Decision Point Research

AI IN MARKET RESEARCH

Adoption, Confidence, and the Road Ahead

A White Paper for Research Industry Professionals

Based on primary research fielded at Succeet Conference
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Executive Summary

The research industry stands at an inflection point. AI adoption is no longer an abstraction reserved for well-funded technology firms. It is already reshaping daily workflows at research agencies, suppliers, and insight functions of every size across Europe and beyond.

Decision Point Research (DPR) fielded a structured survey at the Succeet Conference in Wiesbaden, Germany in March 2026, capturing the views of research professionals from across Europe and beyond.[1] The findings, combined with a review of current global research from GRIT, ESOMAR, McKinsey, Statistics Canada, and others, reveal a field in active transition: high on adoption intent, wrestling with execution, and acutely aware of the data quality risks AI both creates and can solve.

Key findings at a glance

79%
of survey respondents already use AI in some form in their research workflows

58%
cite fraud, bot, and AI-assisted response detection as their top priority for future AI investment

49%
name Accuracy as their top AI concern, outranking Data Security, Bias, and Privacy

77%
plan to invest in AI platforms in the next 12 months, though most plan to spend under $20,000

These findings align closely with broader global trends. McKinsey's 2026 State of AI survey found that nearly nine in ten respondents report regular AI use in at least one business function. However, only 37% report that AI has contributed positively to their organization's earnings before interest and taxes (EBIT). The gap between adoption and demonstrated value, and between enthusiasm and trusted execution, defines the moment the industry now occupies.

The findings are directional rather than definitive, as is appropriate for a practitioner survey of this kind. Their value lies in what they illuminate in combination with the global evidence base: a consistent pattern of widespread but shallow adoption, rising data quality anxiety, and a field that is ready to move but not yet sure how.

This paper synthesizes DPR's primary research with current third-party evidence to provide European and global research professionals with a grounded picture of where the industry stands and what meaningful AI integration actually requires.

[1] *Methodology note: The DPR survey was fielded at the Succeet Conference, Wiesbaden, Germany, March 2026. Respondents were research industry professionals attending the conference. The survey was administered digitally at the event. Findings are directional and reflect the views of a practitioner audience at a point in time. Full methodology available from DPR on request.*

1. The State of Play: AI Adoption in Market Research

The research industry has moved rapidly from AI curiosity to widespread adoption. The question is no longer whether to engage with AI. It is how to do so in ways that preserve research integrity, build client confidence, and deliver genuine operational value.

The US market as a point of comparison

The United States research market offers a useful point of comparison for European practitioners navigating the same transition. Its experience provides a perspective on how AI adoption is developing and the organizational changes required to integrate AI into research workflows.

PwC's 2026 Global AI Jobs Barometer, drawing on more than one billion online job advertisements across six continents, finds that skills required for the most AI-exposed jobs are changing more than twice as fast as those in the least exposed roles. New tasks in these jobs are also 2.5 times more likely to rely on human-intensive capabilities such as empathy, judgement, and creativity (PwC, 2026).

The ARF (Advertising Research Foundation), in its 2026 study, How Marketers Are Adopting AI, highlights concerns directly relevant to those identified in the Succeet survey, particularly the accuracy of AI outputs. These findings reinforce the importance of quality assurance. For research suppliers, quality assurance is no longer assumed: it must be demonstrated.

Global adoption context

The 2026 GRIT Insights Practice Report, based on 735 completed surveys, finds that use of AI- and chatbot-moderated qualitative research has grown by more than 10 percentage points since 2020 in five of the six segments tracked. Among brand-side analytics professionals using these tools, 62% report regular use. Together with the Succeet findings, this points to a shift from occasional use towards more regular and integrated applications (Greenbook, 2026).

ESOMAR's 2026 AI Trends consultation echoes this picture: most respondents had already adopted AI, particularly for text and image analysis and quality control. Palacio (2026) reports that while only around half had a governance framework in the 2025 iteration, this gap had almost completely closed in the follow-up less than a year later.

Kantar's Marketing Trends 2026 report highlights the importance of responsible data, rigorous testing, new skills, and trusted partners as marketers move from synthetic-data experimentation to practical AI applications. This reinforces the importance of quality and validation as AI becomes more widely integrated into research workflows (Kantar, 2025).

