Observability for AI Innovation

Adoption Trends, Requirements and Best Practices

BARC research study

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Foreword

As artificial intelligence (AI) raises the risks and rewards of analytics, organizations recognize the imperative for transparent, trustworthy inputs and outputs. So there is no better time for this report, which surveys 264 data and AI stakeholders across industries about why, where and how they implement observability.

We examine three distinct observability disciplines: data quality, data pipeline and AI/ML model. In each case observability refers to the measurement, monitoring and optimization of these elements. We find that most organizations now have formalized programs for data, pipeline and model observability. Organizations prioritize privacy, auditability, and compliance in their effort to foster Responsible AI. Challenges do persist, of course, thanks to shortages of skills, collaboration and process automation that hinder full adoption of observability.

Another headline is the extension of observability beyond basic tables. Organizations now gather metadata to observe text, images, videos and other semi- or unstructured data objects in support of generative AI (GenAI). As often happens, regional differences persist: North American firms lead in AI adoption and observability maturity, with a stronger emphasis on regulatory compliance, model accuracy and consistent program metrics.

We conducted this survey with a wide range of respondents, from data engineers and data scientists to CxOs and business process owners. Our population includes stakeholders from a variety of business functions and industries, most notably IT and manufacturing respectively. Company sizes are evenly distributed: nearly 1/3 have fewer than 500 employees and nearly 1/3 have 5,000 or more. We also represent North America and Europe in equal portions, with a small fraction of respondents coming from Asia.

As always, you can count on BARC to identify and explain meaningful differences between these various subgroups.

Enjoy!

Timm Grosser and Kevin Petrie
March 2025

Executive Summary

Executive Summary

As AI raises the risks and rewards of analytics, data teams are solidifying their observability programs to strengthen data governance. Engineers, managers and executives now contribute to formal programs for data, pipeline and model observability. While much work remains, cross-functional teams seek to improve privacy, trust, transparency, regulatory compliance and model accuracy.

They also now observe and govern unstructured data such as text, with GenAI adopters and North American firms leading the way. Are we entering a new data renaissance, with clean model inputs driving innovation and corporate reinvention?

Our survey shows real progress in this direction. Here are some highlights.

1 Highlight – AI maturity: a matter of observability and governance

Companies are getting serious about observing data, pipelines and models to support analytics, AI/ML in particular. More than two thirds have formalized, implemented or optimized programs for each of these disciplines. They have familiar governance-related priorities that include privacy, trustworthiness, transparency/auditability, regulatory compliance and model accuracy. Good! Data fundamentals matter more than ever in the age of AI.

As so often happens, people and processes pose greater challenges than technology. The #1 obstacle to observability – training/skills gaps – aligns with other BARC surveys for data management, data literacy and AI adoption. We're also not surprised to see manual processes, organizational confusion, data privacy and a lack of cross-functional collaboration ranked as top obstacles. To overcome these problems, respondents rightly focus on retraining, hiring and acquiring talent. They also aim to strengthen their governance policies and formalize their observability programs. Business process owners already help by playing a major role in observability.

These cross-functional teams have lots of work to do. Only 59 percent of respondents trust their model inputs and outputs, raising concerns about business outcomes as their AI/ML projects move into production. Taking the steps described above will help rectify the situation.

2 Highlight – Observability means more than structured data

While structured tables remain the top focus for observability programs, unstructured objects such as documents and image/video/sound files are now getting much-needed attention. Almost one third of respondents observe these data types in production. Semi-structured data such as JSON or log files have a similar status. This signals the next wave of data demand, driven in no small part by GenAI chatbots that interpret and generate natural language text.

These strong adoption numbers are promising because semi/unstructured data will prove critical to the success of advanced models from predictive ML to GenAI. And it requires different observability techniques than tables. For example, data engineers or data scientists must monitor and control the process of tokenizing, chunking and vectorizing text content, then ensure that the outputs – vector embeddings – accurately support retrieval-augmented generation for GenAI language models. This type of observability includes careful appending and tracking of object metadata. We're pleased to see data teams tackle processes like these.

Executive Summary

3 Highlight – North America leads Europe

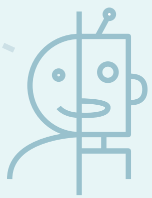
As with other aspects of data and AI, North Americans show higher maturity with AI adoption and observability practices than their European counterparts. An average 88 percent of them (across the three disciplines) have formalized, implemented or optimized their observability programs, compared with an average of 47 percent for Europe. North Americans also prioritize data privacy and regulatory compliance more than Europeans. This shows a mature approach to governance considering that the US has no federal regulations to match the European Union's new AI Act.

In addition, North Americans place a higher priority than Europeans on model accuracy and twice as many of them have formal observability measurements in place. Europeans' heavy reliance on ad hoc measurements is risky – and surprising given their high focus on transparency and auditability. Europeans also favor traditional tables, while North American firms show greater interest in streaming data as well as image, video and sound files to support their higher levels of AI/ML adoption. Europe must close this gap and strengthen its governance programs to support US-level adoption of production AI. The European Union might help with its recent actions to invest in AI "gigafactories" and scale back regulations, encouraging more innovation in the region.

4 Highlight – Lessons from GenAI adoption

As companies adopt GenAI, they must modernize their observability programs to address new types of data, pipelines and models. To assess these trends and requirements, we define three groups according to their adoption of GenAI. These are "users," the 32% of respondents that are in production with GenAI; "testers," the 31% in POC; and "planners," the 31% planning or researching it. (Just 6% have no plans). GenAI users and GenAI testers have more mature observability programs than others. They need to make quick progress, for example by extending their programs to address chatbots and content generation. GenAI users observe all data types, in particular image, video and sound files, more than others.

GenAI introduces new requirements, including observability and governance of unstructured data (40 percent of respondents) and vector databases (33 percent) as well as labeling/managing metadata for unstructured data (33 percent). Nearly as many cite the need to improve the quality of tabular data, which remains the most popular input for AI overall. To maintain trustworthy AI, organizations must connect distributed data landscapes and foster collaboration between teams, ensuring that AI models operate with full transparency and accountability.

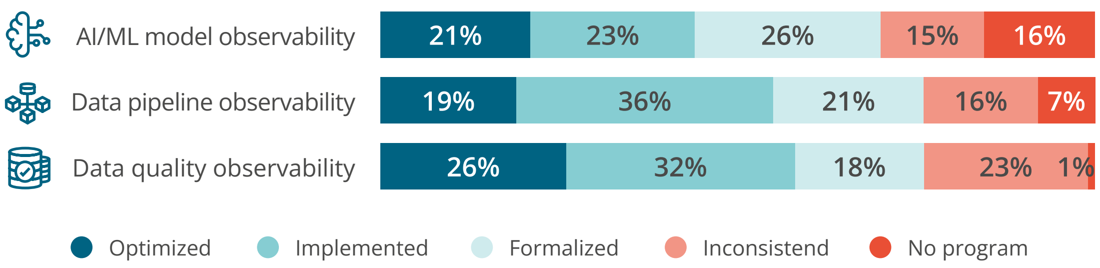


Survey Results

Survey Results

State of Observability

Companies Getting Serious About Observability to Support BI, Analytics and Now AI



