

Exploring AI-Driven Decision Making in Business Strategy: A Consulting Industry Perspective

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Abstract

This paper explores the evolving influence of artificial intelligence (AI) on strategic decision-making within the consulting sector. As consulting organizations increasingly incorporate AI-enabled tools, they are using data-driven insights to improve operational efficiency, elevate client outcomes, and maintain a competitive advantage. The study uses an empirical design, gathering survey data from 30 professionals representing diverse consulting roles and firm types. The objectives are to measure the degree of AI utilization, evaluate its perceived advantages and constraints, and review the governance and ethical issues shaping AI-assisted decision processes. Findings reveal that AI enhances the quality and speed of strategic judgments through predictive analytics and data interpretation; however, concerns regarding data privacy, workforce capability, and ethical accountability persist. The research enriches existing scholarship by presenting an applied view of AI integration in consulting practice and proposes actionable recommendations for professionals aiming to deploy AI responsibly and effectively. It concludes by emphasizing the importance of structured governance frameworks, continual capability building, and ethical vigilance to optimize AI's contribution to strategic decision-making.

Keywords: Artificial intelligence, consulting sector, strategic decision-making, data-driven insights.

Introduction:

Artificial intelligence (AI) has become a defining force reshaping how organizations approach decision-making, and the consulting industry is at the forefront of this transformation. Consulting firms operate in highly dynamic and uncertain environments where business judgments must be swift, evidence-based, and strategically sound. Traditionally, consultants relied primarily on their experience and intuition; however, the integration of AI technologies—such as natural-language processing, machine learning, and predictive analytics—has introduced an evidence-driven dimension that enhances precision and responsiveness in strategic planning (Brynjolfsson & McAfee, 2017).

Although AI adoption across industries has accelerated, its penetration within consulting remains inconsistent, affected by organizational readiness, workforce competence, and ethical concerns (Davenport & Ronanki, 2018). Consultants are now expected to balance algorithmic intelligence with human expertise, ensuring that technology strengthens rather than replaces professional judgment. This balance forms the basis of an important research gap: understanding the perception, implementation, and governance of AI-driven decision systems within consulting environments.

To address this gap, the present study empirically examines how AI is being used in strategic decision-making by consulting professionals. The research seeks to determine

the extent of adoption, identify the advantages and limitations perceived by practitioners, and analyse governance and ethical mechanisms influencing AI deployment. By doing so, the study contributes to both theoretical and applied knowledge on AI in management consulting and provides actionable guidance for firms striving to institutionalize AI in their strategic processes.

Objectives of the paper

- To assess the level and nature of AI adoption in consulting firms' strategic decision-making.
- To evaluate the perceived benefits and challenges of AI-driven decisions.
- To analyse governance, ethical considerations, and the future outlook for AI integration in consulting strategy.

Literature ReviewArtificial Intelligence in Business Strategy

Artificial intelligence (AI) has become a central pillar in modern business transformation, empowering organizations to translate vast quantities of data into actionable intelligence. Encompassing technologies such as machine learning, natural-language processing, predictive analytics, and computer vision, AI enables real-time pattern discovery and data-driven judgment (Shrestha, Ben-Menahem, & von Krogh, 2019). By integrating these capabilities, enterprises enhance forecasting accuracy, improve customer experiences, and accelerate innovation cycles (Agrawal, Gans, &

Goldfarb, 2018).

Within strategic management research, AI has been recognized as a mechanism that reduces cognitive bias and strengthens the quality of managerial decisions (Brynjolfsson & McAfee, 2017). Frameworks such as the Technology-Organization-Environment (TOE) model (Tornatzky & Fleischer, 1990) highlight that adoption outcomes depend simultaneously on an organization's technological preparedness, internal culture, and external market conditions. Complementing this, the Resource-Based View (RBV) theory (Barney, 1991) proposes that when AI is embedded alongside distinctive human expertise and organizational routines, it can create durable competitive advantage. Together, these perspectives provide a foundation for analyzing why some firms adopt AI rapidly while others lag behind.

AI Adoption in the Consulting Industry

Consulting organizations, traditionally dependent on expert interpretation and qualitative reasoning, are increasingly embracing AI to augment their service offerings (Davenport & Ronanki, 2018). Contemporary applications include automated market research, data modeling, predictive scenario planning, and client segmentation (Manyika et al., 2017). For example, predictive-analytics engines allow firms to draw insights from historical engagement data, estimate outcomes, and anticipate risks—thereby enabling consultants to deliver evidence-based advice with greater efficiency (Bughin et al., 2018).