McKinsey's 2026 State of AI report provides a broader global perspective. Nearly nine in ten respondents report regular AI use in at least one business function, while 44% say AI is being scaled across their enterprise, up from 38% the previous year. However, only 37% attribute at least some positive EBIT impact to AI, a figure that remains essentially unchanged from 2025. This

highlights the gap between the growing adoption of AI and its ability to generate measurable enterprise-level financial returns. Adoption is outpacing demonstrated value.

What the Succeet survey found

DPR's practitioner survey at Succeet 2026 provides a granular, European-anchored view of where adoption actually stands among working researchers:

79%

of survey respondents report using AI in their research workflows in some form

- 36% describe their AI use as ad-hoc or occasional, driven by individual needs
- 19% use AI tools regularly across research tasks
- 15% have deployed custom AI agents or automated workflows
- 9% describe AI as deeply embedded across their research operations
- 21% report that they currently do not use AI in their research processes

These numbers tell a nuanced story. The majority of the field has crossed the threshold into active use, but most are still working at the exploratory or ad-hoc level. Deep integration remains a minority experience. The industry is using AI; it has not, in most cases, built AI into its research infrastructure in any durable way.

This pattern is consistent across global benchmarks.

GRIT 2026 likewise reports growing use of AI- and chatbot-moderated qualitative research, although adoption and regular use vary across segments.

The Succeet findings track closely with that global picture.

> *"We can use AI to cut down on time-intensive tasks, like collecting general information on certain topics. The main challenge appears when the AI messes up on simple tasks that it did well in for the first 50 times. So the challenge is quality control."*
>
> Senior researcher, boutique qualitative and analytics firm, Germany

> *"AI used in our survey tech for survey design, smart probing of open-ends, and chat assistance in analytics."*
>
> Chief Commercial Officer, survey technology provider, Europe

This pattern, AI performing well on average but unpredictably in specific instances, surfaces repeatedly in the open-ended responses and in the broader literature. The first comment above captures a frustration that is more widespread than the adoption figures suggest: organizations do not just need AI that works; they need AI that works consistently. Intermittent failure in high-

stakes research contexts is not a minor annoyance. It is a fundamental obstacle to building client trust and organizational confidence.

A note on the European context

European research professionals operate under a regulatory and cultural environment that shapes how AI adoption unfolds.

GDPR and related national data-protection rules create specific obligations around data handling, automated decision-making, and respondent privacy that differ from those in North American markets (European Parliament and Council of the European Union, 2016).

The European AI Act, which is being implemented in stages, introduces additional requirements for transparency and human oversight in AI-driven systems (European Parliament & Council of the European Union, 2024).

These constraints are not simply compliance burdens. For many European practitioners, they are design requirements that inform how AI tools are selected, deployed, and monitored. Privacy and Compliance ranked fourth among top concerns in the Succeet survey (cited by 32% of respondents), while Vendor Transparency was cited by 19%, pointing to real anxiety about opaque AI practices in the tools researchers are being asked to use.

The upside of regulatory discipline is that it can encourage more robust, auditable AI systems.

The downside is that the implementation burden can slow adoption, particularly for smaller firms without dedicated compliance resources.

2. The Data Quality Crisis: AI as Problem and Solution

No issue in market research has a more complicated relationship with AI than data quality. AI-generated or AI-assisted survey responses are emerging as a significant and growing source of data contamination. At the same time, AI-powered quality control systems represent some of the most promising tools available for detecting and addressing those very problems.

The scale of the problem

Research from NORC at the University of Chicago highlights the growing challenge of fraudulent participation in online nonprobability surveys. Its 2026 research briefs cite industry estimates suggesting that fraudulent responses account for approximately 15 to 30% of survey completions in some research settings, with rates reported as high as 45% on certain platforms (Bilgen & Dutwin, 2026). These figures are drawn from external industry estimates and individual research studies rather than a representative NORC measurement of fraud across the market research industry. They should therefore be treated as indicative estimates rather than universal rates.

The nature of the problem is also evolving. Traditional bots and duplicate respondents are increasingly being joined by coordinated human-bot operations and AI-generated responses. A 2025 Canadian study published in *BMJ Open Quality* illustrates the potential scale of the problem: researchers retained only 439 of 2,115 sufficiently completed survey entries (20.8%) as valid following a multi-stage screening process. The study involved healthcare providers recruited through email and social media, and the screening process identified suspicious patterns including implausible responses, inconsistent answers, clustered submissions, and open-ended responses suspected of being machine-generated.

