The Language of Autonomy: Narratives and Strategic Implications of Agentic AI

How global institutions define, frame, and position agentic AI technologies

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Executive Summary

Agentic AI has rapidly emerged as a defining concept in the AI landscape of 2024-2025, featuring prominently in consulting reports, industry white papers, and academic analyses. Despite this surge in attention, institutional definitions of "AI agents" remain fragmented. Some sources position agentic systems as enterprise productivity accelerators; others emphasize risks related to autonomy, orchestration, and governance.

This report analyzes **20 major reports** from consulting firms (McKinsey, Bain, PwC, Deloitte, BCG), academic institutions (MIT, Stanford, Harvard), industry actors (Google, Microsoft, OpenAI), and policy organizations (OECD, WEF, ITI). Using modern text analytics (including keyword frequency analysis, TF-IDF, topic modeling (LDA), and a qualitative taxonomy) we aim to map how discourses around "AI agents" diverge across institutional types.

Some central key findings:

- **Lexical analysis** reveals that while "agent", "agentic," and "system" dominate globally (1,896, 1,293, and 1,090 occurrences respectively), institutional emphases diverge sharply.
- **Topic modeling** identified **4 dominant themes**: AI Foundations & Responsible Development, Organizational Adoption & Workforce Transformation, Technology Products & Workflows, and Business Strategy & Sales. Consulting firms allocate 45.4% of their discourse to technological advancement and productivity themes, compared to only 19.6% in academic reports, which instead prioritize organizational adoption and governance (55.3%).
- **Definitional taxonomy** was more tricky as we lacked time to improve significantly the definition extraction process. Thus, if we put aside the "Other/Uncategorized" definitions, the taxonomy still exposes conceptual fragmentation: 25.4% of definitions frame agentic AI as "copilots/assistants," 26.8% as "autonomous workers," 18% as "multi-agent orchestrators," and 29.8% through a governance lens. Consulting overwhelmingly adopts the "Multi-Agent Ecosystems/Orchestrators" and "Autonomous Workers" frame (43.2% and 36.4% respectively), while policy organizations favor assistance and governance framing (53.8% and 44.3% respectively).

These divergences risk misalignment for organizations attempting large-scale adoption. We recommend that enterprises establish an internal shared definition of agentic AI, align adoption roadmaps with governance considerations, and monitor evolving narratives to anticipate regulatory shifts.

1. Background & Objectives

1.1 The Rise of Agentic AI

Agentic AI refers to systems capable of autonomous decision-making, task initiation, and multi-step coordination without continuous human oversight. These capabilities, such as perceiving context, reasoning through complexity, and acting independently, position agentic AI as a potential inflection point in enterprise automation and workforce transformation.

Yet despite this rising prominence, the term suffers from **definitional ambiguity**. Consulting firms describe agents as productivity multipliers; academics caution about alignment challenges; industry focuses on technical architectures. This fragmentation poses strategic risks: organizations adopting agentic systems may operate under different assumptions about autonomy, governance, and human-AI collaboration.

1.2 Why This Matters

For policymakers, the lack of conceptual consensus complicates regulatory frameworks. For enterprises, divergent narratives create adoption uncertainty: should agents be deployed as assistive copilots or autonomous workers? For researchers, understanding how institutions frame these technologies reveals underlying priorities and potential blind spots.

This analysis addresses a gap in the current discourse: **no systematic study has mapped how global institutions construct the narrative of agentic AI** or examined whether these narratives converge or diverge along sectoral lines.

1.3 Research Question

Primary question:

How do major consulting, academic, industry, and policy reports define and frame agentic AI, and what narratives dominate their discussion of autonomy, productivity, and governance?

Secondary questions:

1. Do institutional actors emphasize similar themes, or do narratives diverge along sectoral boundaries?
2. How do definitions of "AI agent" vary between consulting, academic, industry, and policy discourse?
3. What strategic implications emerge for organizations navigating this fragmented landscape?

1.4 Analytical Objectives

Our analysis employs a multi-method NLP pipeline to:

1. **Identify lexical patterns**: Extract co-occurring terms around "agentic AI", "autonomy," and "copilot" to reveal institutional vocabularies.
2. **Detect distinctive emphases**: Apply TF-IDF to uncover what each institution uniquely stresses.
3. **Extract latent themes**: Use Latent Dirichlet Allocation (LDA) to identify dominant topics and compare their distributions across institutional types.
4. **Construct a taxonomy**: Manually classify explicit definitions into conceptual categories to expose definitional fragmentation.

These objectives support strategic decision-making by clarifying **how the term itself is framed** across key institutional actors.

2. Data & Process

2.1 Corpus Overview

The analysis draws on **20 reports** published between 2024 and 2025, selected for institutional diversity and topical relevance. Sources include:

- **Consulting firms** (7 reports): McKinsey, Bain, PwC, Deloitte, BCG
- **Academic institutions** (4 reports): MIT, Stanford HAI, Harvard
- **Industry & tech players** (5 reports): Google, Microsoft, OpenAI
- **Policy organizations** (4 reports): OECD, WEF, ITI

Selection criteria:

- Published within the last 18 months
- Explicit focus on "agentic AI" or "AI agents"
- Authoritative sources with significant institutional reach
- Publicly accessible documents (PDFs)

Dataset Snapshot

Report Title	Source	Type	Year	Pages
Designing a Successful Agentic AI System	Harvard	Academic	2025	7
The Emerging Agentic Enterprise	MIT	Academic	2025	40
Reimagining Future of Banking with Agentic AI	MIT	Academic	2025	10
Simulating Human Behavior with AI Agents	Stanford HAI	Academic	2025	6
Practices for Governing Agentic AI Systems	OpenAI	Industry	2025	23
A Practical Guide to Building Agents	OpenAI	Industry	2025	34
Agent AI: Towards Holistic Intelligence	Microsoft	Industry	2025	21
The ROI of AI	Google	Industry	2025	8
Transformative Potential of Agentic AI (Google Cloud)	Google	Industry	2025	72
The Agentic Organization: Next Paradigm for AI Era	McKinsey	Consulting	2024	11
Empowering Advanced Industries with Agentic AI	McKinsey	Consulting	2025	8
What is an AI Agent?	McKinsey	Consulting	2025	11

Report Title	Source	Type	Year	Pages
Agentic AI: The New Frontier in GenAI (Executive Playbook)	PwC	Consulting	2024	22
The Business Imperative for Agentic AI	Deloitte	Consulting	2025	26
Technology Report 2025: AI Leaders Extending Edge	Bain	Consulting	2025	77
AI Agents	BCG	Consulting	2025	9
From Prediction to Autonomy: Agentic AI for SMEs	OECD	Policy	2025	13
Updated OECD Definition of an AI System	OECD	Policy	2024	11
Understanding Agentic AI: ITI's Policy Guide	ITI	Policy	2025	16
AI Agents in Action: Foundations for Evaluation	WEF	Policy	2025	34

	filename	word_count	page_count	source_type
0	Bain_report_technology_report_2025.pdf	20593	77	Consulting
1	BCG_AI_Agents_2025.pdf	1601	9	Consulting
2	Deloitte_The_business_imperative_for_Agentic_A...	3966	26	Consulting
3	Google_Agentic_AI_TAM_Analysis_2025.pdf	22140	72	Industry
4	Google_The_ROI_of_AI_2025.pdf	1214	8	Industry
5	Harvard_Designing_a_Successful_Agentic_AI_Syst...	2648	7	Academic
6	ITI_Understanding_Agentic_AI_Policy_Guide_2025...	5992	16	Policy
7	McKinsey_Empowering_advanced_industries_with_a...	2455	8	Consulting
8	McKinsey_The_agentic_organization_contours_of_...	4817	11	Consulting
9	McKinsey_What_is_an_AI_Agent_2025.pdf	3390	11	Consulting
10	Microsoft_Agent_AI_Towards_a_Holistic_Intellig...	6706	21	Industry
11	MIT_Reimagining_the_future_of_banking_with_age...	3789	10	Academic
12	MIT_The_Emerging_Agentic_enterprise_2025.pdf	11952	40	Academic
13	OECD_Explanatory_memorandum_on_the_updated_oec...	3597	11	Policy
14	OECD_From_prediction_to_autonomy_What_agentic_...	4825	13	Policy
15	OpenAI_A_practical_guide_to_building_agents_20...	4183	34	Industry
16	OpenAI_Practices_for_Governing_Agentic_AI_Syst...	12210	23	Industry
17	PwC_Agentic_AI_the_new_frontier_in_GenAI_2024.pdf	6770	22	Consulting
18	Standford_Policy_brief_Simulating_human_behavi...	2320	6	Academic
19	WEF_AI_Agents_in_Action_Foundations_for_Evalua...	11304	34	Policy

Figure 1: Dataset Snapshot

Corpus statistics overview:

- Total documents: **20**
- Total pages: **459**
- Estimated word count: **136,472 words** (post-preprocessing)
- Average document length: **6,823 words**

2.2 Data Collection & Extraction

All reports were sourced as PDF files and processed through a dual-extraction pipeline:

1. **Primary extraction**: `pdfplumber` (Python library optimized for text-heavy PDFs)
2. **Fallback extraction**: `PyPDF2` for documents where `pdfplumber` encountered formatting issues

This dual-method approach ensured >95% text extraction success across all documents. Extracted text was saved as UTF-8 encoded `.txt` files with accompanying metadata (filename, page count, source type, publication year).

2.3 Preprocessing Pipeline

Each document underwent a five-stage preprocessing workflow:

Stage 1: Text Cleaning

- Conversion to lowercase
- Removal of URLs, email addresses, and numeric-only tokens
- Normalization of whitespace and punctuation
- Elimination of PDF artifacts (e.g., `(cid:XX)` encoding errors, figure/table captions)

Stage 2: Tokenization

- Sentence segmentation using NLTK's `sent_tokenize`
- Word tokenization with NLTK's `word_tokenize`
- Preservation of compound terms (e.g., "AI agent" maintained as single token where contextually appropriate)

Stage 3: Stopword Removal

- Standard English stopwords (NLTK corpus: 179 terms)
- **Custom stoplist** of 184 terms containing generic consulting jargon (e.g., executive, summary, chapter, section), overly frequent connectors (e.g., however, therefore, moreover), meta-references (e.g., figure, table, appendix, page), as well as random terms or people names.

Stage 4: Lemmatization

Two main tools were implemented for lemmatization: the spaCy's `en_core_web_sm` model, and the more traditional NLTK librairy one. Here, the purpose is to normalize word forms (e.g., "technologies" → "technology," "orchestrating" → "orchestrate").

Note that lemmatization chosen over stemming for semantic preservation (stemming can produce non-words like "automat" from "automation"), however, with more time, some refractions could have been valuable for a more precise analysis (e.g., “agent” vs. “agentic” terms).