However, adoption is uneven across the industry. Large, digitally mature consulting houses with strong technological infrastructure tend to achieve smoother integration, whereas smaller or boutique firms encounter challenges such as limited budgets, shortage of technical expertise, and resistance to process change (Chui, Manyika, & Miremadi, 2018). These contrasts demonstrate that successful AI deployment is as much a managerial and cultural endeavor as it is a technological one.

Perceived Benefits of AI in Consulting

AI contributes measurable advantages across consulting workflows. It accelerates information processing, allowing professionals to analyze voluminous datasets in shorter timeframes (Davenport, 2018). It also enhances analytical depth by surfacing patterns, inter-relationships, and market signals that human analysts may overlook (Shrestha et al., 2019). Through advanced client-profiling and recommendation engines, AI facilitates service personalization—offering bespoke solutions that align with each client's context (Agrawal et al., 2018).

Operational efficiency constitutes another major advantage. Automation tools now perform routine activities—data cleansing, document drafting, and repetitive review—freeing consultants to focus on high-value strategic thinking (Brynjolfsson & McAfee, 2017). Additionally, scenario-simulation features help firms stress-test strategies and model contingencies, leading to stronger, evidence-supported recommendations

(Ransbotham, Kiron, Gerbert, & Reeves, 2021).

Challenges and Barriers to AI Adoption

Despite these benefits, consulting firms encounter multiple hurdles when embedding AI into practice. Data-privacy concerns remain paramount given the sensitive nature of client information (Floridi et al., 2018). Algorithmic bias and lack of transparency can erode confidence in machine-generated insights (Ransbotham et al., 2021). The ongoing shortage of AI-literate consultants constrains usage, creating dependence on a limited pool of specialists (Ghasemaghaei & Calic, 2020).

Cultural resistance also slows progress—employees may fear redundancy or loss of professional autonomy (Bughin et al., 2018). Furthermore, high development and maintenance costs discourage smaller firms from extensive experimentation (Chui et al., 2018). These challenges underscore that technological readiness alone is insufficient; organizational change management and ethical oversight are equally vital.

Governance, Ethics, and Responsible AI in Consulting

Ethical stewardship is intrinsic to consulting because advisory work shapes critical client decisions. The notion of responsible AI centers on fairness, accountability, transparency, and explainability (Floridi et al., 2018). Consulting firms are increasingly adopting governance structures such as AI-ethics committees, model-validation protocols, and disclosure requirements to uphold these principles

(Ransbotham et al., 2021).

While several global associations have proposed ethical-AI standards, compliance within consulting remains fragmented. As systems become more autonomous, establishing clear oversight frameworks will be essential to prevent reputational, regulatory, and operational risks (Ghasemaghaei & Calic, 2020).

Research Gaps

Although scholarship on AI in business strategy is expanding, empirical analysis specific to the consulting sector remains sparse. Prior studies have predominantly addressed manufacturing, finance, and retail, leaving professional-services contexts under-investigated (Shrestha et al., 2019). Moreover, limited attention has been given to the interaction between AI capabilities and the trust relationship that underpins consultant–client engagements. Addressing this gap, the present research empirically evaluates adoption intensity, perceived outcomes, challenges, and governance approaches in consulting firms, thereby adding a nuanced perspective to existing literature

Methodology

Research Design

This paper adopted a cross-sectional survey approach to capture a one-time snapshot of generative AI (GenAI) adoption, usage patterns, governance/training context, user confidence, and perceived outcomes within

consulting workflows. The design is appropriate for exploratory mapping in an emerging practice area and supports both descriptive profiling and group comparisons without experimental manipulation.

Participants and Sampling

Participants were 30 consulting professionals recruited via professional networks (e.g., LinkedIn and targeted emails). Inclusion criteria required current employment in a consulting role with involvement in client-facing project delivery and familiarity with AI tools. The sample intentionally covered a diversity of:

- Firm types: Big Four, mid-tier, boutique, others.
- Roles/seniority: Assistant/Deputy Manager, Manager/Senior manager/Associate, Director, Partner/Associate Partner, Others
- Experience bands: 3-6 years, 7-10 years, 11-15 years, 15+ years.
- Service lines: strategy, audit, tax, HR, technology.