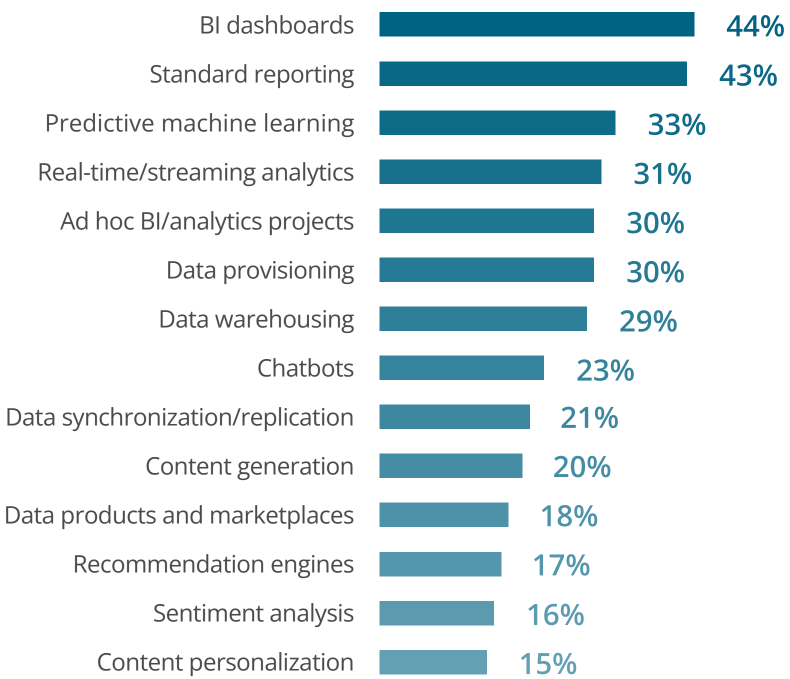


Figure 1: How would you best describe the observability programs in your company? (n=221)

Figure 2: What are your organization's primary use cases that require observability? (n=222)

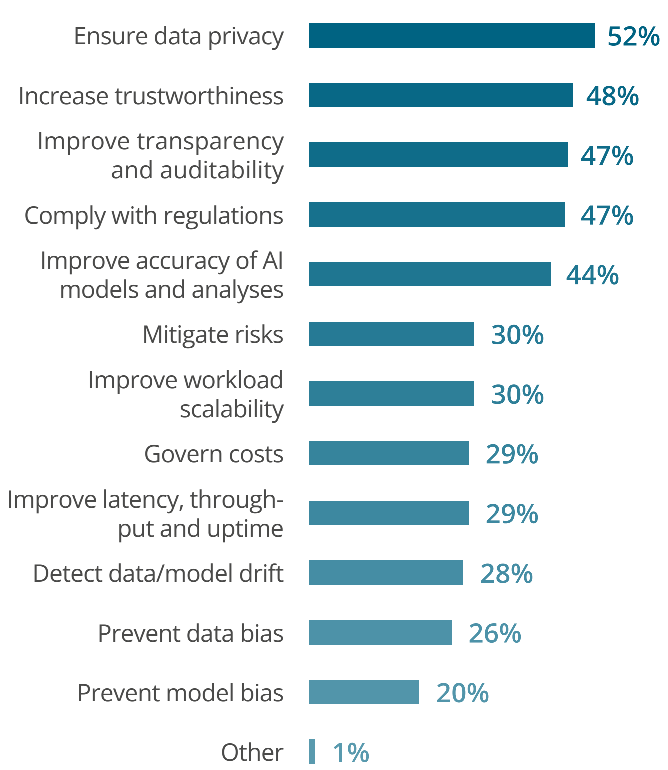
Viewpoint

As AI adoption accelerates, data and AI/ML teams understand the need for a methodical approach to observability of both inputs and outputs. Equal majorities (76 percent) of respondents have formalized, implemented or optimized programs for both data quality and data pipeline observability. While AI/ML model observability has a little less traction overall, more companies have optimized those programs than pipeline programs. All these numbers exceed our expectations and signal serious commitment to programs that go beyond fire drills, point tools or ad hoc projects.

As with other aspects of data and AI, North Americans show higher maturity than their European counterparts, with an average of 88 percent formalized or better vs. an average of 47 percent across the Atlantic. Best in class respondents show an even greater lead over laggards across observability disciplines. GenAI users and testers also have more mature observability programs than GenAI planners, although the difference here is not as pronounced. Together these findings tell a familiar story: aggressive, often US-based adopters of new technology tend to have more mature programs.

So, what types of analytics do these observability programs support? While the traditional use cases for BI dashboards and reporting predominate, modern use cases such as predictive ML and real-time analytics garner nearly one third of responses. Notably, observability to support chatbots and content generation comes in at just 23 percent and 20 percent, despite 63 percent POC/production usage of GenAI. This tells us that GenAI adopters have just started to observe and govern the data, pipelines or models that support chatbots. They need to close this gap quickly to avoid governance issues. In addition, the low observability responses for popular AI/ML use cases such as recommendation engines and sentiment analysis raise similar concerns about enterprise risk levels.

Priorities and Success Measures



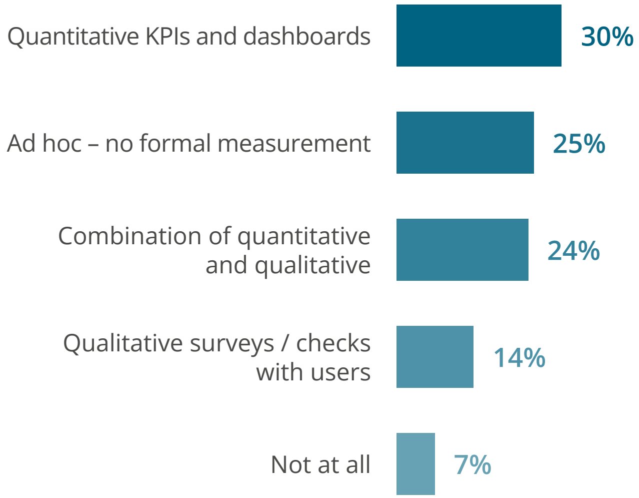


Figure 3: What are your top priorities for data quality, data pipeline and AI/ML model observability? (n=223)

Figure 4: How does your organization measure the success of its observability program/activities? (n=223)

Echoing BARC's annual Trend Monitor, more than 40 percent of observability stakeholders focus on the governance-related priorities of privacy, trustworthiness, transparency/auditability, regulatory compliance and/or model accuracy. No surprises here: data fundamentals matter more than ever and have a direct impact on AI/ML outcomes. However, fewer than a third of respondents prioritize the detection of data/model drift and preventing data or model bias. This flags a risk. AI/ML projects will do more harm than good if data scientists, ML engineers and data engineers fail to adjust to drifting business conditions or ensure fair representation of their communities. We expect data teams to focus more on bias and drift in coming months as AI/ML initiatives gain visibility.

Overall, companies show a mature approach to measuring their success with observability. Two thirds (68 percent) of respondents apply qualitative and/or quantitative metrics to their observability activities. The rest, whose measurements are ad hoc or non-existent, must show fast progress. AI adopters will fail to meet their business goals if they cannot measure observability and align with enterprise-wide governance programs.

Three differences stand out when we compare continents. First, North Americans prioritize data privacy and regulatory compliance more than Europeans (58 percent vs. 43 percent and 53 percent vs. 38 percent respectively). This marks a high level of governance maturity considering the US has no federal regulations to match the European Union's new AI Act. Second, North Americans place a higher priority than Europeans on model accuracy (51 percent to 32 percent), again reflecting higher maturity and more production AI projects. Third, more North Americans than Europeans have formal observability measurements in place (86 percent vs. 43 percent). Europeans' heavy reliance on ad hoc measurements is risky – and surprising given their high focus on transparency and auditability. Europe must close this gap and strengthen its governance programs to support US-level adoption of production AI.