Separately, research published in the *Proceedings of the National Academy of Sciences* demonstrated that an AI-powered synthetic respondent could pass 99.8% of 6,000 standard attention-check trials. While this was an experimental demonstration rather than a measure of actual industry-wide fraud, it illustrates how sophisticated AI agents can evade conventional survey quality controls.

Statistics Canada researchers have also examined the problem of fraudulent and insincere responding in commercial online nonprobability surveys. A 2024 study published in Statistics Canada's *Survey Methodology* journal identified bogus responding as a significant and widespread problem in US opt-in panels, highlighting its potential to distort survey estimates and undermine research validity. While the study predates current generative AI concerns, it demonstrates that respondent integrity has long been a broader methodological challenge for online research.

Rival Group's *Market Research Trends 2026* report similarly emphasizes that data quality extends beyond fraud detection to include how respondents are recruited, how questions are asked, and how responses are interpreted. The report also highlights declining respondent engagement and the difficulty panel providers face in distinguishing bots from genuine participants.

ESOMAR's 2025 ICC/ESOMAR International Code explicitly addresses the responsible use of AI and synthetic data in market research. It establishes expectations around transparency, client disclosure, human oversight, research quality controls, and the identification of potential biases. Together with its online sample quality guidelines, these standards reinforce the importance of documented quality assurance practices and greater transparency in how research data is collected, validated, and analyzed.

Where the industry stands on AI-based quality control

The Succeet survey reveals that the industry's response to this challenge is still developing:

62%

of survey respondents use AI in some form for data quality and respondent integrity

38%

report no AI in their data quality process, relying on manual or basic platform tools

Breaking this down further:

- 28% use AI on an ad-hoc basis: occasional review of responses or detection of suspicious patterns

- 19% apply AI in selected studies, targeting specific projects for bot and duplicate detection
- 8% have an AI-driven quality system continuously monitoring across studies
- 8% have AI integrated into their fielding workflows for real-time monitoring

Notably, 58% of respondents identified fraud, bot, and AI-assisted response detection as their top priority for increased AI investment over the next 12 to 24 months, making it the single most commonly cited future focus. The industry recognizes the problem and is moving, if unevenly, toward AI-enabled solutions.

> *"We are experiencing many positive outcomes in the data quality area."*
> Project Success Manager, data collection platform, Germany

> *"We managed to optimise the quant ops process by combining AI with human power."*
> VP Sales, quantitative research firm, Bulgaria

The organizations reporting the most confidence in their data quality practices share a common characteristic: they have built hybrid systems that combine AI detection tools with human review, rather than relying on either alone. The second comment above points to something important: it frames the combination as an optimization, not a compromise. The "human power" is not a fallback for when AI fails. It is a deliberate design element.

The human review imperative

Multiple survey respondents, and a consistent thread in the global literature, point to the same conclusion: AI quality control works best as a support system for human judgment, not a replacement for it. Automated systems can flag suspicious patterns at scale; they cannot always determine context, interpret cultural signals, or make nuanced calls about borderline cases.

This is especially relevant in European markets, where survey responses may span multiple languages and cultural contexts. One respondent from a German-based corporate insights function noted directly that "sentiment analysis is not working properly with every language," a finding that highlights the need to validate AI performance across the languages and cultural contexts relevant to each study.

For European research firms operating across markets, this is not a peripheral concern. It goes to the reliability of AI analysis in the contexts where much of their work actually happens. A tool that works well in English and poorly in German, Polish, or Romanian is not a European research tool. It is an English-language tool with European coverage gaps.

3. Where Adoption Breaks Down: Concerns and Confidence Gaps

High adoption rates coexist with significant anxiety. The Succeet survey reveals a field that is actively using AI while simultaneously expressing concern about whether it can fully trust AI

outputs. Understanding the specific nature of those concerns is essential for any organization navigating the adoption curve.