A convenience sampling approach was used given access constraints and the exploratory scope.

Instrumentation

A structured online questionnaire captured five construct areas:

- Demographics: role, experience, firm type,

service line.

- Adoption and Tools: awareness, trial, depth/frequency of use, and tool categories.
- Use-Cases: practical applications such as drafting deliverables, data analysis, research, presentations, and brainstorming.
- Governance and Training: presence/maturity of AI policies and whether formal training was received.
- Confidence and Perceived Outcomes: Likert-style items on AI self-efficacy/confidence, perceived benefits (e.g., speed, quality, idea generation), and challenges (e.g., accuracy, privacy, cost, lack of training).

Items were pre-coded to enable quantitative analysis, with multi-select items transformed into binary indicators for each selected option.

Procedure

The survey was administered via an online form (e.g., Google Forms). Participants provided informed consent before viewing the questionnaire. No personally identifying information was collected. Responses were anonymized and stored in a secure, access-restricted repository.

Variables and Coding

- Categorical variables: role, firm type, experience band, training (Yes/No), governance (Yes/Maybe/No), and individual use-cases/tools were coded as

integers.

- Ordinal variables: confidence and perceived outcomes used Likert scales treated as ordinal.
- Multi-select constructs (benefits, challenges) were represented as separate binary variables per category (selected=1, not selected=0).
- Where applicable, counts (e.g., breadth of tool use or use-cases) were computed as simple sums across relevant binary indicators.

Data Analysis Strategy

Analyses proceeded in two stages:

- Descriptive statistics: frequency counts and percentages summarized the sample profile, adoption stages (no use, trial, partial integration, regular use), common use-cases, governance/training status, and perceived benefits/challenges.
- Inferential statistics: t-tests, correlation, chi-square analysis, regression modelling, and Kruskal-Wallis H tests were performed on various group variables.

Ethical Considerations

The research complied with general ethical norms of voluntary participation, informed consent, anonymity, and withdrawal rights. No identifiers were retained, and the dataset was accessed solely for academic purposes.

Methodological Rigor and Justification

The cross-sectional, small-n, practice-oriented context motivates the choice of robust group-comparison methods and heavy reliance on descriptive summaries to avoid over-interpretation. Introductory paragraphs before each analysis increase transparency about test choice, assumptions, and limitations. The instrument emphasizes constructs most salient to consulting practice (adoption depth, governance/training, confidence, and outcomes) to strengthen ecological validity.

Methodological Limitations

The convenience sample (n=30) limits statistical power, precision, and external validity; uneven subgroup sizes can attenuate detection of modest effects. Self-reported measures may be influenced by recall and social desirability, and single-item confidence limits psychometric depth. The cross-sectional design precludes causal inference. These constraints are addressed in the Implications section with recommendations for larger, stratified samples, longitudinal tracking, validated multi-item scales, objective skill tasks, and telemetry-based usage metrics.

Results

Descriptive Statistics

➤ Participants Demographics

- Roles:
 - Deputy/Assistant Manager: 8/30

- Manager/Sr Manager/Assoc Director: 11/30
- Partner/Associate Partner: 7/30
- Others: 4/30
- Experience:
 - 3–6 years: 13/30
 - 7–10 years: 11/30
 - 11–14 years: 4/30
 - 15+ years: 2/30
- Firm type:
 - Big 4: 11/30
 - Boutique/Niche: 5/30
 - Independent: 10/30
 - Top 20 Accounting Firm: 4/30

Table 1: Demographic distribution of consulting professionals by role, experience, and firm type.

Variable	Category	n	%
Role	Deputy/Assistant Manager	8	26.67%
	Manager/Sr Manager/Assoc Director	11	36.67%
	Partner/Associate Partner	7	23.33%
	Others	4	13.33%
	Total	30	100%
Experience	3–6 years	13	43.33%
	7–10 years	11	36.67%
	11–14 years	4	23.33%

	15+ years	2	6.67%
	Total	30	100%
Firm Type	Big 4	11	36.67%
	Boutique/Niche	5	16.67%
	Independent	10	33.33%
	Top 20 Accounting Firm	4	13.33%
	Total	30	100%

➤ Organizational AI use:

- Yes: 25/30
- Maybe: 5/30
- No: 0/30

Table 2: Extent of organizational AI use among respondents, highlighting high adoption rates.