Stage 5: Corpus Construction

Each report treated as a **single analytical unit** (document-level analysis). Morevover tokens aggregated into document-level vocabularies (for TF-IDF), global corpus vocabulary (for frequency analysis), and bag-of-words representations (for LDA topic modeling)

Final corpus characteristics:

- Total tokens (post-processing): 83,298
- Unique vocabulary: 10,211 terms
- Average document length: 4,165 tokens
- Reduction from raw text: 39.0% (preprocessing removed noise while preserving semantic content)

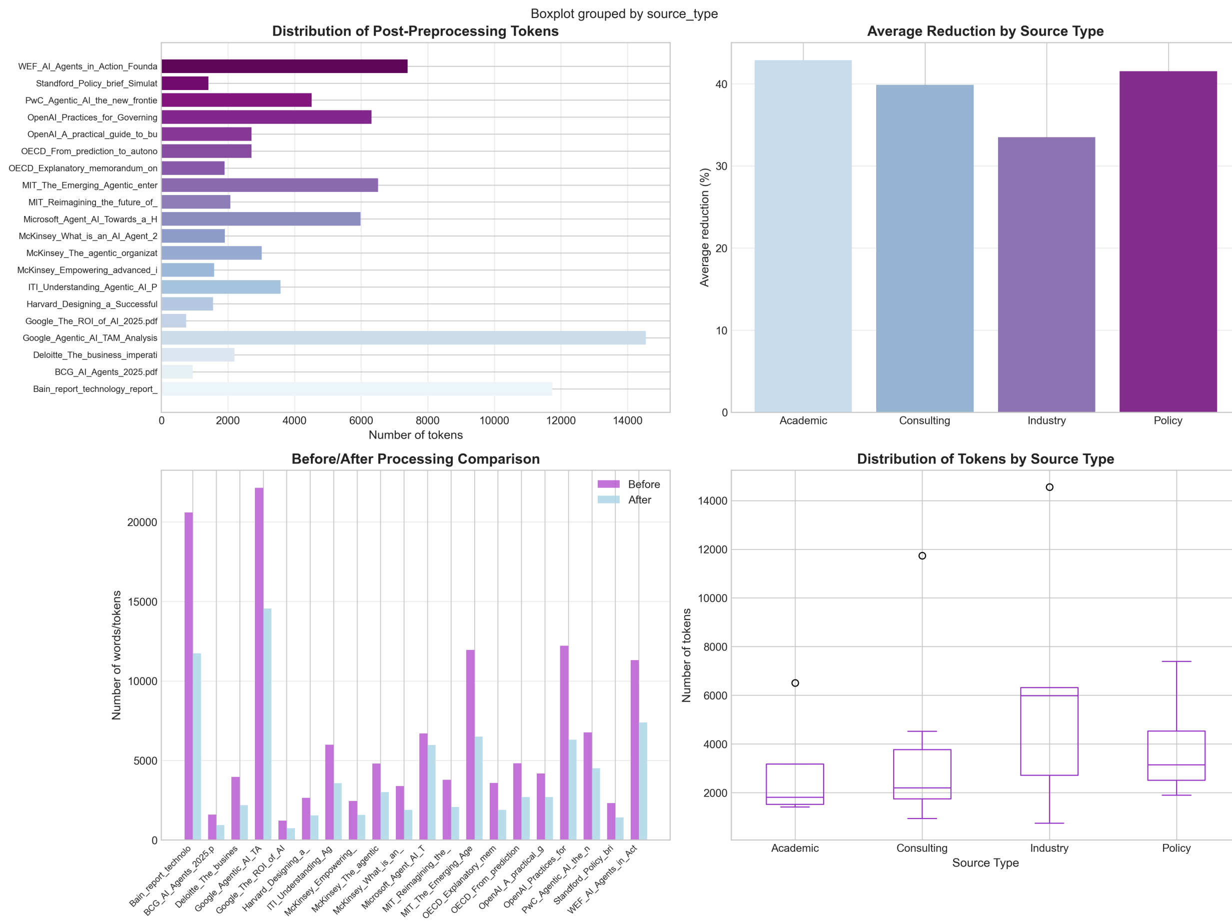

Figure 2: Corpus Construction Statistics

Impact of preprocessing pipeline on corpus size. Average reduction: 39%.

2.4 Methodological Choices

Why document-level analysis?

Reports represent coherent institutional perspectives. Document-level analysis captures how each organization constructs its narrative, enabling cross-institutional comparisons.

Why hybrid (automated + manual) taxonomy?

Pure automated classification struggles with nuanced definitional language. Our hybrid approach aim to combine pattern-matching (for candidate extraction) with expert validation (for conceptual categorization), balancing scalability with interpretive rigor.

3. Analysis & Results

This section presents the empirical findings from the multi-method NLP pipeline.

3.1 Keyword Frequency & Co-Occurrence

Word frequency analysis establishes the dominant vocabulary of agentic AI discourse. By identifying the most frequent terms and their co-occurrence patterns, we reveal which concepts institutions prioritize when discussing AI agents.

3.1.1 Global Vocabulary Distribution

Figure 3 presents the top 30 most frequent terms across the entire corpus. The dominance of **"agent"** (1,896 occurrences), **"agentic"** (1,293), and **"system"** (1,090) confirms that discourse centers on technical entities rather than abstract concepts. Notably, **"human"** (500 occurrences) appears prominently, signaling persistent attention to human-AI interaction despite the focus on autonomy.

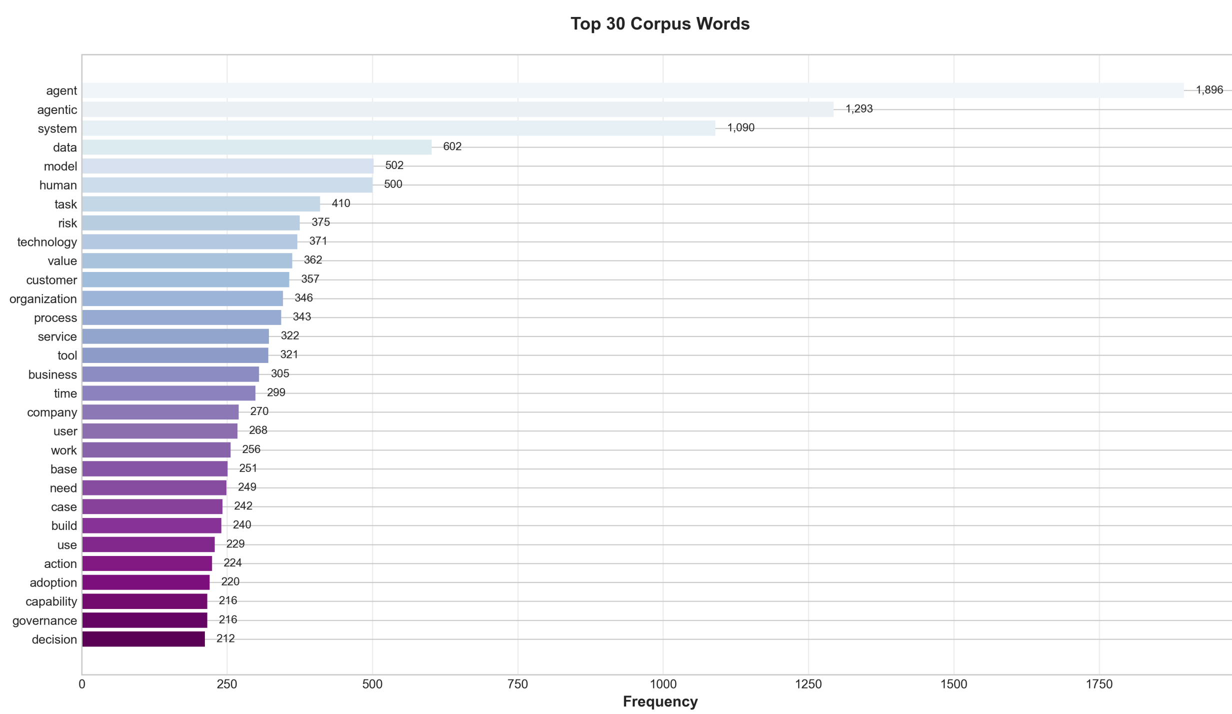

Figure 3: Top 30 Corpus Words

Bar chart showing frequency distribution of the 30 most common terms. "Agent" dominates with 1,896 occurrences, followed by "agentic" (1,293) and "system" (1,090). Business-oriented terms like "data" (602), "customer" (357), and "organization" (346) feature prominently, while governance terms ("governance": 216, "risk": 375) appear less frequently.

The corpus exhibits a **technical-operational lexicon** rather than a governance-centered vocabulary. Terms associated with implementation ("technology," "model," "data") far outweigh those related to regulation or ethics.

3.1.2 Thematic Categorization of Domain Terms

To systematically analyze institutional emphasis, the vocabulary has been categorized into eight thematic domains: Core Concepts, Implementation, Business Value, Workforce, Technology, Governance, Operations, and Assistance. Figure 4 displays the frequency distribution across these categories.

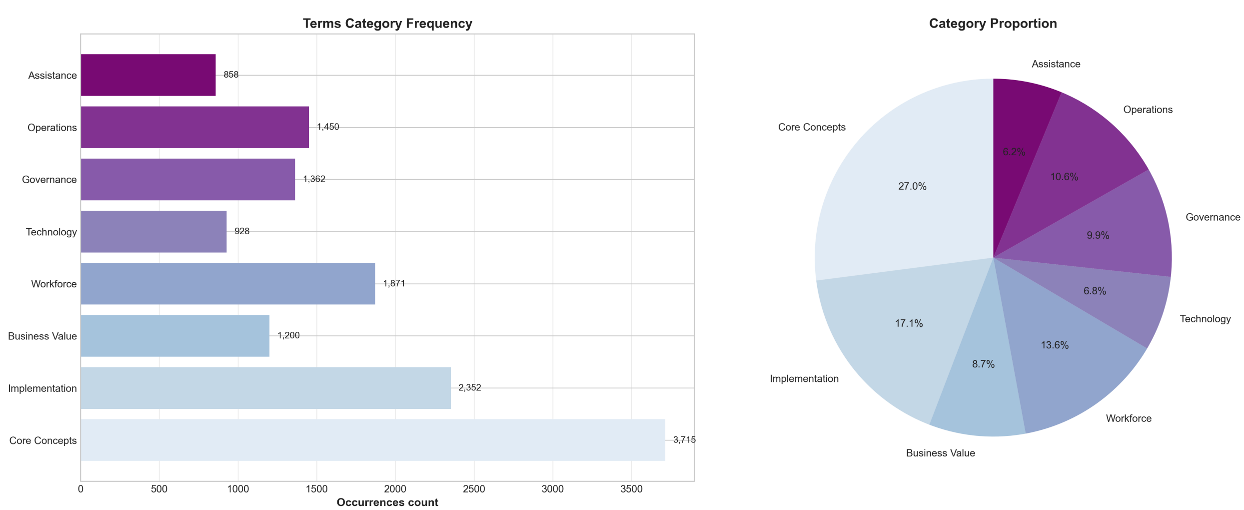

Figure 4: Terms Category Frequency and Proportion

Left: Bar chart showing absolute frequencies. "Core Concepts" leads with 3,715 occurrences (27.0%), followed by "Implementation" (2,352; 17.1%) and "Workforce" (1,871; 13.6%). "Governance" accounts for only 1,362 occurrences (9.9%).

Right: Pie chart visualizing proportions.

4 main key insigths can be extracted from these two plots. First, the **"Core Concepts" clearly dominate (27.0%).** Institutions devote substantial lexical

attention to defining what agents *are* (agent, agentic, autonomy, intelligence). There is also an “**Implementation” emphasis (17.1%)**, with technical architecture terms (system, model, framework, platform) signalling a discourse focused on *how* to build agents rather than *whether* to deploy them. Nonetheless, **"Governance" seems underrepresented (9.9%)** despite widespread policy concern about AI safety. Indeed, its related terms constitute less than 10% of domain-specific vocabulary suggesting a potential **discourse-practice gap** where technical feasibility overshadows regulatory consideration. Finally, **"Business Value" appears to be substantial (8.7%).** Terms like productivity, ROI, efficiency, and cost reflect consulting firms' influence on the narrative.