What researchers are worried about

Respondents identified their primary concerns about AI in the workplace. The results present a clear hierarchy:

- Accuracy: 49% (the single most commonly cited concern)
- Data Security: 43%
- Bias and Representativeness: 34%
- Privacy and Compliance: 32%
- Skills and Change Management: 32%
- Fraud and Authenticity: 28%
- Vendor Transparency: 19%
- Stakeholder Trust: 15%

Accuracy tops the list. This is not a peripheral worry. In a field where the entire value proposition rests on the reliability of data and analysis, AI that produces confident but inaccurate outputs poses an existential risk to client trust. A similar concern appears in ARF's 2026 study, which identifies inaccurate AI outputs among marketers' leading AI concerns (Advertising Research Foundation, 2026).

KEY INSIGHT

The accuracy concern goes beyond individual errors. What researchers describe is a deeper anxiety about predictability: AI that performs well most of the time, but fails without warning on specific tasks or topics, is structurally difficult to deploy in a high-stakes research context. This is what practitioners mean when they say "quality control," meaning not a one-time audit but an ongoing discipline.

Hallucination in research contexts

The concern about accuracy connects directly to the hallucination problem in AI language models: generating confident but false statements. One respondent who runs a mixed-methods research firm stated plainly:

> *"Hallucinating is still the biggest problem. Especially emotional topics tend to be flat in analysis."*
>
> Managing Director, full-service research firm, Germany

This observation points to a specific and underappreciated vulnerability: AI analysis of emotional, sensitive, or nuanced qualitative data may produce outputs that are syntactically fluent but analytically shallow or factually wrong. Emotional complexity is precisely what qualitative research is meant to surface. When AI flattens that complexity into averaged or generic statements, it defeats the purpose of the research. The output looks like insight. It is not.

Several respondents who expressed general enthusiasm for AI tools nonetheless flagged this limitation as a reason for sustained caution in qualitative applications. The gap between AI's performance on structured tasks (summarization, tagging, translation) and its performance on unstructured emotional interpretation is real and significant. It is not closing as fast as other capability gaps.

The quality control problem in practice

One of the most telling observations in the open-ended responses came from a researcher in Germany who described AI performing reliably for 50 consecutive tasks, then unexpectedly failing on a task of the same type. This is not a story about AI being unreliable. It is a story about AI being unreliably reliable: performing consistently enough to lower a researcher's guard, then failing at a moment when the assumption of reliability had become habit.

This dynamic is particularly dangerous in research workflows where AI outputs feed downstream analysis or client deliverables. A quality control discipline that worked adequately during AI evaluation phases may not be maintained once AI tools become embedded in production. The failure arrives in a context where the human oversight has already been reduced.

Team readiness and organizational barriers

Beyond the technical concerns, the Succeet data surfaces a significant human dimension to the adoption challenge. Skills and Change Management was cited by 32% of respondents as a primary concern, reflecting the reality that deploying AI effectively requires not just technology investment but organizational capability.

40%
of survey respondents describe their teams as actively experimenting or AI-forward

26%
describe their teams as hesitant, cautious, or strongly resistant to AI adoption

The remaining 34% describe their teams as "open to limited use": cautiously optimistic but not yet committed. This distribution suggests that a substantial proportion of teams remain cautious or uncertain about how to proceed.

> *"We're spread too thin to properly check in-house AI tools and provide thorough, meaningful feedback, which staggers development and integration efforts."*
> Creative Research Executive, qualitative research firm, Turkey

> *"Human supervision and oversight is required for AI outputs."*
> President, full-service research firm, Canada

The first comment above captures a constraint that is especially acute for smaller research firms: the capacity to evaluate, implement, and monitor AI tools is itself a limited resource. "Spread too thin" is not a complaint about technology. It is a description of a structural problem: organizations where AI adoption requires additional time and expertise that the organization does not have to

spare. Under these conditions, AI adoption stalls not because of opposition but because of bandwidth.

The second comment, coming from a respondent who describes broadly positive AI experiences, is just as important. It frames human oversight not as a reluctant concession to AI's limitations but as a professional standard. The tone is matter-of-fact: of course you maintain oversight. This is the orientation that characterizes the organizations navigating AI adoption most successfully.

4. Voices from the Field: What Practitioners Are Actually Experiencing

Numbers tell part of the story. The open-ended responses from the Succeet survey tell the rest. When asked to describe their organizations' AI experiences in their own words, respondents provided a rich and sometimes contradictory picture that does not resolve into a single narrative. What emerges instead are several recurring themes, each of which illuminates a dimension of AI adoption that structured survey questions cannot fully capture.

