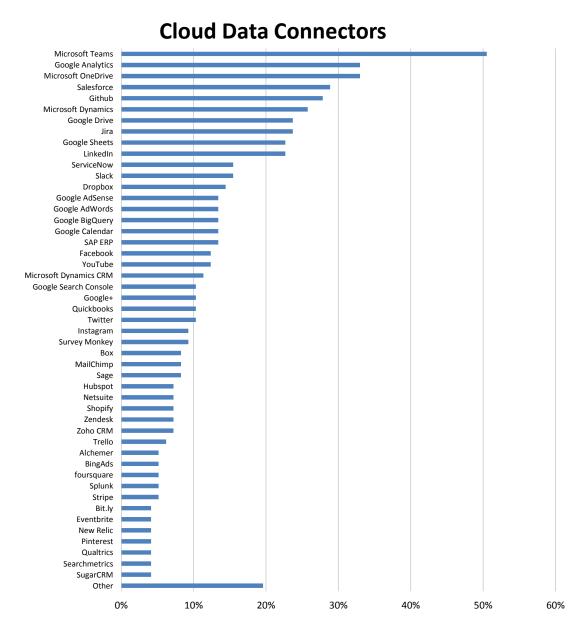


Figure 84 – Cloud application data connectors

Cloud BI Licensing Preferences

In 2025, organizations continue to require an inclusive list of multiple models for cloud BI licensing (fig. 85). For a second consecutive year, a subscription license is the top pick by weighted mean, having moved ahead of free trial and buy, which has since fallen to the fourth-most-preferred licensing model behind managed service and (persistently favorable) perpetual license + annual maintenance. These top four rankings are considered critical or very important by 45%-53% of respondents. Freemium, on-premises option, and pay per use round out the rankings, and every option is considered at least "important" by between 58% and 80% of all respondents. While we expect the subscription model to expand its lead over other cloud-licensing preferences in the near future, all options remain relevant.

Cloud BI Licensing Preferences

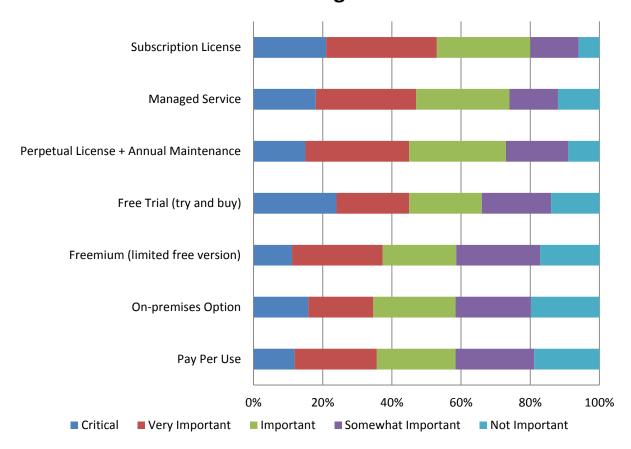


Figure 85 – Cloud BI licensing preferences

Cloud BI Hosting Preferences 2020-2025

Cloud hosting attitudes have shifted during the last seven years of our study (fig. 86). Most apparent is the elevated preference respondents have shown for Bl/analytics software vendor proprietary hosting, which has become their most popular response, as reported by 45%-46% respondents through 2023-2025. During the same period, preference for third-party cloud service provider has crept up from 18% to 19% to 22% in 2025, with a corresponding decrease in those with no preference. Overall, we can say that proprietary vendor hosting, while flat, remains the most popular choice for cloud hosting, while third-party cloud service providers have gained some ground with users.