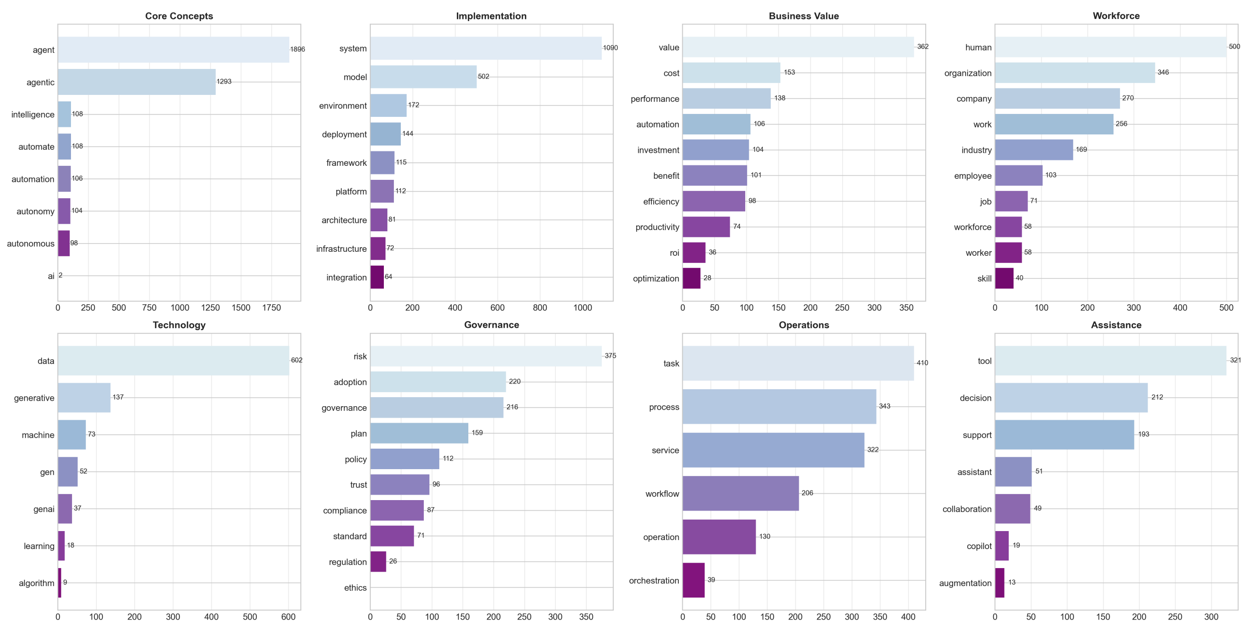

Figure 5: Detailed Frequencies by Category

Eight subplots showing top terms within each category. Notable patterns include:

- *Core Concepts: "agent" (1,896) vastly exceeds "autonomy" (104), indicating focus on entities over principles.*
- *Governance: "risk" (375) dominates, while "ethics" barely registers, suggesting risk management frames governance discussion rather than normative ethics.*
- *Assistance: "copilot" (19) appears rarely despite media attention to Microsoft Copilot, indicating limited penetration of the "assistant" frame in formal*

reports.

3.1.3 Bigram Analysis: Multi-Word Expressions

Bigrams (two-word phrases) reveal how terms combine to form conceptual units. Figure 6 presents the 25 most frequent bigrams.

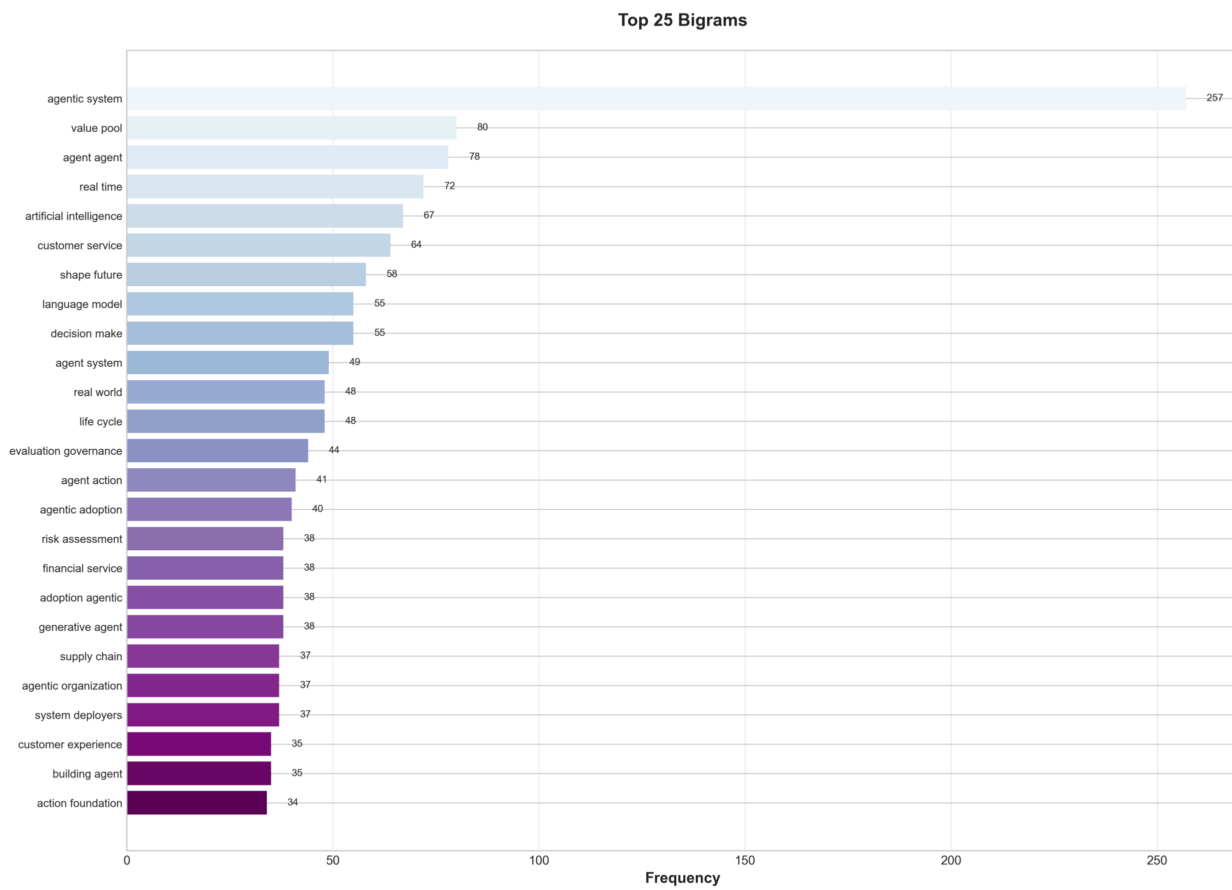

Figure 6: Top 25 Bigrams

"Agentic system" leads with 257 occurrences, followed by "value pool" (80), "agent agent" (78, likely a preprocessing artifact), and "real time" (72). Domain-specific phrases like "artificial intelligence" (67), "customer service" (64), "language model" (55), and "evaluation governance" (44) appear prominently.

The first key insigth to learn from Figure 6 is the dominant collocation of **"Agentic system" (257)**, confirming that agents are primarily framed as **technical systems** rather than autonomous entities or collaborative partners. **"Language model" (55)** and "generative agent" (38), on their end, reflect the **LLM-centric paradigm** underlying current agentic AI implementations (most agents discussed in these reports are built on large language models). As for **"Evaluation governance" (44)** and "risk assessment" (38), both indicate that when governance appears it focuses on **evaluation and risk mitigation** rather than proactive regulation. Nevertheless, **Business terms dominate** with associations such as "value pool," "customer service," "customer experience," "financial service" revealing the **enterprise orientation** of agentic AI discourse, particularly from consulting sources.

3.1.4 Institutional Lexical Divergence

Figure 7 visualizes the document-term frequency matrix as a heatmap, exposing which terms are concentrated in specific reports.

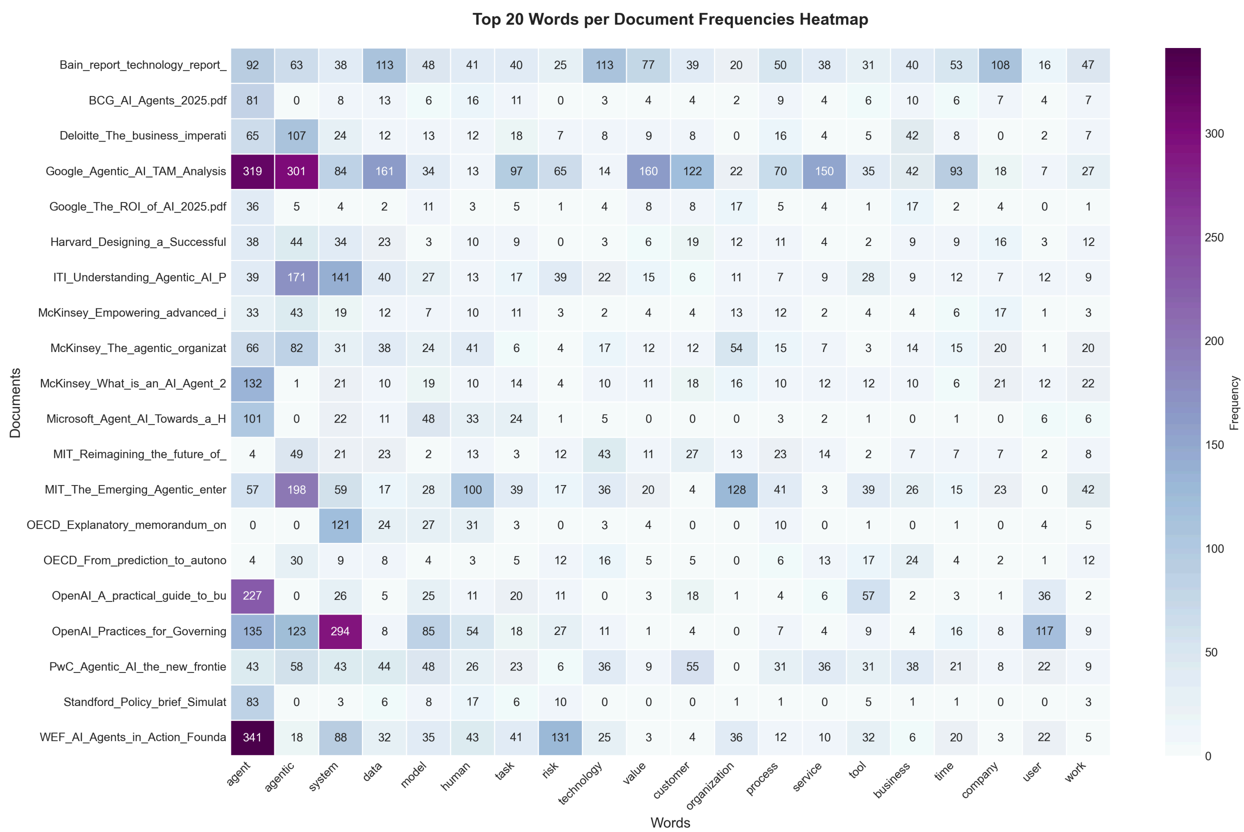

Figure 7: Top 20 Words per Document Frequencies Heatmap

Rows represent documents, columns represent the 20 most globally frequent terms. Dark purple indicates high frequency (300+), light blue indicates low frequency (<50).

