THE WORKLOAD ICEBERG

How Draup Extends MIT's
Iceberg Research to Reveal
the Hidden 80% of Enterprise Work

A Draup Research Whitepaper (November 2025)

Introduction: How MIT's Iceberg Study Inspired This Paper

Last week, on November 26, 2025, MIT researchers introduced Project Iceberg, a groundbreaking analysis that revealed a profound blind spot in how nations measure AI impact. According to the study, only 2.2% of the U.S. labor market shows visible AI adoption today—mostly technology occupations—while a much larger 11.7% of wage value sits beneath the surface, representing cognitive, administrative, and coordination tasks that AI can already technically perform.

MIT's central argument is transformative: The visible indicators of AI impact (job postings, layoffs, tech hiring) represent only the "tip of the iceberg." Most of the exposure lies hidden in white-collar tasks that are not captured by traditional workforce metrics.

This paper is directly inspired by that insight. **But while MIT focuses on the macroeconomy—national labor markets, skill ecosystems, and regional vulnerabilities—enterprises face the same iceberg problem within** their organizations.

- Job descriptions **capture only a fraction of what people do**
- HR often depends on business/unit input for understanding jobs

Deeper insights are often present in these other assets (not all assets are perfect, but additional insights reside)

- Process maps (even though they may omit exception paths)
- Product Roadmaps or Portfolio Plans (Especially for R&D)
- KPIs that track outputs
- Workflows that capture system interactions
- Skill taxonomies (even though they may miss task-level realities)
- Digital tech stack that is getting implemented
- Competitor Plans (Especially in R&D)

MIT revealed a nationwide measurement gap. **Draup extends this insight to reveal the enterprise measurement gap**—the hidden work that determines productivity, cost structures, and AI ROI. At the recently concluded HR Analytics conference in Berlin, Draup presented this in detail.

This paper outlines Draup's Workload Iceberg Framework, a task-level, skills-centered model that operationalizes MIT's insight for CHROs, SWP leaders, and TA leaders

The MIT Iceberg Premise: Most AI Exposure Is Hidden

MIT's Project Iceberg demonstrates three major findings that are essential for enterprises to understand:

1. Visible AI impact is small

- Tech-sector exposure (Surface Index): 2.2% of wage value
- Hidden cognitive exposure (Iceberg Index): 11.7%—5× larger

2. Hidden exposure is everywhere

- Administrative, financial, and professional roles—not just tech roles—show widespread AI capability overlap.

The Gap MIT Identifies at the Macro Economy level Also Exists Inside Every Enterprise

Just as national metrics fail to reveal hidden AI exposure, enterprise metrics fail to reveal hidden work.

HR in Companies track:

- Org charts
- Roles and FTEs
- Job descriptions (internal and external facing)
- Higher-level business inputs and feedback

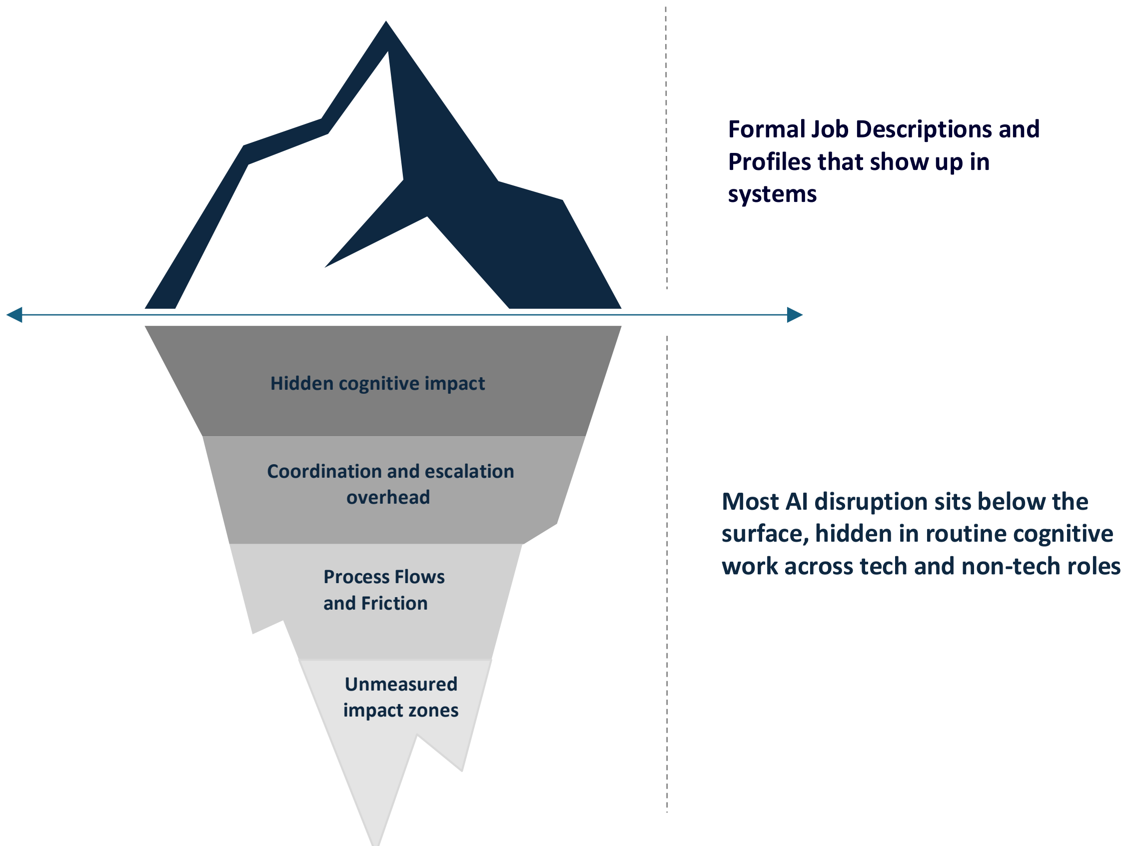
But **these reflect only a portion of the actual work**. The remaining work lies in the various forms in which **Draup has been addressing it at conferences and presentations**.