Survey Results

How to Tackle Challenges in Data Observability

People and Process Present Familiar Obstacles

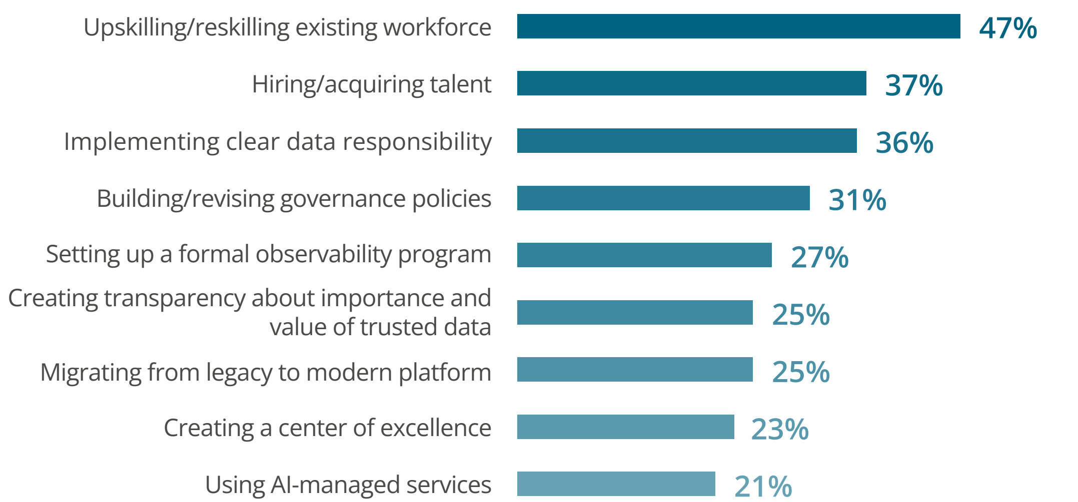


Figure 5: What are your organization's top challenges or obstacles to data, pipeline and AI/ML model observability? (n=233)

Figure 6: How are you addressing these challenges or obstacles? (n=220)

Viewpoint

As so often happens, people and process pose greater challenges than technology. The #1 obstacle to observability – training/skills gaps – aligns with other BARC surveys about data management, data literacy and AI adoption. We're also not surprised to see manual processes, organizational confusion and a lack of cross-functional collaboration rank as top obstacles. Data privacy also remains challenging as companies struggle to comply with new AI regulations and rising consumer expectations. Compounding all these challenges is rising complexity thanks to proliferating data sources, types, users, projects and analytical models.

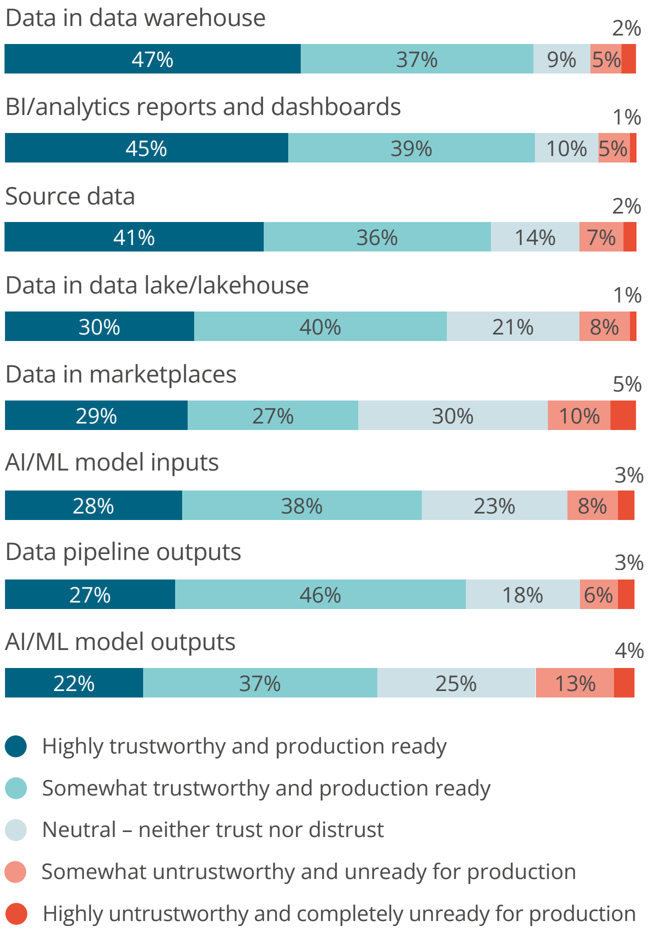
To overcome all these problems, respondents rightly focus on retraining, hiring and acquiring talent. They also aim to strengthen their governance policies and formalize their observability programs. But despite data teams' best efforts, we expect the challenges to persist for some time given the breakneck pace of AI innovation. Companies will struggle to keep up with demands for new AI/ML models, observability techniques and data types – and must maintain a steep learning curve for the foreseeable future.

In addition, while we agree with respondents' overall focus on people and processes, we believe the lack of enthusiasm for modern platforms and AI managed services is a problem. Practitioners can benefit from the innovation and expertise of vendors. Why not migrate to their advanced systems, adopt new tools and outsource administrative hassle to third-party specialists for selected projects? Leaders and laggards alike show a reluctance to take these steps, which puts them at a competitive disadvantage and slows their efforts to modernize. Different regions show halting progress in this regard: more Europeans than North Americans are migrating from legacy to modern platforms (36 percent vs. 18 percent), but more North Americans use AI-managed services (30 percent vs. 10 percent).

Survey Results

Growing Importance of Observing Unstructured Data

AI/ML – A Strong Use Case for Observability



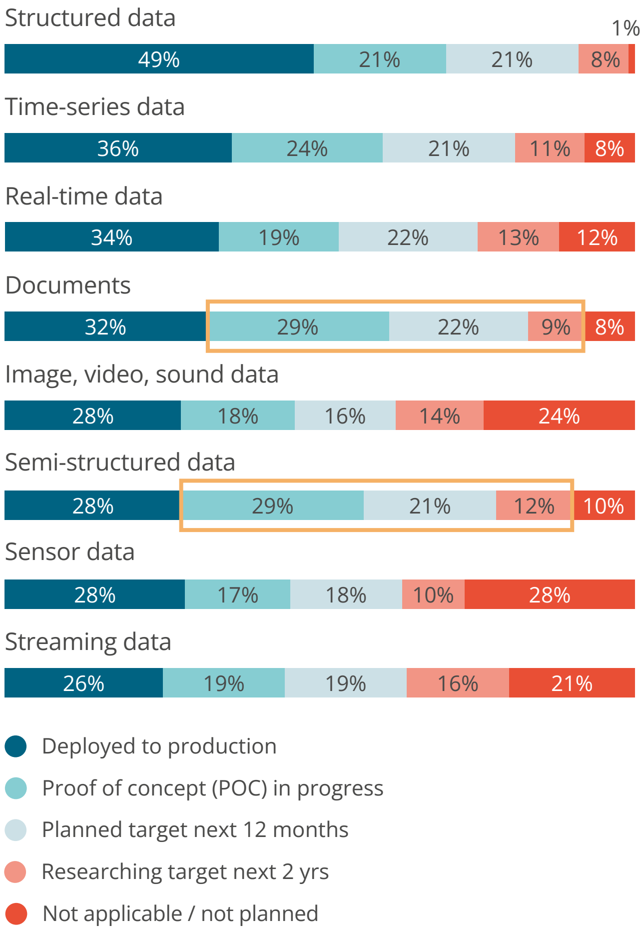


Figure 7: How would you rate the trustworthiness of the following – i.e., each element's ability to enable accurate business insights? (n=221)

Figure 8: Which of the following data types is your organization observing in support of AI/ML projects? (n=213)

Companies place the highest level of trust in data from established data warehouse (DWH) and business intelligence (BI) environments. About three quarters (77 percent) of organizations also trust source data in data & analytics reports or dashboards. However, only 70 percent trust data from a data lakehouse, compared to 84 percent who trust data from a data warehouse. Despite the industry shift toward lakehouse architectures, data warehouses remain highly trusted as the single point of truth in companies.