Google Agentic AI TAM Analysis (Industry) exhibits exceptionally high frequencies for "agent" (319), "agentic" (301), and "technology" (160), reflecting a technical deep-dive. Another key observation revolves arround **WEF AI Agents in Action** (Policy) emphasizing "agent" (341), "system" (88), and "risk" (131). This aligns well with its governance mandate. Additionnally, **OpenAI Practices for Governing** concentrates on "agentic" (135), "system" (294), and "governance" (117), consistent with a regulatory-focused audience. Finally, consulting-wise, **BCG AI Agents** (Consulting) shows near-zero emphasis on certain terms, suggesting a more selective, executive-summary style rather than comprehensive technical coverage.

These oberservations implicate that, even for globally frequent terms, usage patterns vary dramatically across documents, indicating **selective framing** where each institution highlights specific facets of agentic AI to align with its audience and strategic positioning.

3.1.5 Comparative Analysis by Source Type

To systematically compare institutional types, we aggregated term frequencies by source category. Figure 8 displays the top 20 words for each institutional type.

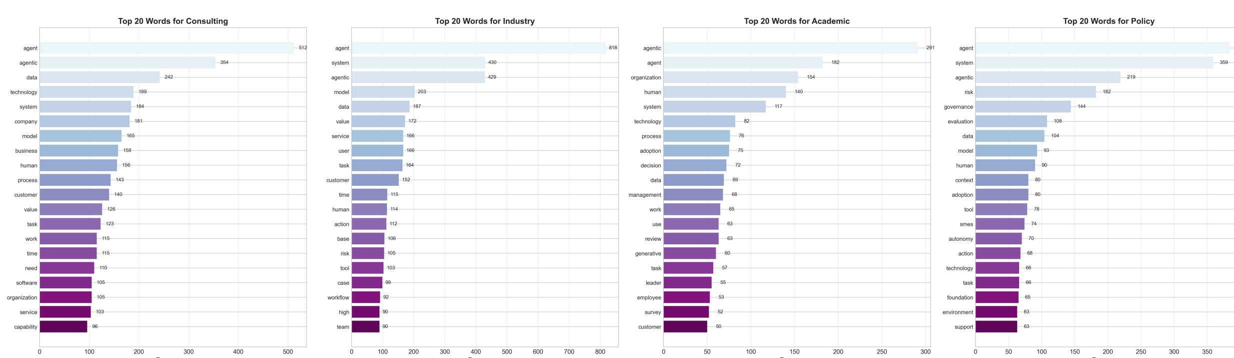

Figure 8: Top 20 Words for Consulting, Industry, Academic, and Policy

Four bar charts side-by-side. Consulting emphasizes "agent", "data", "technology", "business"; "customer", "work." Industry prioritizes "agent", "system", "model", "data", "service", "user." Academic stresses "agent", "agentic", "organization", "human", "process", "decision." Policy highlights "agent", "system", "agentic", "risk", "governance", "innovation."

Comparative insights table

Dimension	Consulting	Industry	Academic	Policy
Top term	Agent (512)	Agent (518)	Agent (291)	Agent (469)
Focus	Business & customers	Systems & models	Organizations & humans	Governance & risk
Unique emphasis	"customer" (140), "work" (118), "task" (123)	"model" (203), "data" (187), "user" (156)	"human" (140), "organization" (120), "process" (79)	"risk" (182), "governance" (141), "policy" (94)
Governance presence	Low (6th-8th position)	Low (not in top 20)	Moderate	**High (2nd-3rd position)**

Combining the visual representation and the comparative insights table currated above, a narrative divergence can be confirmed. For **Consulting firms,** the domain construct agentic AI as a **business transformation tool**, emphasizing customer impact, workforce implications, and task automation. **Industry actors** adopt a **technical implementation lens**, focusing on models, data pipelines, and user interfaces, reflecting their role as technology builders. And while **Academic institutions** maintain a **socio-technical perspective**, foregrounding human-AI collaboration, organizational change, and process redesign, **Policy organizations**, on their end, distinctly prioritize **governance, risk, and regulation**, reflecting their mandate to establish guardrails for emerging technologies.

Figure 9: WordClouds by Source Type

Four word clouds displaying vocabulary emphasis. Consulting cloud features "agent", "data", "technology", "business" prominently. Industry highlights "agent", "system" ,"model", "user." Academic emphasizes "agent", "system", "human", "organization", "governance." Policy cloud displays "agent", "system", "risk", "governance", "policy" as dominant terms.

The word clouds reinforce quantitative findings. Policy discourse is visually distinctive with "governance" and "risk" achieving prominence comparable to "agent," whereas these terms recede in consulting and industry clouds.

3.1.6 Term Category Distribution by Source Type

Figure 10 quantifies how institutional types allocate lexical attention across the eight thematic categories.

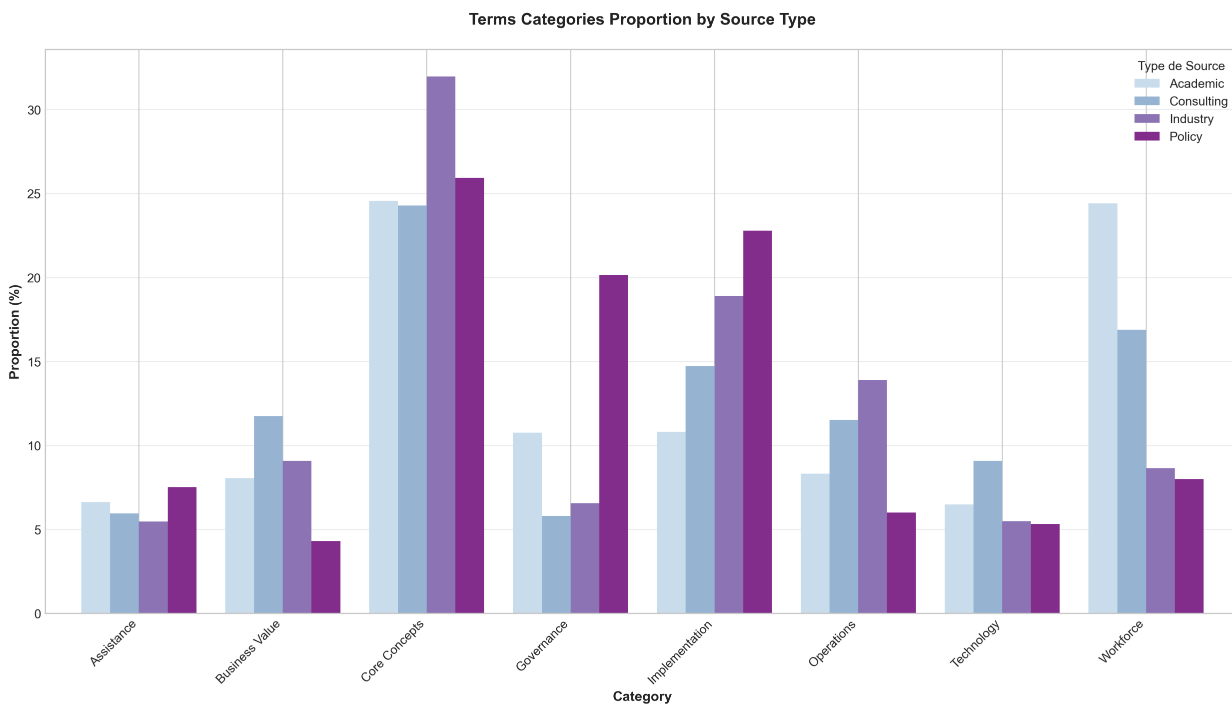

Figure 10: Terms Categories Proportion by Source Type

Grouped bar chart. X-axis shows eight categories, Y-axis shows proportion (%). Four bars per category represent Academic (light blue), Consulting (medium blue), Industry (dark blue), and Policy (purple).

The first key finding here revolves arround **Core Concepts** that appear to be **universal.** All types devote 24-32% of vocabulary to core concepts, with Industry slightly leading (32%) due to technical depth. However, a **gap** is observed for **Implementation.** Indeed, Consulting (18.7%) and Industry (28.9%) emphasize implementation far more than Academic (10.8%) or Policy (14.6%), reflecting builder vs. evaluator roles. A divergence on the **Governance** side is also found with Policy sources allocating 22.8% to governance terms which **triple the**

consulting proportion (6.5%) and double academic (10.8%). This represents the starkest divergence in the data. Additionally, on the **Workforce** discussion, Academic reports (24.5%) and Consulting (17.0%) prioritize workforce implications, while Industry (8.4%) and Policy (8.1%) largely omit labor considerations, which underlines a concerning gap given automation's workforce impact. Lastly, a **Business Value concentration** is observed: Consulting (11.8%) uniquely emphasizes business value, while Academic (8.1%), Industry (8.9%), and Policy (4.2%) de-emphasize economic metrics.