Cloud BI Hosting Preferences 2020-2025

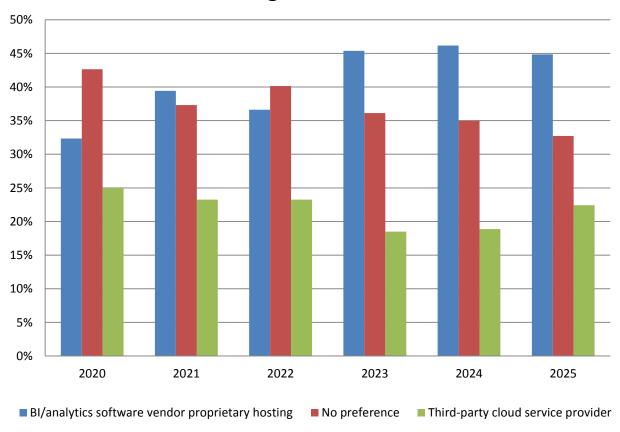


Figure 86 – Cloud BI hosting preferences 2020-2025

Cloud BI Provider Preference

We asked respondents to rank their preferred cloud BI provider from within a list of names (fig. 87). In our 2025 sample, Microsoft Azure receives the highest weighted-mean score, while Amazon AWS receives identical marks for "critical" importance (42%) and somewhat lower marks for combined "critical" and "very important" scores (65% versus 70%). Google Cloud also receives significant user "critical" and "very important" support (56%), while Oracle Cloud and IBM Cloud report combined "critical" and "very important" scores of 44% and 29%, respectively. Alibaba, possibly underrepresented in this study sample, is nonetheless at least "important" to almost half of our respondents.

Cloud BI Provider Preferences

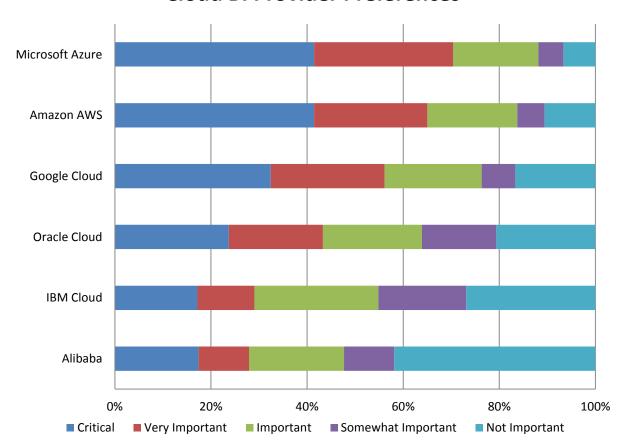


Figure 87 – Cloud BI provider preferences

Vendor Ratings

Analytical Data Products Vendor Ratings

Vendor ratings in Fig. 88 are based on the collective functionality as reported and confirmed by vendors and weighted by user and analyst importance. Included in the assessment are scores for data engineering, data and analytics governance, self-service BI, embedded BI, AI, data science and machine learning, and cloud support. For 2025 we added agentic AI support as an additional criterion.

Included vendors demonstrated sufficient capabilities in at least four of seven categories cited above. Top-rated vendors include Palantir (1st), Domo (2nd), Qlik (3rd), Zoho (4th), and Tableau (5th).

Analytical Data Products Vendor Ratings

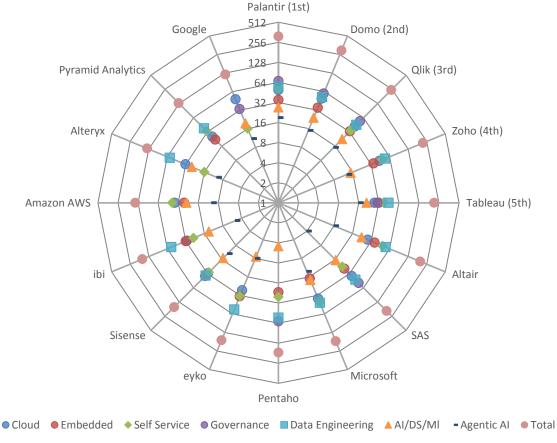


Figure 88 - Analytical data products vendor ratings

^{*}A logarithmic scale is used for the scoring chart to address skewness towards larger values

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