Surprisingly, 15 percent of respondents distrust data from highly curated data marketplaces, and 30 percent are neutral. Given that data marketplaces should inherently offer highly reliable data, this highlights a gap in adoption and accessibility. Organizations struggle to make the relatively new concept of data marketplaces (both internal and external) fully usable for their teams. Stakeholders are more inclined to distrust data from external sources because they have limited views of its lineage. Addressing this challenge will be critical for the success of data product strategies.

A key concern is the trust in AI/ML models, with only 59 percent of respondents saying they trust their output data. This is not surprising but clearly underscores the need for greater transparency and control of AI/ML model pipelines and outcomes – which makes a strong case for all three observability disciplines. The need to reduce the risk of unreliable data becomes especially critical when dealing with agents, since they can make decisions and act autonomously without direct oversight. Strongly correlated, the scope of data usage is evolving, with a growing analytical focus on semi-structured and unstructured data. Most (62 percent) of organizations are exploring the use of semi-structured data (28 percent already use it), while 60% are evaluating unstructured documents. These trends signal the next wave of data demand, reinforcing the critical role of data observability in ensuring trust, quality and usability across diverse data types, especially unstructured data. GenAI in particular drives this demand.

GenAI's Success Depends on Unstructured Data

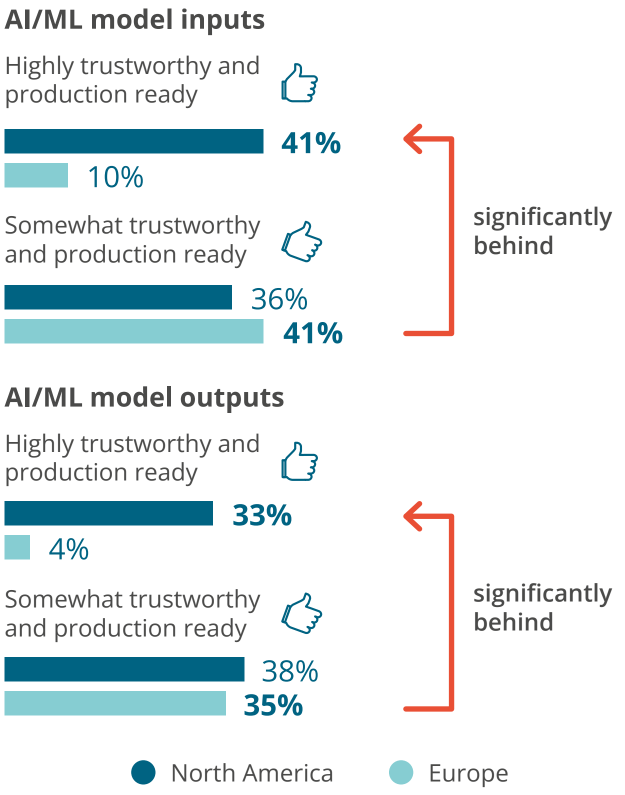


Figure 9: Trustworthiness of data for AI/ML input/ output by region (n=221)

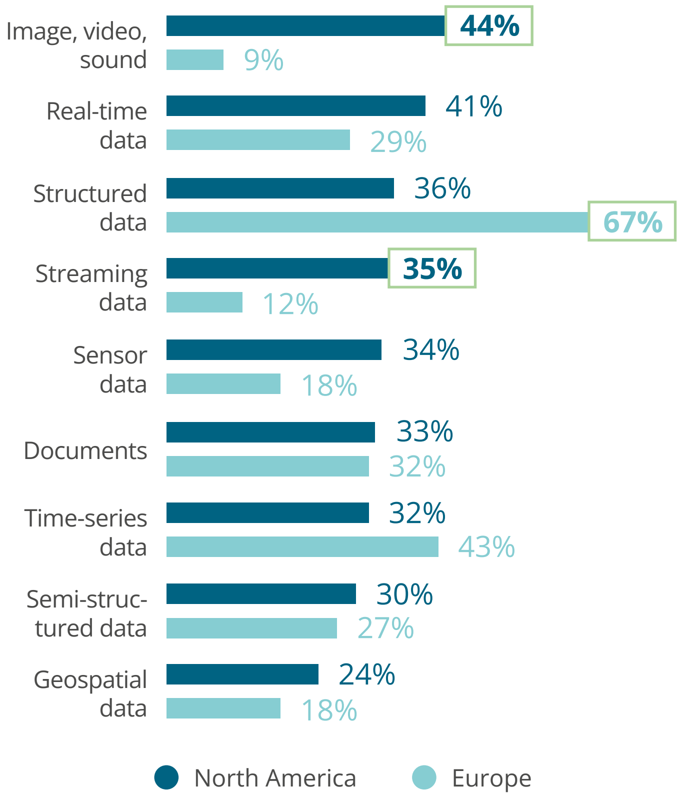


Figure 10: Data types observed in AI/ML projects by region (n=196-214)

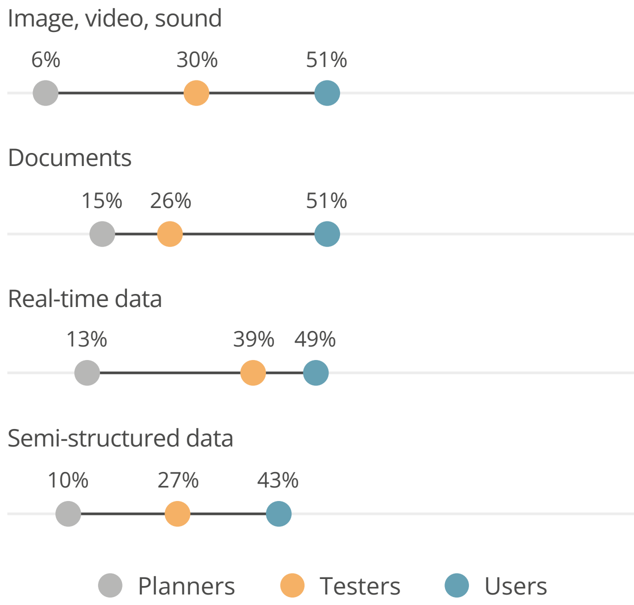


Figure 11: Use of data types by GenAI adoption status "deployed to production" (n=203)

An international comparison reveals that North American companies trust their data more consistently across all sources than their European counterparts. European firms primarily rely on data from warehouses, BI applications and source systems. The biggest gap appears in the input and output data of AI models, where a higher share of North American companies express confidence. European organizations remain more cautious and less trusting of these data sources.

European companies strongly favor structured data, while North American firms show greater interest in streaming data as well as image, video, and sound data. This aligns with the fact that North American companies are more advanced in AI adoption, which pushes up demand for diverse data objects beyond just traditional tables. A comparison between GenAI users and planners underpins the growing relevance of unstructured data. Early adopters leverage all data types at higher rates. The biggest disparity exists in image, video and sound data, which 51 percent of users already use in production, compared to just 6 percent of planners – a gap of 45 percentage points. Significant differences also appear in documents and real-time data (36 percentage points) and semi-structured data (33 percent).

Looking ahead, GenAI planners see the greatest value in investing in semi-structured data, documents and real-time data. As AI adoption accelerates, organizations must expand their data strategies beyond structured data to feed their models the rich, diverse inputs they need to deliver value.