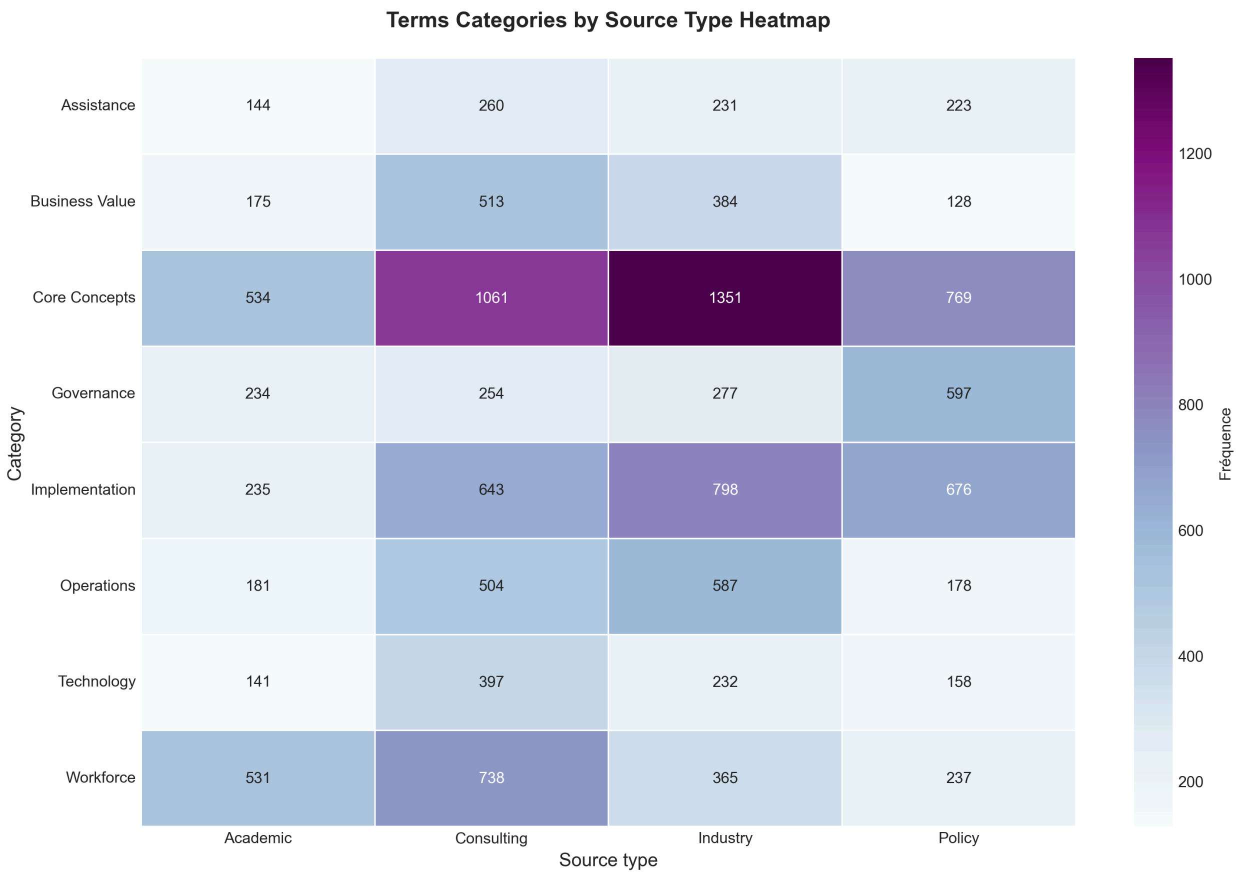

Figure 11: Terms Categories by Source Type Heatmap

Heatmap with categories as rows, source types as columns, and color intensity representing absolute frequency. "Core Concepts" row shows deep purple across all types. "Governance" column reveals stark contrast: Policy (597) vs. Consulting (254).

The heatmap visualizes **conceptual misalignment**. An enterprise following consulting guidance (low governance emphasis) may encounter regulatory friction when engaging with policy actors (high governance emphasis). Similarly, academic concerns about workforce transformation may not penetrate industry implementation practices.

3.2 TF-IDF: Term Specificity Across Reports

While word frequency reveals global patterns, **TF-IDF (Term Frequency-Inverse Document Frequency)** identifies terms that are *distinctively associated* with specific documents. High TF-IDF scores indicate that a term appears frequently in one document but rarely across the corpus, which exposes each institution's unique narrative emphasis.

3.2.1 Methodology

For each document, we calculated TF-IDF scores for all terms and extracted the top 15. These represent the **lexical signature** of each report, i.e. the vocabulary that most strongly differentiates it from others.

3.2.2 Institutional Signatures

Figure 12 displays TF-IDF profiles for six representative documents spanning all four institutional types.

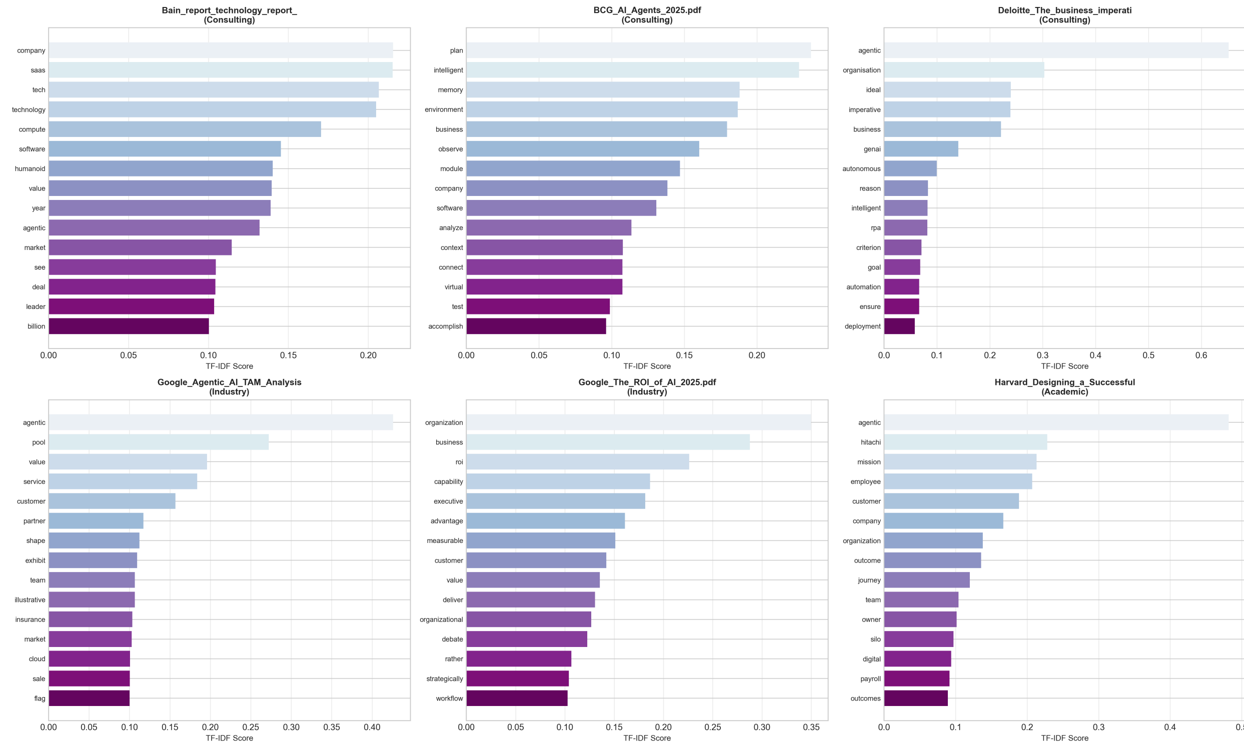

Figure 12: TF-IDF Top Terms by Document (Sample of 6)

Here, **Consulting reports** exhibit high TF-IDF for organizational and business strategy terms ("company", "imperative", "organization"), confirming their role as strategy advisors, while, **Industry reports** uniquely emphasize market-oriented language ("roi", "value", "pool", "partner"), reflecting revenue and partnership focus. Also note that **Academic reports** balance technical depth with human factors ("employee", "mission", "outcome"), maintaining socio-technical orientation.

3.2.3 Direct Contrast Between Consulting and Academic

Comparing TF-IDF profiles for consulting and academic sources exposes divergent strategic framing.

Consulting distinctive terms (aggregated across 7 reports) highligth business ("productivity", "efficiency", "roi", "value", "customer"), organizational ("organization", "company", "imperative", "leadership") and operational ("workflow", "process", "automation", "optimization"). Meanwhile, **Academic distinctive terms** (aggregated across 4 reports) underline human-centric ("human", "employee", "worker", "collaboration"), governance ("governance", "oversight", "risk", "alignment", "trust") and conceptual ("autonomy", "autonomous", "intelligence", "capability").

Consulting firms construct agentic AI as a **business accelerator** (productivity, efficiency, ROI), while academic institutions frame it as a **socio-technical challenge** requiring governance, human oversight, and careful capability management.

These frames are not merely descriptive differences, they shape **adoption priorities**. Consulting-guided enterprises may underweight governance, while academic-informed policymakers may underestimate business imperatives.

3.2.4 Cross-Institutional TF-IDF Patterns

Figure 7 (previously discussed) also functions as a TF-IDF visualization when viewed through the lens of *relative concentration*. Documents with dark purple cells for specific terms exhibit high TF-IDF for those terms.

Pattern 1: Governance concentration in policy reports

WEF, OECD, and ITI reports show concentrated "governance," "risk," and "policy" mentions. These terms achieve high TF-IDF because they appear frequently in policy reports but rarely elsewhere.

Pattern 2: "Agentic" as a universal yet differentiating term

"Agentic" appears globally but achieves high TF-IDF in reports that use it extensively (Deloitte: 0.60, Harvard: 0.50) indicating that *density of usage* varies widely even for core vocabulary.

Pattern 3: Implementation terminology clusters in industry

Terms like "deployment", "integration", "architecture", and "infrastructure" achieve high TF-IDF in industry reports (Google, Microsoft, OpenAI) which reflects their focus on technical enablement rather than conceptual framing.

3.3 Topic Modeling (LDA): Latent Thematic Structure

While lexical analysis reveals surface-level vocabulary patterns, **topic modeling** uncovers latent thematic structures: the underlying conceptual dimensions that organize discourse. To uncover the later, **Latent Dirichlet Allocation (LDA) w**as applied to identify and group documents into coherent topics based on word co-occurrences.

In this report, four major themes consistently show up across the entire corpus.

- **AI Foundations & Responsible Development:** How to build, evaluate, and control these systems.
- **Workforce & Organizational Transformation:** How AI changes jobs, workflows, and leadership priorities.
- **Technical Products & Infrastructure:** The tools, compute, workflows, and software ecosystems behind Agentic AI.
- **Business Strategy & Market Dynamics:** Commercial value, partnerships, and how companies plan to scale AI.

3.3.1 Model Selection and Validation

The first step was to determine the optimal number of topics that best describes the data without over-fragmenting it. To do so, we computed coherence scores as our primary metric, which measures the semantic similarity between high-scoring words within a topic, for models ranging from 2 to 10 topics. Figure 13 displays the coherence trajectory.

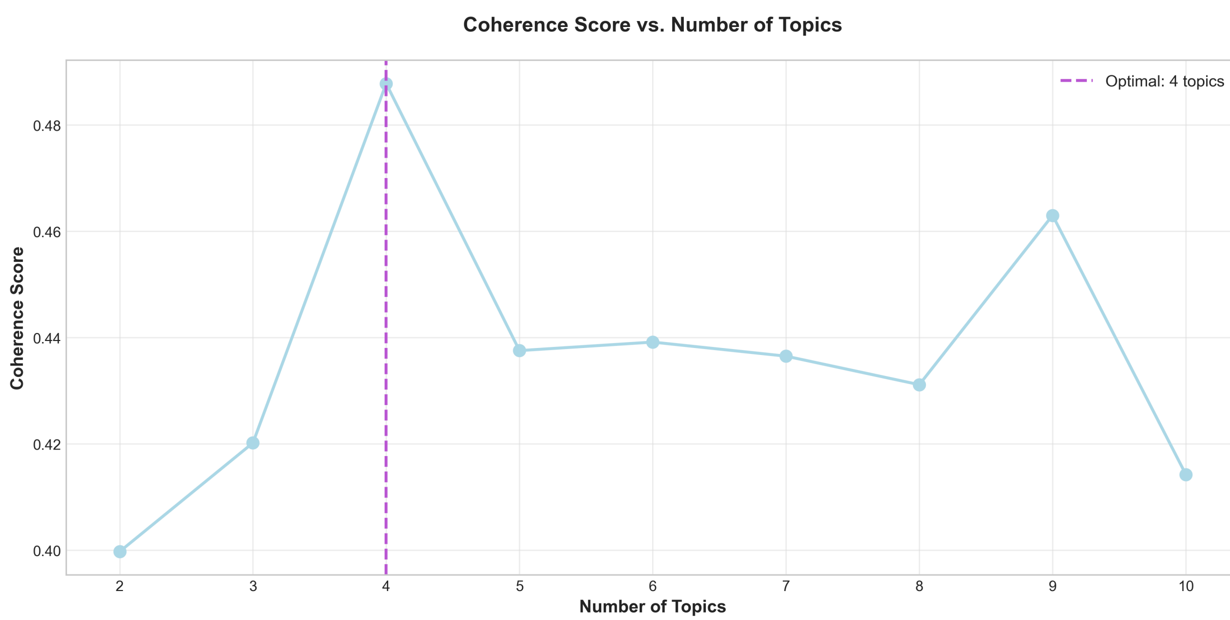

Figure 13: Coherence Score vs. Number of Topics

Line plot showing coherence scores across topic counts. Peak coherence (0.49) occurs at 4 topics, indicated by the vertical dashed line. A secondary local maximum appears at 9 topics (0.46), but the 4-topic model offers superior interpretability.

