AI-Conducted Interviews for Job Analysis: When Small Stratified Samples Outperform Large Standardized Surveys

Abstract

Organizations routinely deploy large-scale standardized surveys (n = 100–500) for job analysis and competency mapping, yet survey instruments systematically obscure tacit knowledge, situated judgment, and real-work practices. This paper asks: under what organizational conditions can a small, stratified sample of AI-conducted interviews (n = 9–15) achieve knowledge quality comparable to or exceeding large surveys? We develop a comparative framework operationalizing seven knowledge-quality dimensions: thematic coverage, tacit knowledge emergence, interpretive depth, real-work fidelity, HR actionability, cross-group comparability, and marginal knowledge gain. Using a computational experiment with a synthetic organizational population (N = 500, stratified across 10 roles, 4 seniority levels, and 5 units), we generate parallel AI interview transcripts and standardized survey responses, apply NLP-based content analysis, and compare knowledge yield across methodological conditions. Results show that AI-conducted stratified interviews achieve 90% thematic coverage, substantially outperforming unstructured interviews (57.3%) and rigorous mixed designs (80.0%), while the survey-only baseline achieves zero coverage on open-ended theme elicitation — a finding that reflects a fundamental epistemological constraint rather than a design failure. Task complexity positively moderates interview effectiveness (95% coverage under high complexity). A rigorous mixed design combining interviews for elicitation with surveys for validation outperforms opportunistic method combination. The equivalence between interview and survey sample sizes is empirically contingent, not fixed: organizational role diversity, seniority variance, and task complexity all shift the threshold. All results are simulation-based and require empirical validation before generalization to real organizations.

Keywords: *job analysis; AI-mediated interviews; tacit knowledge; competency mapping; survey methodology; mixed methods; situated work practice*

1. Introduction

Organizations invest hundreds of millions annually in competency mapping and job analysis. The standard methodology is well-established: design a structured survey instrument, administer it to a representative sample (typically n=100–500), aggregate responses using Likert scales, and produce a standardized competency model for recruitment, training, and

performance management. This approach has dominated organizational research for four decades because it delivers what organizations value: speed, comparability across roles and sites, quantifiable metrics, and defensible documentation (Krosnick, 1999; Dillman, 2000).

Yet practitioners and researchers increasingly report a troubling gap: when managers describe their actual work—the decisions they make, the exceptions they navigate, the relationships they leverage, the knowledge they rely on—the narrative bears little resemblance to the formal job description or the competency model derived from survey data (Suchman, 1987; Orr, 1996). The problem is not that surveys are poorly designed. Rather, it is that **standardized surveys, by design, render invisible the very knowledge that makes work succeed in practice**. Surveys capture what can be easily articulated, quantified, and compared across respondents. They systematically fail to elicit tacit knowledge—knowledge that is embodied, contextual, and difficult to articulate (Polanyi, 1966; Nonaka & Takeuchi, 1995). They obscure the gap between prescribed work (what the job description says you should do) and real work (what you actually do to make things happen) (Suchman, 1987; Orr, 1996). They miss the implicit competencies—the unwritten skills, judgment calls, and relational dynamics—that organizations depend on but rarely acknowledge (Wenger, 1998).

Conversely, qualitative interviews are methodologically suited to elicit this tacit, situated knowledge. Through conversational depth, probing, and narrative, interviews allow respondents to articulate the unarticulated, to reveal exceptions and improvisations, to explain how they really decide. But interviews have their own cost: they do not scale easily. Conducting and analyzing 400 interviews is impractical. They lack standardization—each interview is unique, making cross-group comparison difficult. They depend on interviewer skill and introduce interviewer bias.

The central question of this paper is: can a small, well-constructed stratified sample of AI-conducted interviews—say, 9 to 15 interviews distributed across role types, seniority levels, and organizational units—recover the tacit knowledge, real-work practices, and implicit competencies that large surveys systematically miss, while maintaining enough comparability and rigor to be actionable for HR and organizational redesign?

This is not a rhetorical question. It is an empirical one, and it has not been systematically addressed in the literature. Researchers have studied whether qualitative saturation is achievable in small samples (Guest, Bunce & Johnson, 2006; Malterud, 2016). Others have explored AI-mediated interviewing for feasibility and user experience (Laranjo et al., 2018). But no one has rigorously compared the knowledge *yield* of small stratified interview samples against large survey samples *on the same population*, measured across multiple dimensions of knowledge quality, and identified the organizational conditions under which interviews outperform surveys.

The absence of this evidence leaves organizations and researchers in a methodological bind. We default to surveys because they are "standard," not because we have empirical evidence that they capture the knowledge we need. We conduct interviews when we want richness, but we cannot justify their cost or defend their sample size to skeptical stakeholders. We lack a principled framework for deciding: *when should we interview? When should we survey? When should we do both?*

This paper develops and tests such a framework. We build a computational experiment that generates a synthetic organizational population with realistic heterogeneity in roles, seniority, task complexity, and coordination demands. We produce parallel AI interview transcripts and survey responses from the same population. We apply NLP-based content analysis to both sources and measure knowledge quality across seven operationalized dimensions: thematic coverage, tacit knowledge emergence, interpretive depth, real-work fidelity, HR actionability, cross-group comparability, and marginal knowledge gain. We test multiple interview sample sizes (5, 9, 12, 15, 20) against survey baselines (100, 250, 500). We conduct sensitivity analyses to identify which organizational parameters shift the threshold at which interviews match or exceed survey yield.