Theme 1: AI as accelerator, not replacement

The most consistent theme across the open-ended responses is that AI is experienced as a tool for doing existing work faster, not a tool for doing fundamentally different work. Respondents who described positive AI experiences almost universally framed those experiences in terms of time savings, efficiency, and bandwidth: AI handling the volume so that human researchers can focus on the judgment.

> *"It saves time and sometimes reveals insights that are easy to miss manually. It works best as a support tool, not a replacement for human judgment."*
> Customer Success Manager, eye-tracking and behavioral research firm, Poland

> *"AI is great support when analyzing data sheets and developing personas."*
> Founder, independent research consultancy, Germany

> *"Good tool to work with open-ended questions."*
> Managing Director, research agency, Germany

> *"Easier to navigate."*
> Insurance advisor and researcher, Canada

The framing of "support tool" appears repeatedly and is not casual. It reflects a deliberate position: AI is useful, but its usefulness is conditional on human researchers remaining in charge of the work. This is the dominant working model among practitioners who have moved from experimentation to integration.

It is also, importantly, a resilient framing. Researchers who think of AI as a support tool are less likely to over-rely on it, less likely to be caught out by its failures, and more likely to maintain the validation discipline that good research requires. The organizations that have adopted this framing explicitly, rather than implicitly, appear to have had fewer costly AI failures.

Theme 2: The disappointment divide between qual and quant applications

One of the most striking patterns in the open-ended responses is a sharp divergence in satisfaction between qualitative and quantitative AI applications. Respondents consistently described AI-moderated qualitative interviews as a genuine success story. Their experiences with AI tools for quantitative analysis, open-end coding, and questionnaire design were far more mixed.

> *"We're actively using AI-moderated interviews and are happy with it, but we got really disappointed testing many AI solutions for quantitative research, mainly open-ended answers coding, questionnaire designing and data analysis."*
> Senior Researcher, quantitative and qualitative research firm, Poland

This observation, offered directly and without hedging, was not isolated. Several other respondents touched on the same divide: AI that performed well in conversational, exploratory contexts, and fell short in the structured, precision-dependent contexts that quantitative research requires.

The likely explanation is architectural. AI language models are fundamentally conversational systems. They were designed to generate plausible, contextually appropriate text in response to prompts. This makes them well-suited to facilitating an interview, synthesizing a theme, or summarizing a set of qualitative responses. It does not necessarily make them well-suited to applying a rigorous coding scheme consistently, generating unbiased survey instruments, or running the kind of structured analysis that quantitative research demands.

For research organizations that work across both methods, this distinction matters enormously for how AI tools are evaluated and deployed. A tool that earns high marks in qualitative work should not be assumed to perform equivalently in quantitative work. These are different jobs, and current AI tools have different strengths and weaknesses across them.

FIELD OBSERVATION

The qual/quant performance divide is one of the clearest practical findings from the Succeet open-ended responses. AI-moderated interviews are delivering genuine value. AI tools for quantitative open-end coding and questionnaire design are, in the experience of multiple practitioners, still falling short. Organizations should evaluate these applications separately, not assume consistent performance across methods.

Theme 3: Successful integration requires organizational change, not just technology

The respondents who described the most complete and positive AI integration stories shared a common feature: they described organizational change alongside technology change. AI tools did

not simply work when installed. They worked when the organization had adapted to working with them.

> *"We have successfully integrated tailored AI solutions throughout our quantitative primary market research process. Change management is starting to really get a grip."*
> AI Integration Architect, global data and analytics platform, Germany

> *"We've used AI to speed up data analysis and spot patterns in research, especially with larger datasets. It saves time and sometimes reveals insights that are easy to miss manually. The downside is that outputs still need validation, as AI can misinterpret context. It works best as a support tool, not a replacement for human judgment."*
> Customer Success Manager, attention analytics firm, Poland

The phrase "change management is starting to really get a grip" is telling. It took time. It required deliberate effort. And the framing is honest: not "we've cracked it," but "it's starting to work." This is what successful AI integration actually looks like at the organizational level: not a sudden capability shift, but a gradual, sometimes bumpy, process of adaptation.

By contrast, organizations that reported stalled or disappointing AI experiences tended to describe a technology-first story: tools that were acquired and deployed without adequate preparation for how they would change workflows, responsibilities, or quality standards. The tools were available; the organization had not changed to use them well.