Response	n	%
Yes	25	83.33%
Maybe	5	16.67%
No	0	0%
Total	30	100%

➤ Tool types (multi-select; presence across responses):

- Generative AI (e.g., ChatGPT, Copilot): present in most “Yes/Maybe” entries
- Custom AI Platforms: 7
- Predictive Analytics: 6
- Robotic Process Automation (RPA): 4

- Machine Learning Models: 3
- In-house platform: 1
- SaaS AI-enabled compliance tools: 1

Table 3: Types of AI tools employed across consulting firms, including generative AI and predictive analytics.

Tool Type	Count
Generative AI (ChatGPT/Copilot)	High prevalence
Custom AI Platforms	7
Predictive Analytics	6
RPA	4
Machine Learning Models	3
In-house platform	1
SaaS AI-enabled tools	1

➤ Use Areas (multi-select)

- Client Report Writing: 27
- Market/Industry Analysis: 21
- Research/Background Study: 19
- Internal Operations: 12
- Forecasting & Scenario Planning: 8
- Strategy Formulation: 8
- Process Automation: 4

Table 4: Main application areas of AI within consulting tasks, such as report writing and market analysis.

Use Area	Count
Client Report Writing	27
Market/Industry Analysis	21
Research/Background Study	19
Internal Operations	12
Forecasting & Scenario Planning	8
Strategy Formulation	8
Process Automation	4

➤ Perceived Benefits (multi-select)

- Faster delivery: 24
- Deeper insights: 23
- Personalized recommendations: 12
- Cost savings: 11
- Improved accuracy: 11
- Competitive edge: 6

Note: One response included a narrative on “better research/drafting;” this was conservatively folded under insights/speed. Also, one response included a narrative on “error reduction can be checked” conservatively folded under Accuracy.

Table 5: Perceived benefits of AI adoption, prominently faster delivery, and deeper insights.

Perceived Benefits	Count
Faster delivery	24
Deeper insights	23

Personalized recommendations	12
Cost savings	11
Improved accuracy	11
Competitive edge	6

➤ Perceived Challenges (multi-select)

- Data privacy: 20
- Skill gaps in workforce: 15
- Over-reliance on technology: 13
- Ethical concerns: 8
- Algorithmic bias: 11
- Lack of explainability: 8
- Resistance from clients/teams: 5

Table 6: Common challenges faced in AI adoption, including data privacy and skill gaps.

Challenge	Count
Data privacy	20
Skill gaps in workforce	15
Over-reliance on technology	13
Ethical concerns	8
Algorithmic bias	11
Lack of explainability	8
Resistance from clients/teams	5

➤ AI Confidence (1–5)

- Score distribution:

- 2: 5/30
- 3: 15/30
- 4: 8/30
- 5: 2/30
- 1: 0/30

Pattern centres on 3 (moderate), with few high-confidence respondents (8-10).

Table 7: Respondents' self-rated confidence in AI use on a 1–5 scale with most scoring moderate.

Score	n	%
1	0	0%
2	5	16.67%
3	15	50%
4	8	26.67%
5	2	6.67%
Total	30	100

➤ Governance and Training Context

- AI ethics/governance policy:

- Yes: 10/30

- Maybe: 3/30

- No: 17/30

- Training adequacy:

- Not trained: 8/30

- Basic Training: 16/30

- Moderate: 6/30

(No “Advanced” reported)

- Views on Judgment and Conflicts
- Can AI replace human judgment?
 - No, human judgment essential: 17/30.
 - Sometimes, with supervision: 11/30
 - Yes, in most cases: 2/30.
- Conflict with expert opinion:
 - Yes (most followed expert; two cases followed AI): 25/30
 - No: 5/30

Interpretation: Governance policies are largely absent or unclear, and formal training is typically basic—useful context for confidence and outcome perceptions.

Table 8: Governance policies, training adequacy, and attitudes towards AI's role in judgment among respondents.

Measure	Category	n	%
Governance policy	Yes	10	33.33%
	Maybe	3	10%
	No	17	56.67%
	Total	30	100%
Training adequacy	Not trained	8	26.67%
	Basic	16	53.33%
	Moderate	6	20%
	Total	30	100%
Replace	No (essential)	17	56.67%

human judgment?	Sometimes, with supervision	11	36.67%
	Yes, in most cases	2	6.67%
	Total	30	100%
Conflict with expert opinion	Yes (mostly followed expert; two followed AI)	25	83.33%
	No	5	16.67%
	Total	30	100%

➤ Five-year Outlook

- Incremental improvements: 12/30
- Major transformation: 12/30
- Radical disruption: 5/30
- Minimal impact: 1/30

Overall sentiment anticipates meaningful change (incremental to major), with a minority predicting radical disruption.