- Workflows (in Workday, ServiceNow, Jira, Salesforce, SAP etc.)
- KPIs & OKRs
- Processes maps (Even with some limitations)
- Digital Tech Stack that is implemented (Many HR leaders do not study this crucial link)
- Contextual judgment
- Coordination loops
- Escalations/Contracts
- Cognitive load (Emotional aspects)
- Other forms of Documentation (multiple formats)
- Oversight Required
- Informal processes
- Exception handling

This **invisible work** is where most:

- value is created,
- quality issues originate,
- delays accumulate,

- AI automation potential exists.



Just as MIT warns policymakers that they are "planning on yesterday's signals," enterprises risk designing AI strategies based on a tiny, visible fraction of work. Draup's objective is to close this measurement gap.

Draup's Methodology: Making the Invisible Measurable

Draup converts hidden work into structured, analyzable datasets.

A. **Workload Decomposition—**We deconstruct enterprise roles into:

   - Workloads
   - Tasks
   - Subtasks
   - Skill primitives
   - **Digital tool interactions (tech stack)**

- In the Etter model, **Draup introduces an Input Repository**, a dedicated layer that ingests and interprets multiple document types related to a job. This layer is essential for developing a deep, accurate understanding of the role

Data sources include:

- JDs
- Process maps
- SOPs
- Audit logs
- Call transcripts
- Case management data
- Benchmark role libraries
- Any form of document that will have
- Product and Portfolio Plans
- Draup's proprietary task engine (which brings **peer task data sets). This is a very crucial aspect of unlocking the hidden layer**

B. Task-Level Modeling—Draup's task platform includes:

- 500,000+ tasks
- 50,000+ skills
- Complexity and cognitive load scores
- Task adjacency networks
- Skill transferability
- Task-automation feasibility

This turns hidden cognitive work into measurable units.

C. Dynamic Skills Architecture

Draup's DSA framework includes:

- Root Skills
- Core Skills
- Digital Skills
- AI Model Skills
- Sunrise Skills (Core)
- Sunset Skills (Core)
- Peer complexity
- Skill convergence

- Task–skill weighting models

DSA is the enterprise equivalent of MIT's skills-based Iceberg Index—far deeper and more operational.

D. ETTER: Agentic Simulation of Task-Level AI Exposure

ETTER is the only enterprise system that:

- Measures automation feasibility across GPT-5, Claude, Gemini
- Simulates human → AI → human loops
- Redesigns workloads
- Calculates financial ROI
- Generates new role architectures
- Maps skills required for the new design

MIT models adoption across the economy. ETTER models adoption inside workflows.