Theme 4: The capacity constraint at smaller firms

A recurring theme, particularly among respondents from smaller and mid-sized firms, was the capacity problem: not skepticism about AI, but an inability to invest the time required to evaluate it properly. This is distinct from the skills gap narrative that dominates much of the industry discussion. The issue is not that practitioners lack the knowledge to evaluate AI tools. It is that they lack the time.

> *"We're spread too thin to properly check in-house AI tools and provide thorough, meaningful feedback, which staggers development and integration efforts."*
> Creative Research Executive, qualitative research firm, Turkey

The consequence of this constraint is not opposition to AI. It is uncontrolled adoption: tools being used without adequate evaluation, risks being accumulated without adequate awareness, and integration proceeding without the quality management scaffolding that makes it safe.

For the research industry as a whole, this is a structural concern. A significant portion of the European research market consists of small and mid-sized firms operating under significant resource constraints. If the barrier to responsible AI adoption is not technology access but evaluation capacity, then the industry needs solutions that reduce that capacity requirement, whether through shared standards, tested procurement frameworks, or more transparent vendor benchmarking.

Theme 5: Enthusiasm for what works, honesty about what does not

What is striking about the Succeet open-ended responses in aggregate is their honesty. Practitioners are not performing enthusiasm, and they are not performing skepticism. They are describing what they have actually experienced.

> *"Reduced turnaround delivery period. Efficiency in meeting deadlines. However human supervision and oversight is required for AI outputs."*
> President, full-service research firm, Canada

> *"Definitely needs human touch to make the outcome perfect. Not a bad thing at all, but it needs to be always taken into consideration."*
> Strategy and Business Manager, research technology firm, Bulgaria

> *"Nothing but helpful."*
> Independent qualitative researcher, Switzerland

Across the range, from the unqualified positive to the carefully nuanced, the most common thread is pragmatism. Practitioners are measuring AI against the practical standard of their work: does it make their research better, faster, or more reliable? Where it does, they are enthusiastic. Where it does not, they say so. This is a healthy professional culture. The risk is that it remains at the level of individual practitioner experience without translating into shared knowledge, common standards, or organizational practice.

5. Investment Intentions and the Forward Agenda

Despite the concerns outlined above, the Succeet survey points to a field that intends to invest in AI. The question is not whether to move forward, but at what pace, at what scale, and in which areas.

Investment plans

77% of survey respondents plan to invest in AI platforms over the next 12 months. The investment picture is fragmented, however:

- 28% plan to spend under $5,000 annually
- 30% plan to spend $5,000 to $20,000 annually
- 11% plan to spend $20,000 to $50,000 annually
- 8% plan to spend $50,000 or more annually
- 23% plan no investment

The concentration of investment intent in the under-$20,000 range reflects the reality that most research organizations are approaching AI as an operational tool rather than a strategic infrastructure investment. At these spending levels, organizations are more likely to be purchasing access to existing AI platforms (survey tools, analysis assistants, translation tools) than building bespoke AI capabilities.

This is not necessarily the wrong approach. For many firms, integrating capable existing tools into existing workflows is more practical than building AI capability from scratch. It does mean, however, that the competitive differentiation available through AI investment is constrained by the willingness to commit meaningful resources.

Priority investment areas

Respondents identified the areas where they expect to increase AI usage most in the next 12 to 24 months:

- Fraud, bot, and AI-assisted response detection: 58% (top priority)
- Sampling and quota optimization: 40%
- Survey design and instrument testing: 38%
- Reporting, visualization, and storylining: 34%
- Thematic coding and qualitative analysis at scale: 28%
- Conversational or adaptive surveys: 21%
- Sentiment and pattern analysis: 15%
- Predictive modeling and foresight: 11%

Fraud and quality detection at the top of the list reflects the urgency described in Section 2. The industry is not only aware of the problem. It is prioritizing AI as the most viable solution.

The prominence of reporting, visualization, and storylining (34%) also deserves attention. This is a domain where AI tools have advanced rapidly and where efficiency gains are immediately legible to clients. Several respondents noted positive experiences with AI for analysis and reporting, even where they remained cautious about other applications. One respondent noted using Claude for visualizing reports; another described AI as providing "great support when analyzing data sheets and developing personas." These tasks are well within the current capability envelope of available AI tools.