Survey Results

The Role of Observability Tools

Observability is Critical – But No One Wants to Pay Extra for It

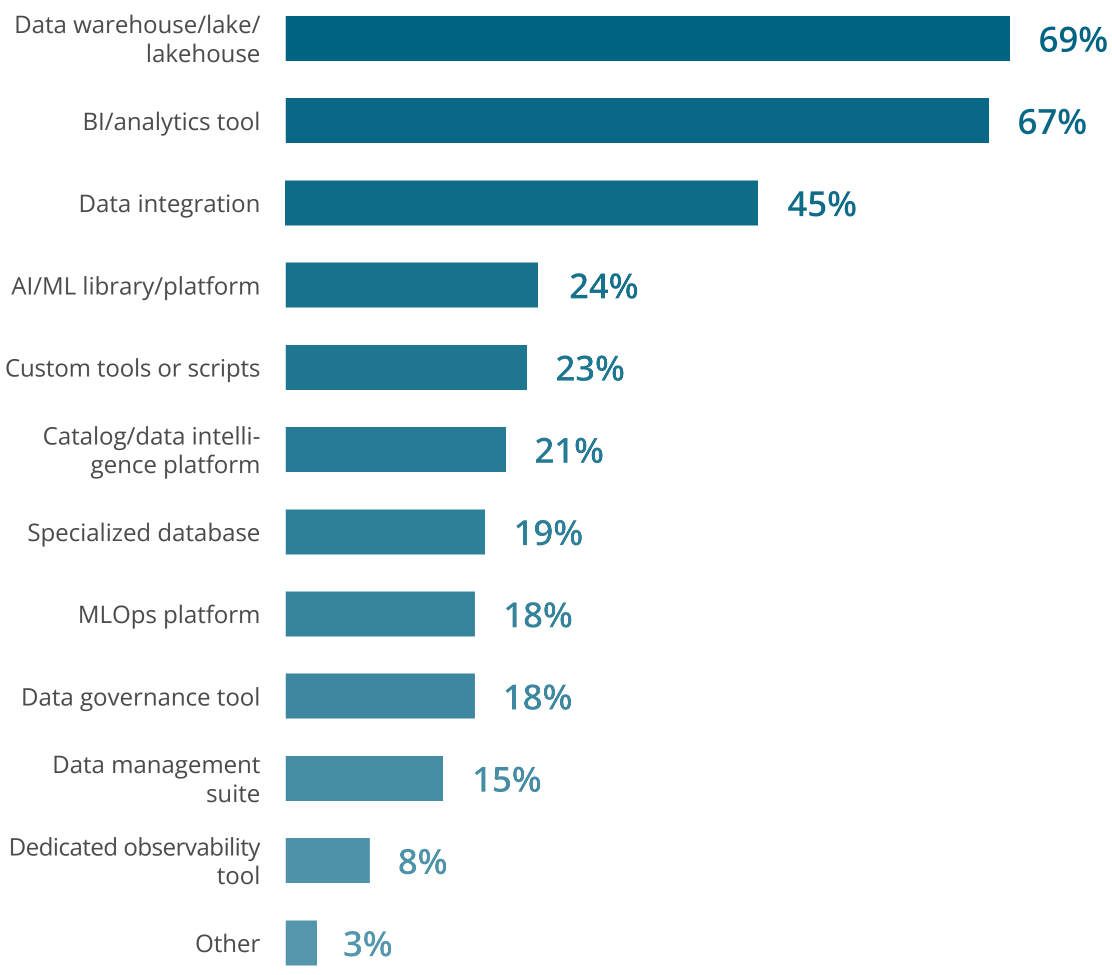


Figure 12: Tool categories for data observability (n=116)

Viewpoint

Technology alone does not drive data observability – organizations must first establish strategic and organizational processes and frameworks. However, as data landscapes grow more complex, technology becomes essential for scaling observability efficiently, leveraging automation and enhanced user experiences.

So, what tools are companies using for observability? The answer is clear from our survey participants: existing data solutions more than specialized observability tools. More than half rely on existing data warehouses, lakehouses or BI tools, while 45 percent use data integration tools. In contrast, only 8 percent use dedicated observability tools. AI/ML platforms, data intelligence solutions and governance tools – despite offering observability capabilities – remain underutilized.

Almost half (40 percent) of North American respondents rely on custom tools or scripts, compared to 22 percent in Europe. Even when analyzing GenAI users vs. planners or best-in-class organizations vs. laggards, this pattern remains largely unchanged.

It appears that cost-benefit considerations or rudimentary observability requirements lead organizations to rely on existing data solutions rather than investing in specialized tools. However, as data dependencies grow in increasingly heterogeneous data environments, demand for cross-system observability will rise. New AI/ML requirements will also push organizations to adopt dedicated observability tools that offer scalability, automation and system-wide transparency.

Data Observability Tools: Are Priorities Misaligned?

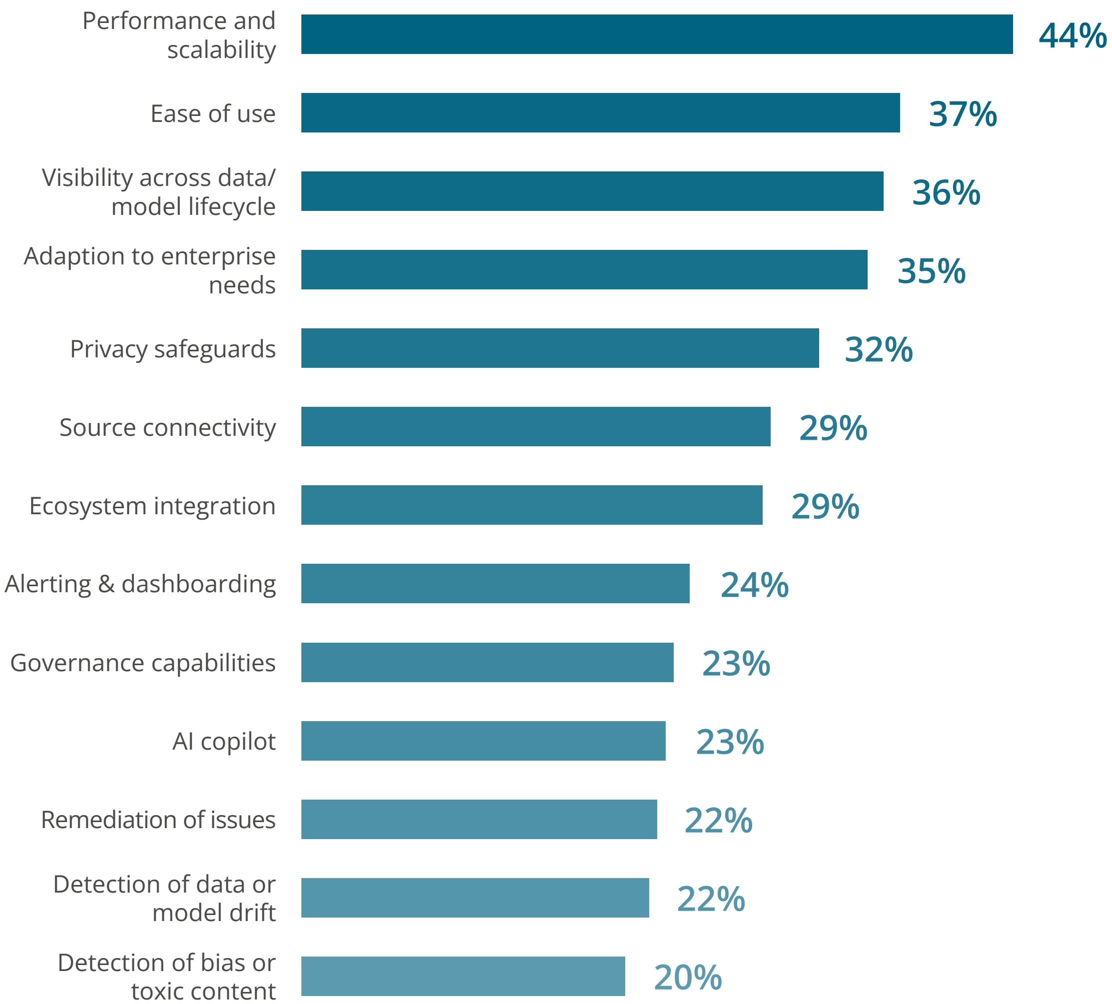


Figure 13: Requirements for data observability tools (n=223)