3.3.2 Topic Identification and Labeling

Figure 14 presents the four extracted topics with their top 12 keywords ranked by probability.

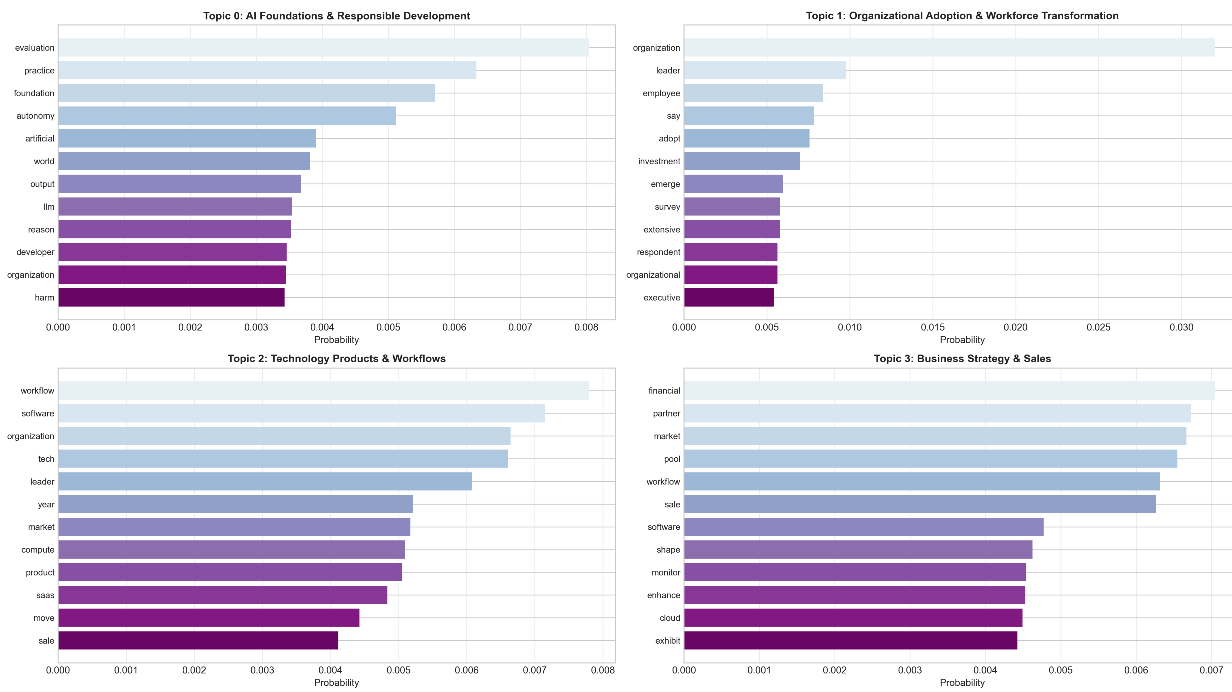

Figure 14: Topic Keywords (Top 12 per Topic)

The LDA model with 4 topics revealed distinct thematic pillars. We labeled these topics based on their top-weighted keywords:

- T0: AI Foundations & Responsible Development
- T1: Organizational Adoption & Workforce Transformation
- T2: Technology Products & Workflows
- T3: Business Strategy & Sales

3.3.3 Global Topic Distribution

Figure 15 quantifies the prevalence of each topic across the entire corpus.

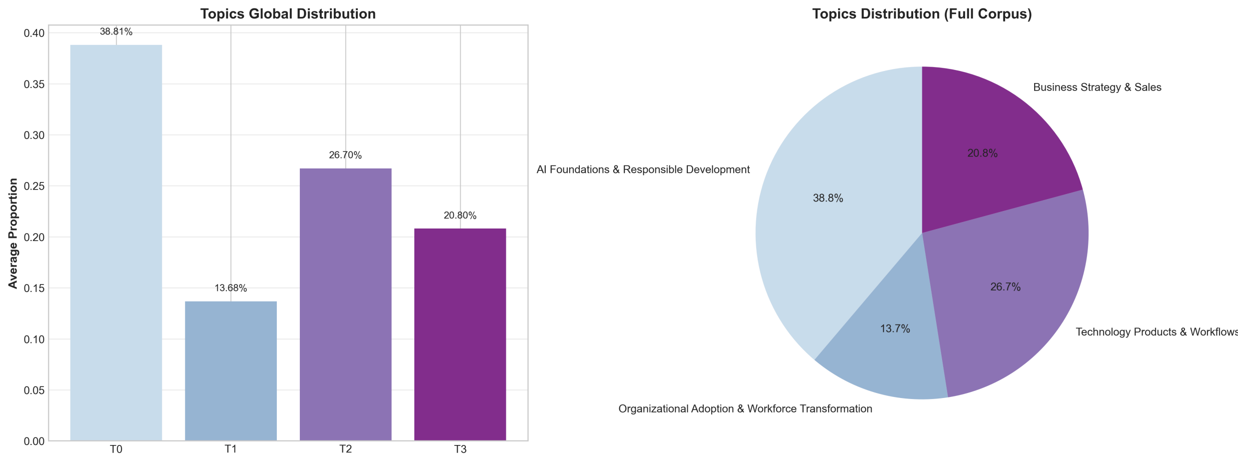

Figure 15: Topics Global Distribution

Left: Bar chart showing average topic proportions. T0 (38.81%) dominates, followed by T2 (26.70%), T3 (20.80%), and T1 (13.68%).

Right: Pie chart visualizing the same proportions.

The dominance of foundational discourse (T0) suggests that agentic AI remains in a **conceptual consolidation phase** where institutions prioritize establishing shared understanding over scaling deployment, despite concurrent hype about imminent enterprise transformation.

3.3.4 Comparative Topic Emphasis

Figure 17 visualizes the same data as grouped bars for direct comparison.

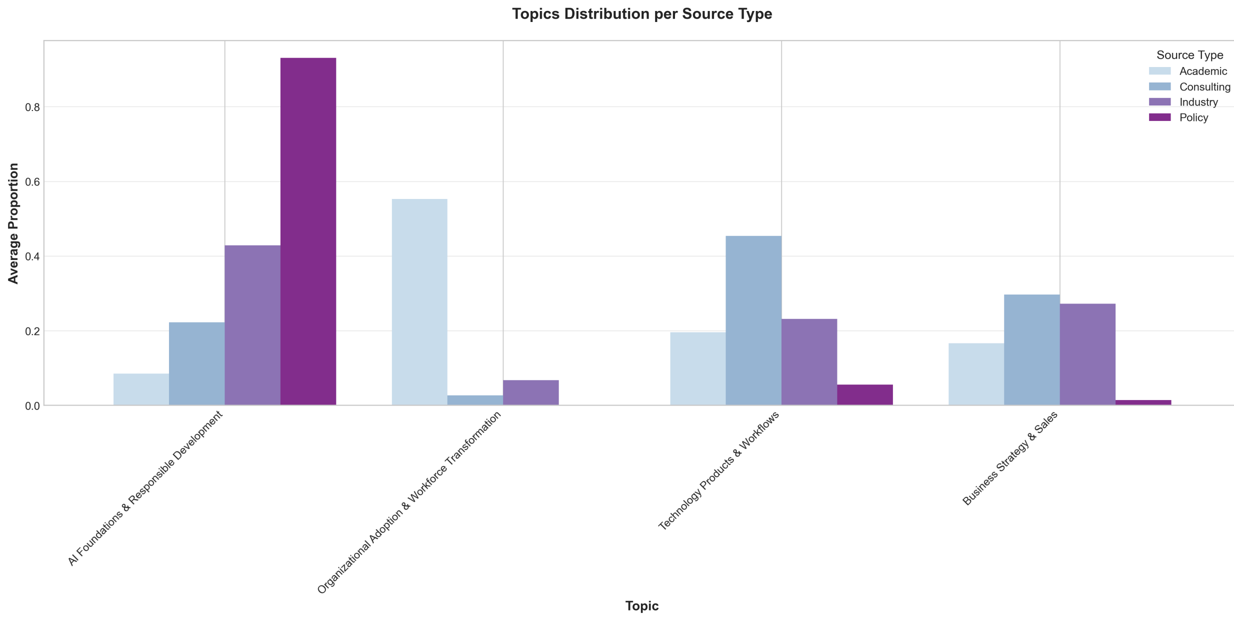

Figure 17: Topics Distribution per Source Type (Grouped Bars)

Four topics on X-axis, bars grouped by source type. Policy's near-total focus on T0 (purple bar ~0.93) dominates visually, while Academic's emphasis on T1 (light blue bar ~0.55) stands alone.

We observe three narratives with minimal overlap. First the **Policy narrative (93% T0)** with "Agentic AI requires foundational governance before deployment.", emphasizing evaluation, standards, and responsible development. Secondly the **Academic narrative (55% T1 + 17% T0)** represented by "Agentic AI is an organizational transformation challenge.". This narrative focuses on workforce readiness, leadership, and adoption strategies. Lastly, the two remaining domain can be grouped as a single narrative, the **Consulting/Industry narrative (45% T2 + 30% T3),** with "Agentic AI is a market opportunity requiring product implementation.". The latter combines technical solutions with business strategy.

These narratives operate on **different "planes"** where policy seeks to regulate, academics seek to prepare organizations, and industry seeks to monetize.

3.3.5 Document-Level Topic Distributions

Figure 18 (optional, detailed visualization) shows how each document mixes topics, revealing intra-institutional variation.