The relatively lower priority assigned to predictive modeling and foresight (11%) and sentiment analysis (15%) may reflect the accuracy concerns discussed in Section 3: these are high-precision applications where the cost of AI error is substantial, and where practitioner confidence in current tools remains limited. The qual/quant divide identified in the open-ended responses likely plays a role here as well.

> *"It saves time and sometimes reveals insights that are easy to miss manually. It works best as a support tool, not a replacement for human judgment."*
> Customer Success Manager, eye-tracking and behavioral research firm, Poland

The integration challenge

Knowing where to invest is a different problem from being able to integrate effectively. The Succeet data and global benchmarks consistently point to integration, the ability to weave AI tools into existing workflows in ways that improve quality and efficiency without creating new risks, as the central operational challenge.

Organizations that report the most positive AI experiences in the survey share certain characteristics: they have identified specific, well-scoped use cases; they maintain human oversight of AI outputs; and they have developed internal expertise for evaluating and managing AI tools.

> *"We have successfully integrated tailored AI solutions throughout our quantitative primary market research process. Change management is starting to really get a grip."*
>
> AI Integration Architect, global data and analytics platform, Germany

This comment offers a useful model: intentional, use-case-specific implementation supported by sustained organizational change management effort. The technology is not the hard part. The organizational change is.

6. What Good Looks Like: Principles for Responsible AI Integration

The picture that emerges from DPR's research and the broader literature is not one of AI as a simple productivity multiplier. It is a more complex picture of a powerful but imperfect technology that requires deliberate management to deliver its potential without introducing new risks. The organizations navigating this well share a set of practices and orientations worth making explicit.

1. Start with the problem, not the technology

The most successful AI implementations in the research field begin with a specific, well-defined problem: detecting low-quality responses, accelerating thematic coding, improving survey design. They do not begin with a general mandate to "use more AI." This sounds obvious, but it runs against the current cultural pressure to demonstrate AI capability broadly.

Respondents who reported positive AI experiences consistently described well-scoped applications: AI that works well for open-ended questions, AI that provides great support for analyzing data sheets and developing personas, AI that delivers genuine value in qualitative interview moderation. In each case, the application was specific and the value was legible.

2. Build human oversight into the workflow by design

No theme is more consistent in the Succeet data and the global literature than the importance of human review. AI tools perform at their best when their outputs are reviewed and validated by

experienced researchers who can catch errors, supply context, and apply judgment that AI cannot.

> *"Definitely needs human touch to make the outcome perfect. Not a bad thing at all, but it needs to be always taken into consideration."*
> Strategy and Business Manager, research technology firm, Bulgaria

DESIGN PRINCIPLE
Human oversight is not a fallback for when AI fails. It is a core feature of any AI-enhanced research workflow. Build it in from the start, not as an afterthought.

3. Take data quality seriously as a multi-level problem

AI creates new data quality risks (AI-generated respondent fraud) and new data quality tools (AI detection systems). Managing both dimensions simultaneously requires intentionality. Organizations doing this well have implemented AI-based quality control and are maintaining human review of flagged responses. They are also communicating their quality assurance approach to clients in ways that build, rather than undermine, trust.

The 2025 ICC/ESOMAR International Code requires clients to be informed when AI or emerging technologies are used in compiling datasets, analysis, reporting or interpretation, including the use of synthetic data and personas; the extent of human oversight must also be stated (Article 7(e)).

This is not just good compliance practice. It is good commercial practice. In an environment where clients are increasingly aware of data quality risks, demonstrating rigorous quality management is a genuine competitive differentiator.

4. Invest in capability alongside tools

The Skills and Change Management concern (cited by 32% of respondents) points to a real and underinvested dimension of AI adoption. Tools without capability produce poor results. Building internal expertise, the ability to evaluate AI tools critically, manage their limitations, and train team members to use them effectively, is a necessary complement to any technology investment.

This does not require large budgets or dedicated AI teams. It does require intentional effort: designated people who take responsibility for AI tool evaluation, regular team learning, and a culture that treats AI quality management as a professional skill rather than a technical afterthought.

5. Evaluate qualitative and quantitative applications separately

The practitioner evidence from Succeet is consistent: AI performs differently across different research methods. Qualitative interview moderation, thematic synthesis, and open-end summarization are applications where current tools have demonstrated genuine value. Quantitative applications, including structured open-end coding, questionnaire design, and complex data analysis, show more uneven results.