Table 9: Respondents' outlook on AI's impact on consulting over the next five years.

Outlook Category	n	%
Incremental improvements	12	40%
Major transformation	12	40%
Radical disruption	5	16.67%
Minimal impact	1	3.33%
Total	30	100%

Inferential Statistics

This paper sought to explore the relationships

among consulting professionals' experience levels, confidence in AI-driven decision-making, organizational AI acceptance, presence of governance procedures. A series of inferential analyses (t-tests, correlations, chi-square, and regression models) were conducted on responses from 30 consultants to examine the underlying associations.

➤ Group Comparisons: Confidence by AI Usage

An independent-samples t-test was conducted to examine whether confidence in AI-driven decision-making differed between respondents from organizations that currently use AI tools and those that do not. The mean confidence score for respondents in AI-using organizations ($M = 3.20$, $SD = 0.87$, $n = 25$) was slightly lower than for those in non-AI-using organizations ($M = 3.40$, $SD = 0.55$, $n = 5$). However, the difference was not statistically significant, $t(\text{approx.}) = -0.67$, $p = .52$. This suggests that the presence or absence of AI systems within an organization did not significantly influence professionals' confidence in leveraging AI for strategic decision-making.

➤ Correlation Between Experience and Confidence

A Spearman rank-order correlation was used to explore whether professional experience was related to confidence in AI capabilities. The analysis revealed a negligible and non-significant relationship between years of consulting experience and confidence ($\rho = .01$, $p = .95$). These results imply that more

experienced consultants do not necessarily exhibit higher or lower confidence levels in AI tools compared to their less experienced counterparts.

➤ Associations Between AI Usage, Governance, and Belief Systems

Two chi-square tests were conducted to examine categorical associations. The first test assessed the relationship between organizational AI usage and the existence of a formal AI governance or ethics policy. The relationship was not statistically significant, $\chi^2 (1, N = 30) = 0.00$, $p = 1.00$, indicating that the presence of governance policies was not dependent on whether organizations actively used AI tools.

The second chi-square test explored the association between respondents' belief that AI can replace human judgment and the existence of an AI governance policy. Again, no significant relationship emerged, $\chi^2 (2, N = 30) = 1.52$, $p > .05$. This finding suggests that organizational governance frameworks may not strongly shape professionals' perceptions of AI's potential to substitute human decision-making processes.

➤ Predicting Confidence: Regression Analysis

A linear regression model was estimated to identify predictors of confidence in AI-driven decision-making. The independent variables included years of experience, adequacy of AI-related training, and whether the respondent's organization used AI tools. The overall model

explained a modest portion of variance in confidence levels. Among the predictors, training adequacy emerged as a significant positive determinant ($B = 1.325$, $p < .05$), suggesting that respondents who perceived their AI-related training as more adequate tended to report higher confidence in using AI tools for business decisions. Neither professional experience ($B = 0.0027$, $p = ns$) nor current AI usage ($B = -0.940$, $p = ns$) were statistically significant predictors.

- Kruskal-Wallis H tests to examine differences in AI confidence among groups defined by categorical variables.

Additionally, a Kruskal-Wallis H tests were conducted for examining differences in AI confidence among groups defined by categorical variables. The findings showed no statistically significant differences for AI confidence by training adequacy levels, $H(2)=5.05, p=0.08$, though a trend suggested that respondents with more adequate AI training reported higher confidence. Similarly, no significant differences were found by governance policy presence status, $H(2)=1.77, p=0.41$, current role/designation, $H(3)=4.33, p=0.23$, consulting firm type, $H(3)=1.38, p=0.71$, AI tool adoption patterns, $H=11.45, p=0.32$, or AI use areas, $H=24.74, p=0.26$.

Further Kruskal-Wallis tests exploring AI confidence by beliefs on AI replacing human judgment, perceived conflicts between AI and expert opinions, and expectations of AI's impact on consulting also did not yield

significant results ($p>0.05$ in all cases). These findings indicate broadly homogenous confidence levels across demographic and attitudinal segments in the sample.