Viewpoint

As new challenges arise, so do new demands for data observability tools. Survey respondents highlight foundational capabilities such as performance and scalability (44 percent), ease of use, and adaptation to enterprise needs (35 percent or more) as essential. Visibility across the data/model lifecycle also ranks as a key requirement. Surprisingly, only one in five companies lists detection of data/model drift or bias/ toxic content detection as critical. Since the core function of observability is to ensure trustworthy data by monitoring data, pipelines and AI/ML models, we believe this should rank higher. Companies still have work to do in this area, and we anticipate its importance will grow as AI/ML adoption continues to mature in the coming years.

Instead, organizations seem more focused on general tool capabilities rather than core observability features. Privacy safeguards, source connectivity and ecosystem integration all rank higher than governance and issue remediation. This suggests that companies prioritize seamless integration and operational efficiency over advanced anomaly detection. Observability functions should be given more weight here than platform features.

A noteworthy insight is that 23 percent of respondents are already demanding a copilot feature. These AI-driven assistants, while new, have become somewhat mainstream. Their effectiveness still varies depending on use cases. As shown in the BARC report "Preparing and Delivering Data for AI", data quality ranks as the top data management use case for AI agents. This reinforces the growing expectation that AI-powered automation will become a standard in data observability.

Survey Results

Teamwork matters

Observability Involves Many Stakeholders

Business Role Is Big but Should Be Bigger; Data/AI Team Collaboration Remains Ad Hoc

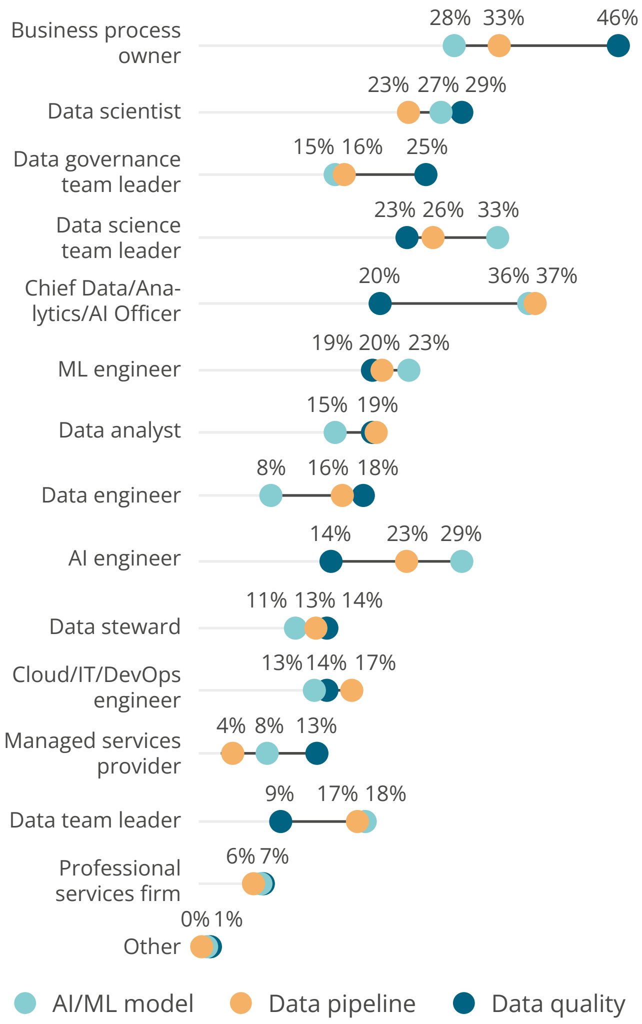


Figure 14: Please indicate which of the following stakeholders manage or oversee observability processes in support of AI/ML projects (n=209 for AI/ML model, n=206 for data pipeline, n=215 for data quality)

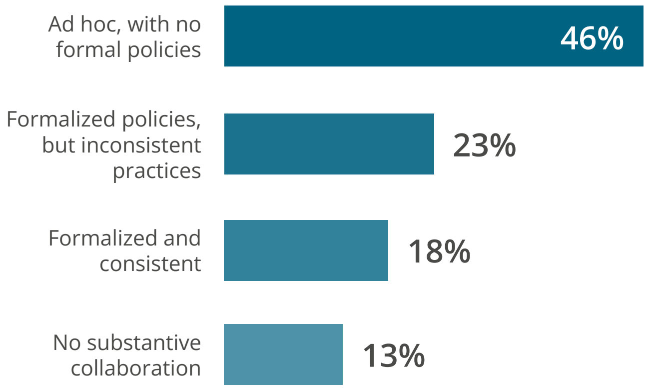


Figure 15: How would you describe the collaboration between your data management and AI/ML teams? (n=189)

Business process owners top the list of observability stakeholders, reaching almost 50 percent for data quality and averaging 36 percent across disciplines. While this shows promise, we believe all companies should have a business stakeholder managing or overseeing observability for AI/ML. After all, AI/ML projects must start with a business objective and stay grounded in business "truth" amidst changing conditions. Specialists such as data scientists and data engineers must collaborate with business process owners throughout the lifecycle of data, pipelines and models.

Observability processes also need much higher CDO, CDAO or CAIO oversight to ensure they reinforce rather than break governance policies. Of particular concern: just 20 percent of respondents say these CxOs manage and/or oversee data quality observability.

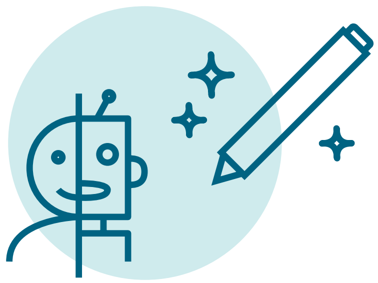
Given the high stakes involved, we expect the role of CxOs and business stakeholders to rise as more AI/ML projects reach production. The lower percentages for various technical roles, meanwhile, do not raise concerns given the variety of titles and overlapping responsibilities.

Whatever their title, we assume that data/AI specialists manage these observability programs. The big surprise among specialists is the prominence of data scientists. They play a bigger role than data engineers in all three categories of observability – even data quality, with a 29 percent showing vs. 18 percent! This reveals a promising trend: data science teams prioritize clean model inputs as a critical success factor for AI/ML projects.