Workload Activity	Directive	Feedback Loop	Task Iteration	Learning	Validation	Negligibility
Software Development and Implementation	Generating boilerplate code and standard functions automatically	Debugging code with automated error detection and suggestion systems	Collaborating with AI to refine code structure and logic while maintaining control over implementation	Researching and learning new programming languages, frameworks, and development methodologies	Using AI to review code quality, identify potential bugs, and suggest optimizations	Making critical architectural decisions that require deep domain expertise and business context understanding
Technical Architecture and Design	Generating standard design documentation templates and diagrams	Refining system architecture models based on performance feedback and requirements changes	Collaborating with AI to explore design alternatives and evaluate trade-offs	Studying emerging architectural patterns, technologies, and industry best practices	Verifying design consistency and adherence to architectural standards and principles	Making final decisions on architecture trade-offs based on business context and strategic goals
Technical Leadership and Mentorship	Scheduling team meetings and tracking action items and deadlines	Analyzing team performance metrics and suggesting process improvements	Developing training materials and technical guidance with AI assistance	Staying current with industry trends and technologies to guide team direction	Reviewing technical guidance and mentorship materials for accuracy and completeness	Building interpersonal relationships and trust with team members through personal interaction
System Analysis and Optimization	Generating performance reports and analytics from system logs and metrics	Monitoring system metrics and adjusting optimization strategies based on results	Collaborating with AI to identify performance bottlenecks and potential solutions	Researching optimization techniques specific to the technologies in use	Verifying optimization results against benchmarks and performance requirements	Making critical decisions about trade-offs between performance, maintainability, and other system qualities
Business Requirements Analysis	Formatting and organizing requirements documentation and specifications	Refining requirements based on stakeholder feedback and changing business needs	Collaborating with AI to translate business needs into technical requirements	Understanding domain-specific business processes, terminology, and objectives	Checking requirements for completeness, consistency, and alignment with business goals	Building stakeholder relationships and facilitating requirements gathering sessions requiring emotional intelligence

Etter output for the role of Application developer

What Draup's Workload Iceberg Reveals

Across industries, we observe consistent patterns.

Insight 1: Automation Potential Lives in the Hidden Layer

AI feasibility spikes in:

- documentation
- review loops
- analysis prep
- validation steps
- exception handling
- coordination work

These are never reflected in JDs .

Insight 2: Role Convergence Begins in Invisible Tasks

- Cloud + Data + Security
- Finance + Analytics + Automation
- HR + Case Management + AI review
- Engineering + Testing + AI oversight

Convergence starts long before job architecture catches up.

Insight 3: Skills Move Faster Than Jobs

Sunrise skills appear in hidden workloads first:

- prompt engineering
- test validation
- orchestration oversight
- AI tool chaining
- cognitive QA
- data readiness tasks

MIT shows the capability moves faster than the official skill demand. Draup shows the same phenomenon inside companies.

Insight 4: Workforce Planning Must Shift from Job Roles to Workloads → Tasks → Skills

Traditional SWP:

- headcount
- demand–supply
- job families

New SWP:

- workload volume
- task frequency
- cognitive burden
- skill velocity
- Agentic AI augmentation patterns

Insight 5: R&D Workloads and tasks are often unclear

R&D tasks are often inherently ambiguous because they emerge from iterative experimentation, evolving hypotheses, and continuous learning loops. Unlike structured operational work, R&D activities rarely follow a predefined sequence—teams explore multiple directions in parallel, pivot based on new findings, and refine ideas through rapid prototyping and testing. This makes the true nature of R&D work fluid, non-linear, and difficult to capture through traditional task lists or job descriptions.

Conclusion: MIT Exposed the National Iceberg; Draup Exposes the Enterprise Iceberg

MIT created a landmark national insight: AI exposure is mostly invisible.

Draup extends this insight into the enterprise: Most work is invisible. Most AI value lives in that invisible layer.

For HR to lead in the age of AI, it must evolve from traditional policy execution into a discipline that resembles management consulting. That means going beyond roles, job descriptions, and surface-level signals—and instead mapping the *true nature of work*: the cognitive loops, decision pathways, informal coordination, exception handling, and tacit tasks that actually drive enterprise value. Only by understanding these hidden structures of work can HR redesign roles, architect dynamic skills, deploy AI responsibly, and shape a future-ready workforce.

Example: HR Mapping the "True Work" of a Call Center Agent Using joint listening

On paper, the job description for a *Call Center Agent* says:

- Answer customer calls
- Resolve issues
- Document the interaction

But when HR sits next to the agent using a **double-jack headset**, the *real work* becomes visible:

1. **Cognitive Loop: Interpreting the Customer's Emotion**
    - The agent quickly detects frustration, confusion, or urgency.
    - This emotional interpretation completely shapes the resolution path—something no JD captures.
2. **Hidden Task: Silent Systems Diagnostics**
    - While speaking, the agent is simultaneously checking CRM tickets, browsing knowledge bases, and cross-referencing history.
    - This multi-threaded work is the real cognitive load.
3. **Coordination Loop: Back-Channel Slack Messages**
    - During the call, the agent quietly messages Tier-2 support:
      "This customer says their account is locked after MFA—anything flagged today?"
    - These hidden coordination steps never appear in process maps.