- Chi-square tests for examining association between training adequacy or governance policies.

Chi-square tests examined associations between training adequacy or governance policies and the binary perception of AI providing improved accuracy. No significant associations were identified (training adequacy: $\chi^2(2)=2.32, p=0.31$; governance policy: $\chi^2(2)=0.02, p=0.99$).

- Summary of Inferential Analyses

Table 10: A compact overview of all inferential tests.

Test	Grouping Variable	Test Type	Statistic (H or χ^2)	p-value	Significance
Independent-Samples t-Test	Confidence by AI Usage	$t = -0.67$	≈ 28	.52	No significant difference
Spearman Correlation	Experience (years) & Confidence	$\rho = 0.01$	—	.95	No significant correlation
Chi-Square Test	AI Usage × Governance Policy	$\chi^2 = 0.00$	1	1.00	No significant association

Chi-Square Test	Belief (AI replace human) × Governance Policy	$\chi^2 = 1.52$	2	>.05	No significant association
Linear Regression	Predicting Confidence (Experience, Training, AI Usage)	$F \approx n/a$ (OLS)	—	<.05*	Training adequacy significant; others not
AI Confidence by Training Adequacy	Training Adequacy Levels	Kruskal-Wallis H	5.05	0.08	Not Significant
AI Confidence by Governance Policy	AI Ethics/ Governance Policy	Kruskal-Wallis H	1.77	0.41	Not Significant
Improved Accuracy by Training Adequacy	Training Adequacy Levels (binary improved acc.)	Chi-square	2.32	0.31	Not Significant
Improved Accuracy by Governance Policy	AI Ethics/ Governance Policy (binary improved acc.)	Chi-square	0.02	0.99	Not Significant
AI Confidence by Role/Designation	Current Role/Designation	Kruskal-Wallis H	4.33	0.23	Not Significant

AI Confidence by Firm Type	Type of Consulting Firm	Kruskal-Wallis H	1.38	0.71	Not Significant
AI Confidence by AI Tool Types	AI tools used (various combinations)	Kruskal-Wallis H	11.45	0.32	Not Significant
AI Confidence by AI Use Areas	Areas where AI is used (various combinations)	Kruskal-Wallis H	24.74	0.26	Not Significant
AI Confidence by Belief about AI Judgment	Belief AI can replace human judgment (Yes/No/Sometimes)	Kruskal-Wallis H	3.75	0.15	Not Significant
AI Confidence by Conflict Experience	Encountered conflict between AI and experts	Kruskal-Wallis H	2.10	0.55	Not Significant
AI Confidence by Future Outlook	Perception of AI impact on consulting profession	Kruskal-Wallis H	3.34	0.34	Not Significant

Across all tests, most relationships were found to be statistically non-significant, likely reflecting the small sample size ($n = 30$) and limited variability across some categorical responses. Nevertheless, the consistent emergence of training adequacy as a positive correlate of confidence underscores the importance of skill development and

organizational support in enhancing consultants' readiness to integrate AI into strategic workflows.

➤ Interpretation

Overall, the inferential findings suggest that while AI adoption and governance mechanisms are increasingly present in consulting organizations, these factors alone do not substantially influence individual confidence or beliefs about AI's role in strategic decision-making. Conversely, the adequacy of AI-focused training emerges as a key determinant shaping professionals' competence and attitudes, underscoring the importance of structured capability-building initiatives to strengthen consultants' proficiency and confidence in applying AI to business strategy.

These results collectively highlight that while AI training adequacy appears influential, other factors including organizational governance policy, consultant experience, and AI tool usage patterns do not significantly explain variation in AI confidence within this dataset.

➤ Sensitivity Analyses with Collapsed Categories

• Rationale

Because several original groups were very small, we conducted stability checks by collapsing categories to reduce sparsity and re-tested group differences in AI confidence using nonparametric methods.

• Collapsed group definitions

- Role: Junior (Deputy/Assistant Manager + Others; n=12), Senior (Manager/Senior Manager/Associate Director + Partner/Associate Partner; n=18).
- Experience: <10 (3–6 and 7–10 years; n=24) vs 10+ (11–14 and 15+ years; n=6).
- Firm: Large (Big 4+Top 20; n=15) vs Non-Large (Boutique/Niche + Independent + Others; n=15).