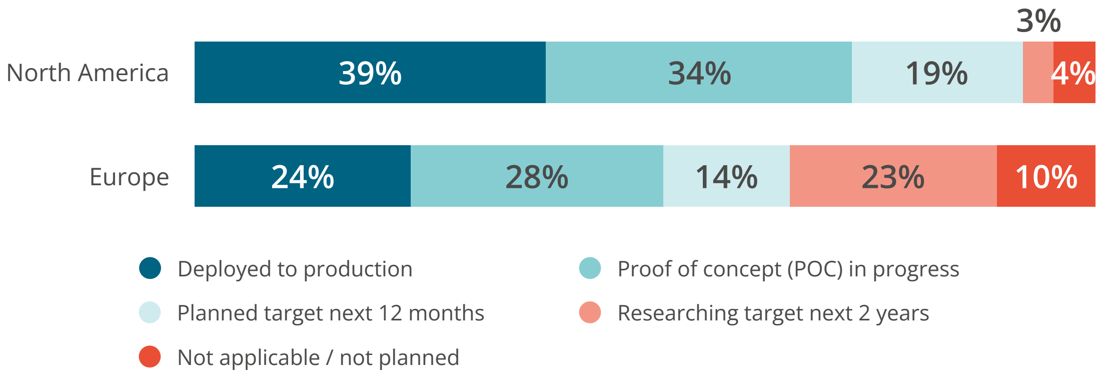
Despite this, companies need to focus more on effective teamwork. Almost half (46 percent) say their data management and AI/ML teams collaborate in an ad hoc fashion, with no formal policies, and another 13 percent report no substantive collaboration. About one quarter (23 percent) have formalized collaboration policies but inconsistent practices and only 18 percent collaborate in a formalized, consistent way. This situation should improve as companies address the challenge: recall that 36 percent are implementing clear data responsibility, 31 percent are building/revising governance policies and 27 percent are setting up a formal observability program. Europeans in particular need to take these steps and strengthen governance overall.

Survey Results

The Next Wave – Does GenAI Change the Game?



GenAI is Reshaping Data Observability – Are Companies Keeping Up?



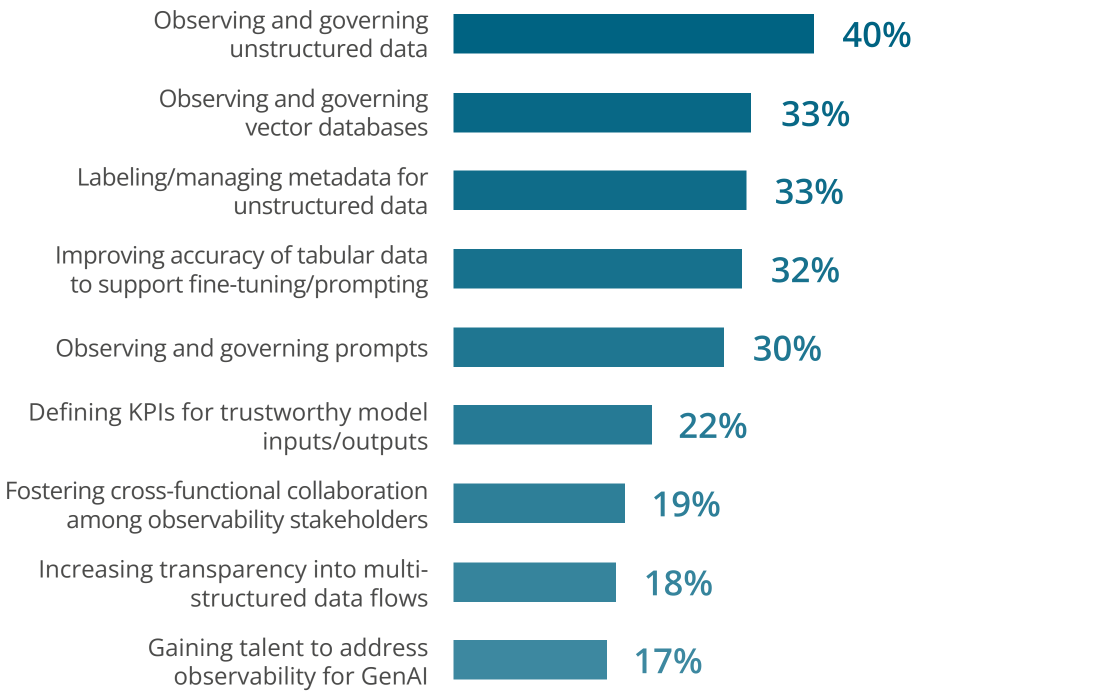


Figure 16: Adoption status of GenAI by region (n=223)

Figure 17: New GenAI observability requirements (n=180)

Viewpoint

Generative AI (GenAI) is rapidly transforming data observability. As organizations adopt automated decision-making and GenAI, they need reliable, high-quality outputs. About one third (32 percent) of companies actively use GenAI (we refer to them as "users"), 31 percent are testing it ("testers") and 37 percent plan to adopt it ("planners"). However, the pace of adoption differs significantly between regions: 73 percent of North American companies are either using or testing GenAI, compared to just 52 percent in Europe, where 10 percent of organizations admit they don't engage with GenAI at all.

This widespread AI adoption brings serious new challenges for data observability. The top three emerging requirements involve both structured and unstructured data:

- 40 percent of organizations highlight the need for observability and governance of unstructured data.
- 33 percent stress the importance of monitoring AI-enabling technologies such as vector databases and labeling unstructured data for AI usability.
- However, 32 percent see a critical need to improve tabular data accuracy to enhance fine-tuning and prompting processes.

Despite AI's reliance on multi-structured data, only 18 percent of respondents recognize the need for transparency in AI pipelines, and just 19 percent emphasize the importance of collaboration among observability stakeholders. This is a problem because trust in AI outputs is only possible when organizations achieve full visibility across input, processing and output.

AI-driven observability is increasingly focused on unstructured data processing and monitoring. To build trustworthy AI, organizations must connect distributed data landscapes and foster collaboration between teams, ensuring that AI models operate with full transparency and accountability.

Recommendations

Recommendations

1 Formalize and optimize observability programs

Organizations should transition from ad hoc monitoring to structured observability programs that cover data quality, pipeline integrity and AI/ML model transparency. Implementing formalized observability ensures compliance, improves trust in data-driven decisions and prevents costly errors caused by undetected data drift, inconsistencies or pipeline failures.

2 Strengthen governance policies and regulatory compliance

As AI adoption accelerates, regulatory requirements increase along with the need for trusted AI outcomes. Organizations should establish clear governance policies and observability standards for data usage, model performance and compliance with AI regulations. Strengthening data privacy, auditability and accountability frameworks ensures responsible AI deployment while maintaining trust among stakeholders and customers.

3 Formalize cross-team collaboration

Establish structured collaboration policies between data management and AI/ML teams, moving beyond the current ad hoc collaboration that 46 percent of companies report. Create clear workflows and communication channels that connect business process owners, data scientists, data engineers and C-level stakeholders to ensure comprehensive oversight of data quality and model performance.

4 Establish formal success metrics

Move beyond ad hoc measurements by implementing formal qualitative and quantitative metrics for observability success. This should include specific KPIs for data quality, pipeline performance and model accuracy, with regular reporting and review processes.

Recommendations

5 Expand unstructured data capabilities

AI models increasingly rely on semi-structured and unstructured data such as images, videos and log files. Develop robust observability practices for unstructured data (text, images, video, audio) given its growing importance, especially for GenAI applications. This includes implementing proper metadata management, establishing monitoring processes for vector databases, and creating specific quality metrics for unstructured data types.

6 Strengthen skills and training programs

Close the skills gap – the #1 reported obstacle – by implementing comprehensive training programs focused on data observability. This should cover both technical skills for data teams and basic data literacy for business stakeholders. Consider partnering with external experts and leveraging AI-managed services to supplement internal capabilities.

7 Enhance model monitoring

Increase your team's focus on detecting and managing data/model drift and bias, as these are currently underemphasized with less than one third of respondents prioritizing them. Implement automated monitoring systems that can track model performance, data quality and potential biases in real time.