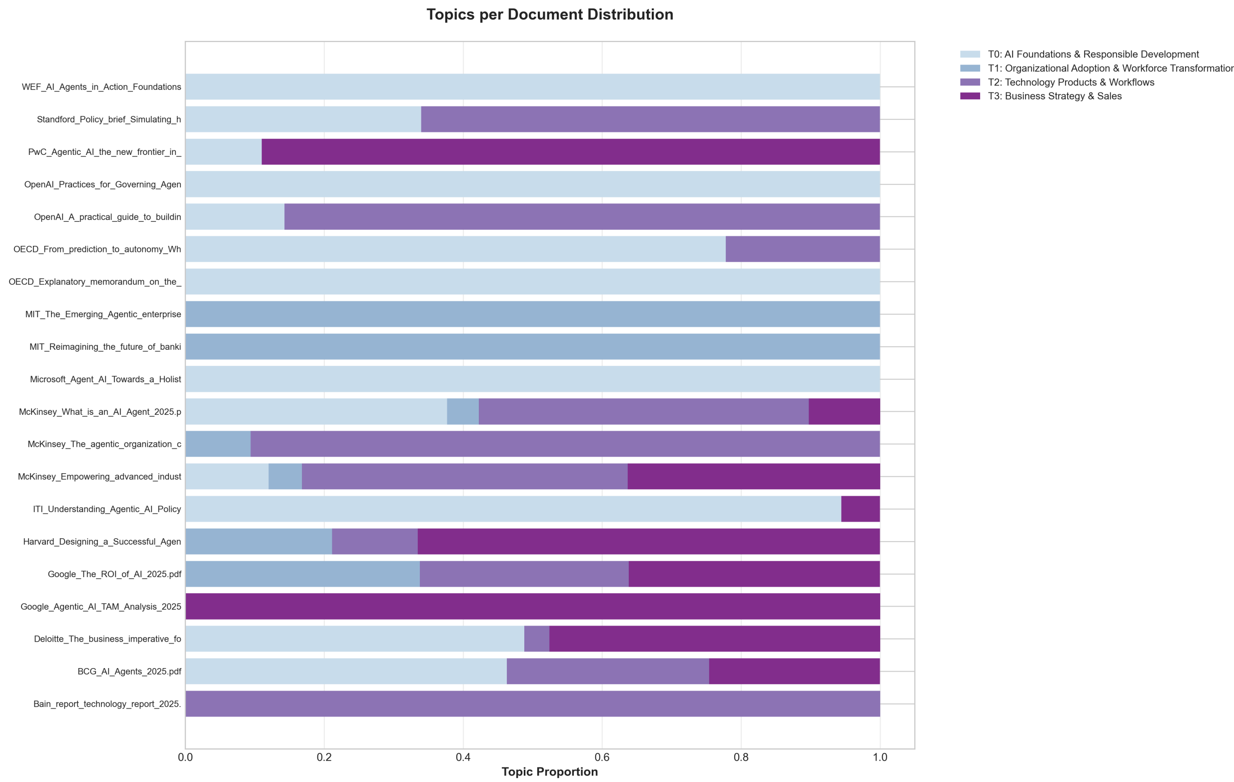

Figure 18: Topics per Document Distribution (Stacked Bars)

Horizontal stacked bars for all 21 documents. Each bar segments into four colored sections representing topic proportions.

Here, the analysis helps to understand the primary focus of each document and how each topic is involved in its core text.

We observed that documents tend to specialize. For example, several documents contain only one topic. For **WEF AI Agents in Action (Policy)**, T0 represents 98% with minimal other content, meaning pure governance focus. Another remarkable example is **Google TAM Analysis (Industry)** with 100% of T3, meaning exclusively business strategy and market sizing.

Nonetheless, the sources also tend to speak about the same topics, with variations, across their various documents. For example, the **McKinsey Empowering Advanced Industries (Consulting)** is a mix of 3 topics (30% T1, 40% T2, 20% T3), giving a more balanced discussion across adoption, technology, and strategy, reflecting consulting's integrative role.

Therefore, even within institutional types, document-level variation exists. Some consulting reports adopt academic-like organizational focus, while some academic papers engage technical implementation. However, **type-level patterns remain robust**, indicating institutional mandates shape discourse more than individual author choices.

3.3.7 Hierarchical Clustering of Documents

Figure 19 try to perform hierarchical clustering based on topic distributions, revealing which documents share thematic profiles.

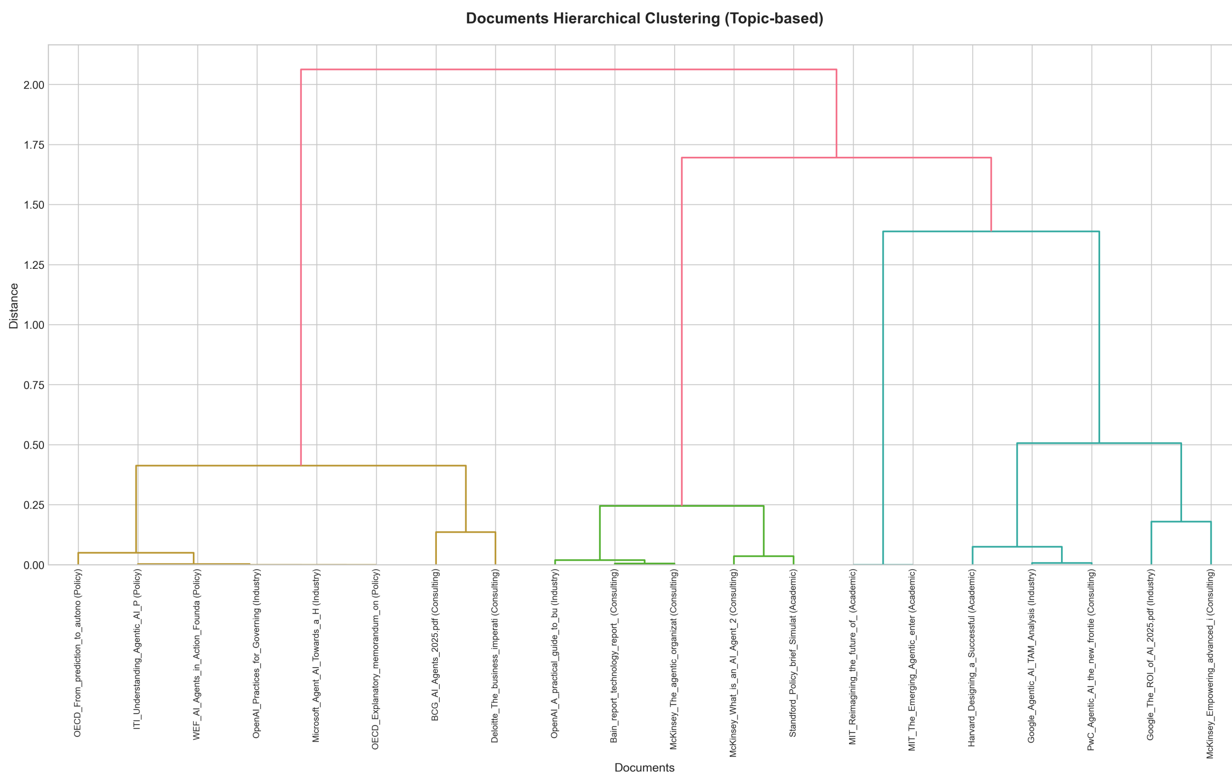

Figure 19: Documents Hierarchical Clustering (Topic-based)

Dendrogram showing document similarity based on cosine distance of topic vectors. Four main clusters emerge, color-coded.

Four clusters can be distinguished from the figure, with, first, **Cluster 1 (Yellow, low distance)** reuniting documents by T0 dominance such as Policy documents (OECD, WEF, ITI) and OpenAI Governance. The second cluster, **Cluster 2 (Green)**, regroups Academic papers (MIT, Harvard), and a select consulting document (McKinsey Agentic Organization) for an organizational focus. Additionally, **Cluster 3 (Cyan)** is a mixing of Consulting and Industry sources with balanced topic distributions. Finally, the last cluster, **Cluster 4 (Magenta),** aims for usiness-strategy-heavy consulting (Bain, Google ROI) with T3 dominant.

3.4 Mini-Taxonomy of Definitions of “Agentic AI”

To understand what people actually mean when they use the term "Agentic AI", the report provide an analysis of the corpus texts to find explicit definitions. To do so, the definitions are grouped into four main categories defined as such:

- **AI as Copilots:** Helpers that assist humans with tasks.
- **AI as Autonomous Workers:** Systems that do the work independently.
- **AI as Orchestrators:** Managers that plan and organize complex workflows.
- **AI as Governance Challenges:** A focus on the risks and the need for control.

3.4.1 Data Processing Challenges

Getting this data was difficult. At first, the initial text-cleaning tools seemed too aggressive as they stripped out punctuation and small words so badly that the definitions became unreadable. However, with more moderate cleaning, a lot of “noise” (irrelevant data) impacted the data. This section was thus tricky as it needed a well balanced cleaning middle ground: keeping some noise to ensure not to lose the actual definitions, and then filtering the results carefully.

3.4.2 Methodology

To structure the extracted text segments, we employed a hybrid classification approach combining **keyword matching** and **manual semantic clustering**.

For the extraction, the sentences containing structural markers of definitions (e.g., "is defined as," "refers to," "an agent is") are isolated.

Then , for the clustering part, the segments were mapped to four conceptual archetypes based on their primary function as such:

- **Copilots:** Focus on human-in-the-loop assistance (Keywords: *assist, help, support*).
- **Autonomous Workers:** Focus on independent task completion (Keywords: *autonomous, independently, replace*).

- **Multi-Agent/Orchestrators:** Focus on systems management (Keywords: *ecosystem*, *multi-agent*, *workflow*).
- **Governance:** Focus on risk and control boundaries (Keywords: *risk*, *guardrails*, *safety*).

Note: A significant portion of mentions fell into "Other/Uncategorized" due to vague marketing language or broad generalizations that lacked specific functional descriptors.

3.4.3 Global Definition Landscape

Figure 20 illustrates the distribution of identified definitions across the entire corpus.

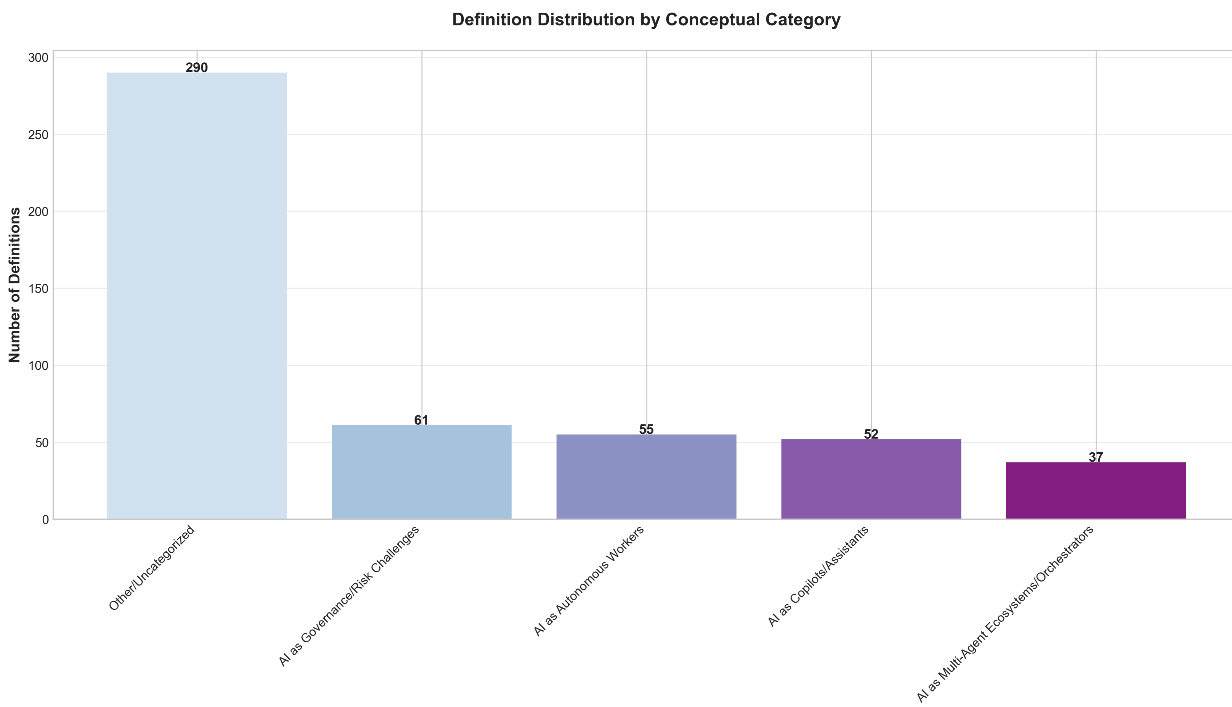

Figure 20: Definition Distribution by Conceptual Category

Bar chart showing the frequency of definition types. "Other/Uncategorized" dominates (290), followed by Governance (61), Autonomous Workers (55), Copilots (52), and Orchestrators (37).