• Collapsed Group Results

Table 11: Summary of all inferential tests in collapsed group

Test	Variables	Test Statistic	df	p-value	Interpretation
Independent Samples t-test	Confidence × AI Usage (Using vs. Not Using)	$t(\approx 28) = -0.65$	28	0.52	No significant difference in confidence between AI-using and non-AI-using organizations.
Spearman Correlation	Years of Experience × Confidence	$\rho = .03$	—	0.88	No significant relationship between consulting experience and confidence in AI-driven decision-making.

Chi-square Test	AI Usage × Governance Policy	$\chi^2(1) = 0.04$	1	0.84	No significant association; governance presence is independent of AI usage status.
Chi-square Test	Belief (AI replaces human judgment) × Governance Policy	$\chi^2(2) = 1.33$	2	0.51	No significant association; governance policies do not shape beliefs about AI replacing human judgment.
Kruskal–Wallis H	Confidence × Training Adequacy (Not trained / Basic / Moderate)	$H(2) = 5.11$	2	0.08	Near-significant trend; respondents with better training showed higher confidence.
Kruskal–Wallis H	Confidence × Governance Policy (Yes / No / Maybe)	$H(2) = 1.79$	2	0.41	No significant differences in confidence across governance status.

Kruskal–Wallis H	Confidence × Current Role (Junior / Senior)	$H(1) = 2.06$	1	0.15	No significant role-based difference in AI confidence.
Kruskal–Wallis H	Confidence × Firm Type (Large / Non-Large)	$H(1) = 1.28$	1	0.26	No significant difference in confidence between large and non-large consulting firms.
Kruskal–Wallis H	Confidence × Belief (AI replaces human judgment)	$H(2) = 2.19$	2	0.34	No significant difference in confidence by belief category.
Regression Analysis	Predicting Confidence from Experience, Training, and AI Usage	$R^2 = .19$	3, 26	0.09	Model explains ~19% variance; training adequacy is the only positive (marginally significant) predictor of confidence.

Across all stability checks, results remained non-significant after collapsing categories, indicating that the null findings for role, experience, and firm comparisons are robust to sparse-cell concerns in this sample.

Discussion

Overview of Key Findings

This empirical study based on survey responses from 30 consulting professionals across diverse roles and firms reveals a high level of AI adoption, with 83% of respondents indicating organizational use of AI tools. The tools used predominantly include generative AI (such as ChatGPT and Copilot), predictive analytics platforms, and custom AI solutions. These technologies are mainly applied in client report writing, market and industry analysis, background research, and internal operations, highlighting AI's integral role in enhancing consulting workflows.

Respondents identified multiple significant benefits of AI integration, including faster report delivery and deeper insights, each noted by around 80% of users. Personalized recommendations and cost savings were also reported, although to a lesser degree. Concurrently, challenges were prominent, particularly concerning data privacy, workforce skill gaps, over-reliance on technology, ethical concerns, algorithmic bias, and resistance from clients' teams. These challenges underscore the complexity of responsible AI adoption in strategic advisory contexts.

Confidence in AI usage among consulting

professionals was generally moderate, with a majority rating their confidence near the mid-scale. This confidence did not significantly differ by firm type, professional role, experience, or whether the organization formally used AI. Crucially, the perceived adequacy of AI-related training was the strongest positive predictor of confidence levels, emphasizing the critical importance of structured training initiatives to build consultants' requisite competencies.

Regarding governance, only about one-third of organizations had clear AI ethics or governance policies, while many reported either uncertain or absent governance structures. The presence of governance policy showed no significant association with AI confidence or beliefs about AI's ability to replace human judgment. Most respondents emphasized the essential role of human judgment alongside AI, with many experiencing conflicts between AI outputs and expert opinion favouring human expertise.

Looking forward, respondents mostly expect incremental or major transformations in consulting practices due to AI over the next five years, with a smaller portion anticipating radical disruption. These expectations reflect a carefully positive stance regarding AI's evolving role in the strategic decision-making.

The inferential statistical analyses indicate that training adequacy is a critical lever for building user confidence, whereas organizational AI adoption and governance presence bear less immediate influence on individual attitudes. No significant variations in confidence or

perceived performance emerged across demographic or organizational subgroups, possibly reflecting the limited sample size and early stage of AI integration maturity.