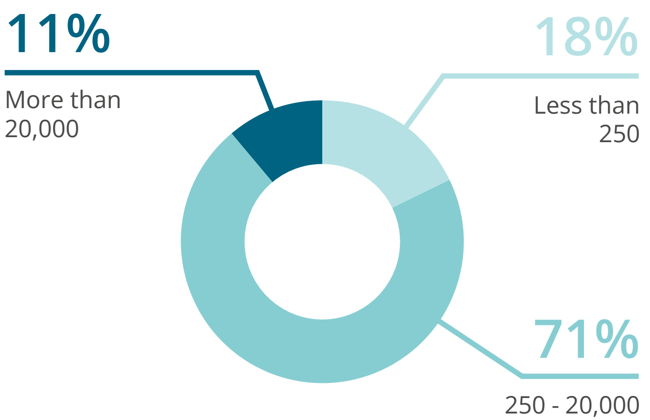
8 Modernize observability infrastructure

While many organizations rely on existing analytics platforms for observability, the growing complexity of AI-driven environments calls for dedicated observability tools. Dedicated tools offer advanced capabilities for monitoring data quality, pipeline performance and model behavior across complex environments, providing automation and unified visibility that basic data warehouse or BI tools cannot match. These advantages justify the incremental cost of a dedicated tool in many cases.

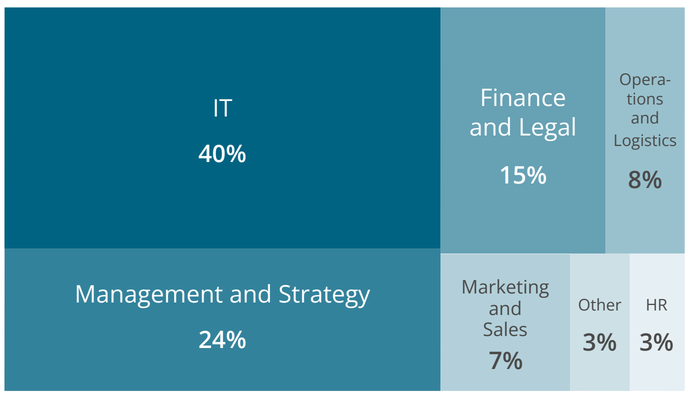
Methodology

Demography

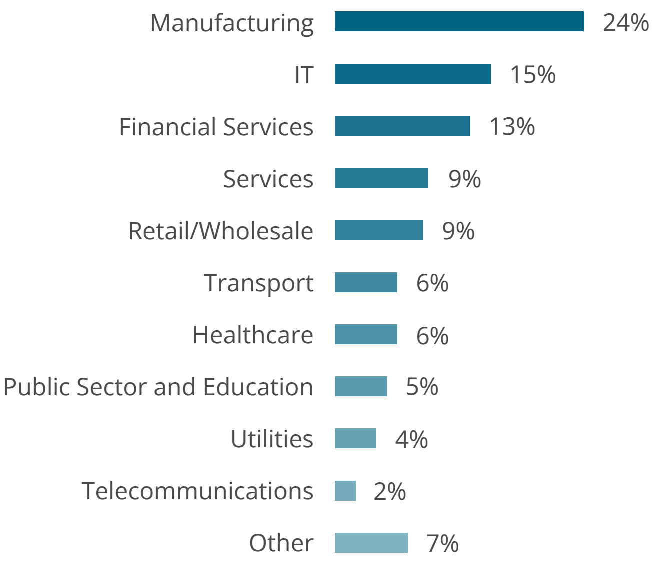
Number of Employees



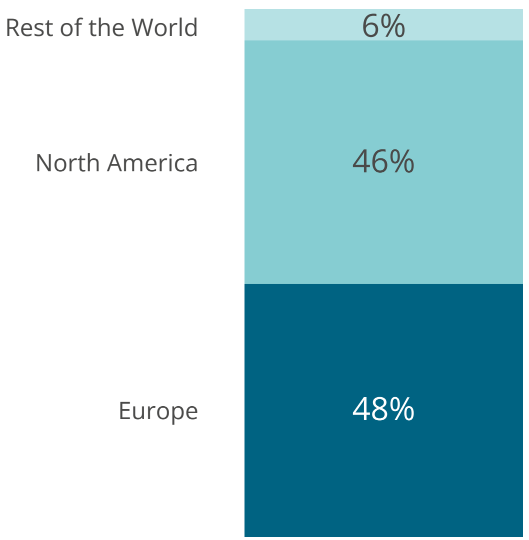
Role



Industry



Region



Information on the Survey

The research employs a quantitative approach utilizing survey responses from a qualified panel of respondents. The design of the survey instrument allows for a detailed exploration of participant subject matter expertise. It focuses on data, pipeline and AI observability, implementation status, challenges to success, solution approaches, and reflects on how AI is changing requirements.

The respondent population is global with significant European and North American audiences, and a total sample size of 264 completed surveys. Random sampling was used to ensure representation across different job roles, company sizes and industries. Participants were included based on their knowledge of their company's Data, Pipeline and AI Observability strategy and projects.

Company Profile

About BARC

BARC is the leading analyst firm in Europe for technology and the successful use of data & analytics. Our BARC Digital Workplace division complements this focus with expertise in ECM, BPM, CRM and ERP.

Research

BARC user surveys, software tests and analyst assessments in blogs and research notes give you the confidence to make the right decisions. Our independent research gets to the heart of market developments, evaluates software and providers thoroughly and gives you valuable ideas on how to turn data, analytics and AI into added value and successfully transform your business.

Consulting

The BARC Advisory practice is entirely focused on translating your company's requirements into future-proof decisions. The holistic advice we provide will help you successfully implement your data & analytics strategy and culture as well as your architecture and technology. Our goal is not to stay for the long haul. BARC's research and experience-founded expert input sets organizations on the road to the successful use of data & analytics, from strategy to optimized data-driven business processes.

Events

Leading minds and companies come together at our events. BARC conferences, seminars, roundtable meetups and online webinars provide more than 10,000 participants each year with information, inspiration and interactivity. By exchanging ideas with peers and learning about trends and market developments, you gain new impetus for your business.

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Sponsor Profiles

Sponsor Profile

About Collibra

Collibra frees your data from the constraints of silos by unifying data and AI governance across your entire ecosystem, regardless of source or compute engine, for ultimate flexibility in how you manage data. Our Collibra Platform gives you automated visibility, control and tracing from input through output, and it automates documentation and data traceability for AI use cases to power speed, data observability and safety.

Our enterprise metadata graph enriches data context with every use, and our intuitive UX brings technical and business users into the fold to access and steward data. Accelerate and strengthen every data and AI use case when everyone in your organization can trust, comply and consume. Collibra delivers true Data Confidence.

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Sponsor Profile

About Precisely

As a global leader in data integrity, **Precisely** ensures that your data is accurate, consistent, and contextual. Our portfolio, including the Precisely Data Integrity Suite, helps integrate your data, improve data quality, govern data usage, geocode and analyze location data, and enrich with complementary datasets for confident business decisions. Over 12,000 organizations in more than 100 countries, including 93 of the Fortune 100, trust Precisely.

Take the first step toward data integrity

At Precisely, we've been empowering businesses like yours to make confident decisions built on trusted data for more than 50 years. Every data journey is unique, and it's often a complex and ongoing process with many steps between defining a data strategy and deriving useful insights. You can more easily and effectively build data integrity when the core capabilities you need are working together – and our Precisely Data Integrity Suite does just that.

The Data Integrity Suite accelerates your journey with market-leading capabilities as SaaS services that seamlessly work together to address all aspects of data integrity. The Suite's business-friendly user experience, high-speed catalog of business and technical metadata, and use of AI support fluid business and IT collaboration and accelerate delivery of trusted data to your business whenever and wherever it's needed.

Precisely is recommended by leading industry analyst organizations and closely collaborates with a world-class network of partners.

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