The overwhelming volume of "Other" definitions (290 counts) indicates that "Agentic AI" is still a buzzword often used without precise technical meaning.

Among the explicit definitions, **Governance/Risk (61)** is the leading category, suggesting that the discourse is currently more concerned with *controlling* these systems than defining their exact operational mechanics.

3.4.4 Sector-Specific Definition Preferences

Figure 22 provides a granular heatmap of the intersection between Source Type and Conceptual Category, allowing for precise volume comparison.

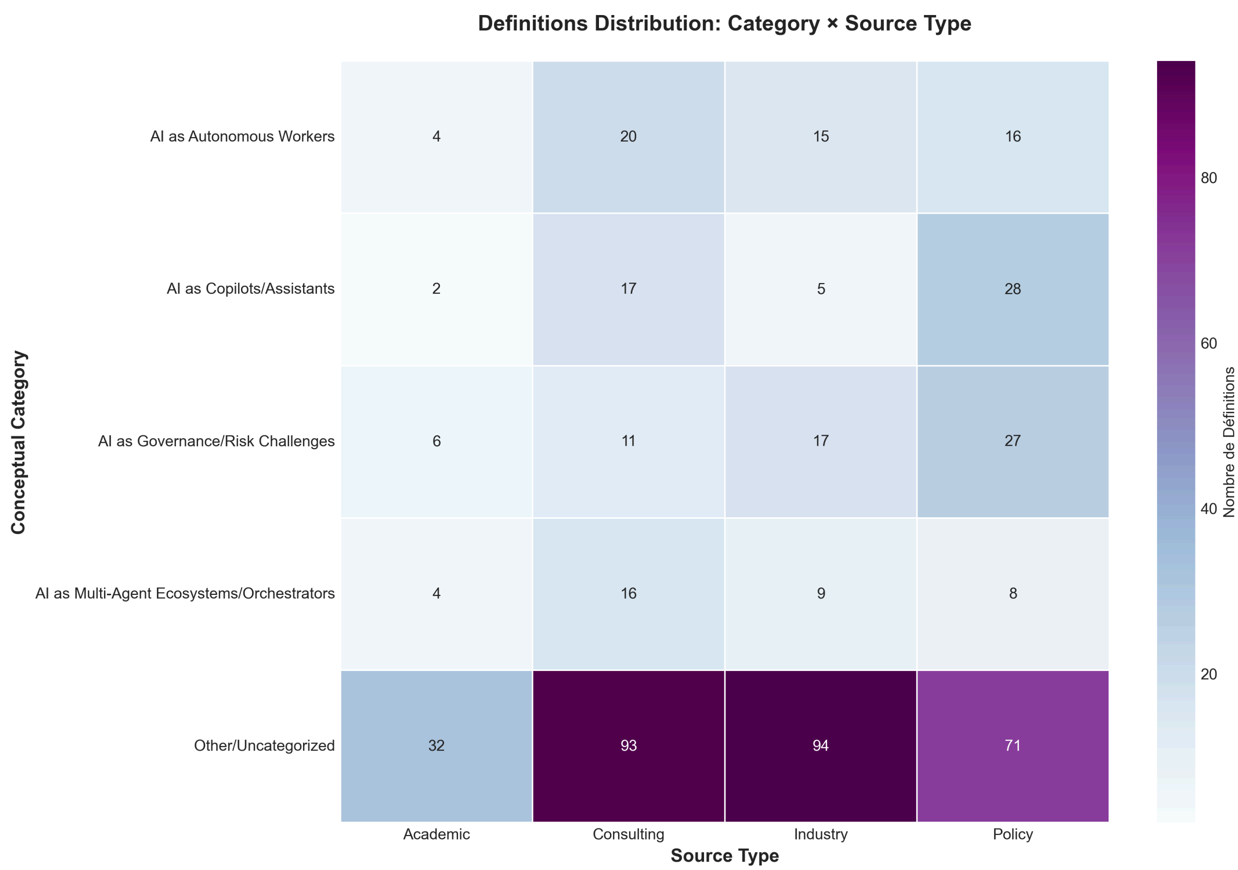

Figure 22: Definitions Distribution Heatmap (Category × Source)

Heatmap showing exact counts. Darker purple indicates higher frequency.

On the first hand, the Policy dominant cluster could be defined as "Safety"-related topics. Indeed, its documents corpus seem to refer agents as **Copilots (28 mentions)** or **Governance Challenges (27 mentions)**. They rarely define agents as "Autonomous Workers" (16). This is likely to avoid implying a loss of human agency.

On the other hand, a **"Automation"** cluster, mainly related to the Consulting sources, can be defined. Those institutions appear to be leading definers of **Autonomous Workers (20)** and **Multi-Agent Orchestrators (16)**. Their focus is stressed on the economic output of the agent (doing the work) rather than the method of interaction (assisting a human).

Moreover, an interesting finding is regarding the Academic sources as they have the lowest definition count across the board (Total ~46 specific definitions). This could suggest academic literature use of the "Agentic" term is less established in pure research than in applied strategy.

Finally, this figure also underlines a **source bias** (i.e. depending on who is talking). Where **Tech companies** define it as **autonomy,** as they want to emphasize that their products can work on their own, **policymakers** define it as **risk**. They are focused on safety and regulations. The heatmap shows a dark spot under "Policy," meaning they almost exclusively talk about governance. Lastly, **consultants** define it as **Help**. They view agents as "Copilots" or "Workers" that companies can hire them to help implement.

3.4.6 Summary of Definition Analysis

As far as it got, the taxonomy analysis seems to confirm the findings of the topic modeling. This is not a discussion of a single technology, but two distinct visions using the same name.

Vision A (Policy/Governance)	Vision B (Consulting/Market)
Agentic AI is a sophisticated **tool** (Copilot) that requires strict boundaries.	Agentic AI is a **workforce** (Autonomous/Orchestrator) that drives efficiency.

The "Other/Uncategorized" segment (see Appendix) remains the largest block, reminding us that for the majority of the market, "Agentic AI" remains an undefined aspirational term.

4. Insights & Strategic Implications

Our analysis confirms that "Agentic AI" is not currently a unified concept. Instead, it is a fragmented landscape where the definition depends entirely on the source1.

The "Productivity vs. Safety" Gap

The discourse is split into two conflicting realities. Consulting and Industry reports largely frame agents as "Autonomous Workers" or technical systems designed to independently drive business value and ROI2. In sharp contrast, Policy organizations frame these same systems as "Copilots" or sources of risk that require strict human oversight.

The Danger of Selective Listening

This divergence creates a strategic blind spot.

- **The Compliance Trap:** Consulting reports allocate only 6.5% of their focus to governance, compared to 22.8% in policy documents. An organization following only consulting advice risks deploying systems that fail future regulatory standards.
- **The Autonomy Illusion:** Industry reports focus heavily on technical "architecture" and "deployment", often glossing over the workforce transformation challenges that Academic sources.

Strategic Conclusion

To succeed, organizations must stop viewing these narratives as separate options. A robust AI strategy must merge the technical ambition of the industry sector with the governance guardrails of the policy sector. The goal is not just to deploy an "autonomous" agent, but to build a system that is productive enough to satisfy the business case, yet safe enough to satisfy the regulators.

5. Recommendations

Based on the clear differences found in how institutions talk about Agentic AI, this report offer three general recommendation regarding the definition of the term “Agentic AI”:

1. **Establish a unified internal definition of agentic AI**

   Organizations should clarify whether “agentic AI” refers to copilots, autonomous workflows, or full multi-agent ecosystems before initiating adoption roadmaps.

2. **Align strategic planning with governance-sensitive definitions**

   Reports with a strong governance focus highlight potential risks; these should inform enterprise implementation to avoid regulatory misalignment.

3. **Monitor narrative shifts over time**

   As agentic AI evolves quickly, institutions update their narratives. Tracking these changes helps anticipate regulatory or technological shifts that could impact adoption strategies.

6. Limitations & Next Steps

This analysis relies on a limited corpus of English-language reports published by Western consulting firms and institutions. The scope may not reflect perspectives from non-Western policy environments or industry actors. Time constraints limit the use of advanced semantic models.

Future work could integrate:

- Sentiment analysis
- More advanced NLP techniques such as embedding-based clustering (e.g., sentence-BERT)
- Additional reports from public agencies or non-profit organizations
- Cross-lingual comparisons

Also, as mentioned earlier, a better and deeper processing of the texts should be beneficial to improve the taxonomy section of this report.

7. Conclusion

This study shows that **institutions do not mean the same thing when they talk about "agentic AI."** Even though "agent" is a common term and is increasingly used throughout various domains, its meaning changes depending on who uses it.

Our the main research question asked about the definition and framing of the "agentic AI" term and the dominant narratives. For such, the results reveal **strong fragmentation**.

- **Consulting firms and industry** mainly present agentic AI as a **productivity engine**, often described as an **autonomous worker** or a **workflow orchestrator** able to complete tasks end-to-end.
- **Policy organizations** focus on **governance, risk, and human oversight**, framing agents as tools that must remain controlled.
- **Academic institutions** emphasize **organizational adoption**, workforce impacts, and human–AI collaboration.

Overall, the dominant narrative depends on the institution's priorities: **business value**, **technical architecture**, **organizational change**, or **regulation and safety**.

Do institutional actors emphasize similar themes, or do narratives diverge?

The report stress a clear divergence linked to seemingly-inherent core values and motivations. **Consulting** prioritizes business value, **Industry** focuses on implementation and models, **Academia** highlights human and organizational dimensions, and **Policy actors** center on governance and risk.

These differences create **sectoral boundaries** rather than shared narratives.

How do definitions of "AI agent" vary?

Definitions fall into four main categories:

1. **Copilots** (assist humans),
2. **Autonomous workers**,
3. **Multi-agent orchestrators**,
4. **Governance or risk-focused definitions**.

No single definition dominates across sectors. Each actor uses the definition that matches its own objectives whether it'd be productivity (consulting/industry), safety (policy), or socio-technical understanding (academia).

It is still important to highlight that this report also demonstrated the heavy dominance of "Other/Uncategorized" definitions. Therefore future definitions unknown for now may also arise in the next years as the technology matures.

What strategic implications emerge for organizations?

The fragmented landscape creates **three main risks**:

1. **Regulatory misalignment** if organizations follow only consulting or industry advice while ignoring governance concerns.
2. **Incomplete adoption strategies** that overlook workforce or organizational impacts.
3. **Miscommunication** between companies, researchers, and regulators due to incompatible definitions.

To navigate this, organizations should first **establish a clear internal definition** of agentic AI, then **align adoption plans with governance expectations**, and finally **monitor evolving narratives** as the concept continues to shift.

In a nutshell, agentic AI is not yet a unified concept as it reflects **multiple, competing visions**.

Success will depend on an organization's ability to **combine technical ambition, business value, and robust governance into a coherent strategy**, rather than adopting any one narrative in isolation.