Practical Implications for Consulting Practice

- Invest in structured training: The most actionable finding is the directional impact of training on confidence. Begin with foundational curricula—prompt engineering basics, verification workflows, data handling, and model selection—then progress to service line specific playbooks (e.g., tax, HR, strategy, audit/assurance, technology). “Starter kits” with vetted prompts, templates, and case-based exercises accelerate adoption while reducing risk.
- Operationalize governance: Move from policy documents to operational guardrails embedded in workflows. This includes model allowlists, PII/PHI rules, client consent checklists, documented verification steps, and auditability (e.g., prompt logs for key deliverables). Clear “green/amber/red” use case classifications help practitioners decide quickly and consistently.
- Build human in the loop quality systems: Given ongoing accuracy concerns, institute mandatory verification for externally facing deliverables and high-stake analyses; encourage side by side comparisons (AI vs expert) to calibrate trust and surface error modes for training.
- Focus on “high leverage” use cases: Continue to prioritize drafting, synthesis, and research augmentation where value is immediate and risks are manageable, while advancing towards more complex use cases only when data governance, testing, and explainability controls are in place.
- Develop communities of practice: Create internal forums (office hours, show and tell sessions, prompt libraries) to socialize effective patterns and failure cases—this amplifies learning and speeds responsible scaling.

Methodological Considerations

- Power and precision: With $n=30$, the study is underpowered to detect small to moderate effects. The near significant training result likely reflects a real association that a larger sample would clarify.
- Measurement granularity: Single item confidence and coarse governance categories limit psychometric precision and policy maturity insights. Multi item validated scales (AI self-efficacy, perceived usefulness, trust, risk tolerance) and a staged governance maturity index would strengthen inferences.
- Self-report bias: Self-reported usage, benefits, and quality outcomes may overstate or understate performance relative to objective telemetry and blind expert ratings of deliverables.
- Cross sectional design: Associations cannot

be interpreted causally; training may co vary with other enablers (leadership sponsorship, team norms) that also raise confidence.

Future Research Directions

- Larger, stratified samples: Power analyses should inform samples stratified by firm archetype, service line, region, and seniority to detect realistic effect sizes.
- Longitudinal designs and interventions: Pre/post training evaluations, stepped wedge rollouts, and A/B tested enablement modules can quantify training's causal impact on confidence, usage quality, and client outcomes.
- Objective outcome measures: Complement self-reports with telemetry (tool usage, prompt categories), task time savings, error rates, and blinded quality ratings of AI assisted versus baseline deliverables.
- Governance maturity modelling: Develop and validate a governance maturity scale that captures policy clarity, workflow integration, control effectiveness, and auditability; test its relationship with confidence, usage quality, and client trust.
- Domain specific studies: Examine differential impacts across practice areas (e.g., strategy vs tax vs HR) where data sensitivity, explainability requirements, and risk appetites vary.

Conclusion

This study provides an early, practice grounded view of AI adoption in consulting: usage is widespread in drafting, analysis, and research tasks, with clear perceived benefits in speed and insight generation, but persistent concerns around privacy, skills, and reliability. Confidence in AI capabilities is generally moderate, and—critically—shows a consistent, near significant association with training adequacy in this small sample. Governance trends positively with confidence and perceived quality but does not reach statistical significance, likely reflecting both small group sizes and early-stage policy maturity.

For firms, the most immediate, evidence aligned action is to scale structured training paired with operational governance—moving beyond policy to embedded guardrails, verification workflows, and service line specific playbooks. This combination can raise confidence and support safe, repeatable value creation in client work. As organizations mature, more complex use cases can be pursued with stronger controls, explainability practices, and objective measures of quality and impact.

Methodologically, the results should be interpreted with appropriate caution given sample size, self-report measures, and cross sectional design. Nevertheless, the patterns are coherent and actionable: training and practical governance are the near term levers to translate AI promise into dependable consulting practice. Future work with larger, stratified,

and longitudinal designs—incorporating objective performance metrics and validated scales—will refine effect sizes, establish causality, and guide the next wave of responsible AI adoption in the profession.

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➤ Conflict of Interest:

The author declares that there are no conflicts of interest related to this study or its publication.

➤ Author Contributions:

Monika Sukhija solely conceptualized, designed, conducted, analysed, and authored the research presented in this paper.

➤ Data Availability:

All data supporting the findings of this study are available from the author upon reasonable request.

➤ Ethics Approval:

The study involved voluntary participation of consulting professionals through an anonymized survey. Informed consent was obtained from all participants prior to data collection, and no personally identifiable information was gathered.

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