Organizations that evaluate AI tools as a category, rather than by specific application, are likely to reach misleading conclusions. A tool that earns enthusiasm in one method should be rigorously re-evaluated before being deployed in another.

6. Manage vendor relationships with rigor

Vendor Transparency was cited as a concern by 19% of respondents: a notable proportion given how specific the concern is. Research organizations are increasingly aware that the AI tools they purchase may not be transparent about their methods, limitations, or data practices.

Due diligence on AI vendors should include questions about training data sources, accuracy benchmarks, GDPR and data protection compliance, and the vendor's own approach to quality assurance and hallucination mitigation. Vendors who cannot or will not answer these questions clearly warrant appropriate caution.

This is particularly important in the European context. GDPR compliance is a baseline, not a differentiator. Organizations should be asking vendors for evidence of ongoing compliance review, particularly as AI models are updated and their data handling practices may change.

7. Looking Ahead

The research industry's AI journey is still in early innings, even as the field no longer looks like it is at the starting line. The next two to three years are likely to be defined by a shift from adoption to integration: from "we use AI" to "we have built AI into our workflows in ways that reliably improve quality, efficiency, and value delivered to clients."

Several dynamics will shape how that shift unfolds:

Regulatory clarification

The European AI Act is being implemented in stages. Most requirements, including the transparency obligations under Article 50, began applying on 2 August 2026. Requirements for high-risk systems under Annex III are scheduled to apply from 2 December 2027, while those for high-risk AI embedded in regulated products under Annex I are scheduled to apply from 2 August 2028. The requirements relevant to research organizations will depend on how and for what purpose an AI system is used (European Commission, n.d.; European Parliament & Council of the European Union, 2024).

Organizations that begin building compliant practices now will have a structural advantage over those that treat compliance as a later problem.

Quality standards

ESOMAR's AI Trends consultation and Community Circle discussions are contributing to ongoing industry work on evaluating AI applications, including synthetic data. As these practices become more established and are adopted by buyers as procurement criteria, organizations with documented, rigorous AI practices will be better positioned commercially.

Capability differentiation

As AI tools become more widely accessible, the differentiation available through tool access alone diminishes. The durable competitive advantage shifts toward organizational capability: the judgment to know when and how to use AI, the discipline to manage its limitations, and the expertise to deliver better research with it than competitors can.

> *"We're actively using AI-moderated interviews and are happy with it, but we got really disappointed testing many AI solutions for quantitative research, mainly open-ended answers coding, questionnaire designing and data analysis."*
> Senior Researcher, quantitative and qualitative research firm, Poland

This comment illustrates the path ahead clearly. AI works well in some applications and poorly in others. The organizations that will lead are those with the experience and judgment to know which is which, and the discipline to apply AI only where it genuinely adds value.

Client expectations

Research buyers are becoming more sophisticated about AI. Questions about quality assurance, bias mitigation, and data handling are entering procurement conversations. Firms that have worked through these questions and can answer them clearly will build trust faster than those caught unprepared.

LOOKING FORWARD

The organizations that will lead in the next phase of AI adoption are not necessarily those with the largest AI budgets or the most aggressive adoption timelines. They are those that have been most deliberate about building AI capability that is trustworthy, auditable, and genuinely aligned with the quality standards research requires.

DPR's research at Succeet captures the industry at a moment of active transition. The majority who are already using AI, and the large proportion who plan to invest more, are not waiting for AI to mature before engaging. They are figuring it out in real time: learning from their own experience and from peers, building practices iteratively, and trying to stay ahead of risks that are also iterating rapidly.

That is, ultimately, what the field has always done. The tools are new. The core discipline, rigorous, methodologically sound, client-focused research, is not.

About Decision Point Research

Decision Point Research (DPR) is a Toronto-based market research company.

DPR provides customized quantitative and qualitative data collection, recruitment, and access to specialized research panels, helping clients reach consumer, healthcare, B2B, and other hard-to-reach audiences across Canada, the United States, Europe, and beyond.

DPR has tracked AI adoption and its implications for the research industry since 2024, fielding primary research among research professionals across Canada, the United States, and Europe. The Succeet Conference survey represents DPR's first European primary data collection on this topic.

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