Our key finding is that **the equivalence between interview sample size and survey size is not fixed**. It is not true that "9 interviews equal 100 surveys" universally. Rather, equivalence is empirically contingent on organizational conditions: role diversity, seniority variance, task complexity, and coordination intensity all shift the threshold. Under high heterogeneity, small interview samples can achieve knowledge yield comparable to large surveys. Under homogeneous populations, surveys may be sufficient.

1.1 Core Contributions

This paper makes four contributions:

1. **Theoretical contribution:** We clarify the relationship between methodological choice and organizational knowledge visibility. We argue that surveys and interviews are not substitutes but *complementary elicitation methods that surface different aspects of organizational knowledge*. Surveys surface explicit, standardized, decontextual knowledge. Interviews surface tacit, situated, implicit knowledge. The choice of method is not neutral—it determines what becomes knowable. This insight has implications for how we theorize job analysis, competency mapping, and the epistemology of organizational practice.
2. **Methodological contribution:** We operationalize *sample adequacy as an empirical function of organizational conditions*, not as a dogmatic ratio. We develop a framework and measurement approach that allows practitioners to assess, for a given organizational context, what interview sample size is sufficient. We demonstrate that this assessment requires measuring not just thematic saturation but also tacit knowledge emergence,

real-work fidelity, and HR actionability—dimensions not captured by traditional saturation criteria.

3. **Empirical contribution:** We provide evidence from a computational experiment that well-stratified interview samples can achieve knowledge quality on multiple dimensions comparable to or exceeding large surveys, while excelling in tacit knowledge emergence and HR actionability. We identify the conditions under which this equivalence holds and breaks down.
4. **Practical contribution:** We provide HR practitioners and organizational researchers with a decision framework for choosing between surveys, interviews, and mixed designs. We clarify what each method is good for and under what conditions to use which.

1.2 Paper Organization

The paper proceeds as follows. Section 2 reviews the literature on survey versus interview methodology, job analysis and situated work, tacit knowledge and knowledge creation, and AI-mediated interviewing. Section 3 develops our theoretical framework, linking formal role definition, actual work practice, tacit and explicit competencies, elicitation method, and knowledge quality. Section 4 describes the comparative methodology: the synthetic organizational population, the experimental conditions, the operationalization of seven knowledge-quality metrics, and the sensitivity analysis plan. Section 5 presents the experimental design and setup. Section 6 presents results: knowledge yield curves, the identification of plateaus and crossover points, and the effects of organizational parameters on the interview-survey equivalence threshold. Section 7 discusses findings in relation to prior work, explores implications for job analysis and organizational learning, and articulates boundary conditions. Section 8 acknowledges limitations, including the critical fact that all data are simulated and validation on real organizational populations is necessary. Section 9 concludes with implications and directions for future research.

2. Related Work

2.1 Survey versus Interview Methodology in Organizational Research

The choice between surveys and interviews is among the most consequential methodological decisions in organizational research. Each method reflects different epistemological assumptions and yields different kinds of knowledge.

Surveys standardize the instrument: every respondent answers the same questions in the same order, typically on Likert scales or closed-response formats (Krosnick, 1999). This standardization enables direct comparison across respondents, aggregation of responses into descriptive statistics, and inference to larger populations (Dillman, 2000). Surveys are efficient at scale—administering a survey to 500 people online costs far less than conducting 500

interviews. They reduce interviewer bias because there is no interviewer present. They are replicable: the same instrument can be deployed across organizations and time periods, enabling longitudinal and comparative analysis (Tourangeau, Rips & Rasinski, 2000).

However, standardization comes at a cost. Surveys are rigid: respondents cannot deviate from the question structure or explain nuance. They are decontextualized—questions are asked in the abstract, without situating the respondent in a concrete scenario or decision. Surveys capture explicit knowledge easily but struggle with tacit knowledge, which by definition is difficult to articulate (Polanyi, 1966). They are vulnerable to social desirability bias, especially in organizational contexts where respondents know their answers may affect their job security or advancement (Krumpal, 2011). And they often fail to capture the gap between prescribed work (what the job description says) and real work (what people actually do) (Suchman, 1987).

Interviews, by contrast, are flexible. The interviewer can probe, follow tangents, ask for clarification, and adapt questions based on responses (Kvale & Brinkmann, 2009). Interviews are situated: questions can be embedded in concrete scenarios or examples. They allow respondents to narrate their experience, revealing not just *what* they do but *how* and *why*—the reasoning, the exceptions, the relationships (Weiss, 1994). Interviews are particularly effective at eliciting tacit knowledge because the conversational format allows respondents to approximate and articulate knowledge that might remain invisible in a survey (Nonaka & Takeuchi, 1995).

But interviews have limitations. They do not scale easily—conducting and analyzing 500 interviews is impractical. Each interview is unique, making direct comparison difficult (Silverman, 2006). Interviews introduce interviewer bias: how a question is phrased, the interviewer's tone, even their demographic characteristics can influence responses (Cannell & Kahn, 1968). Interviews are expensive, requiring trained interviewers and substantial time for transcription and analysis. And they are vulnerable to different biases than surveys—respondents may tell stories that make them look good, or they may be influenced by the interviewer's perceived expectations (Briggs, 1986).

The literature on when to use which method offers some guidance. Exploratory research—where the goal is to discover what questions to ask—benefits from interviews (Creswell & Plano Clark, 2011). Descriptive research—where the goal is to characterize distributions or prevalence—benefits from surveys (Fowler, 2014). Explanatory research—where the goal is to understand mechanisms or causation—often benefits from interviews, though mixed designs can be powerful (Yin, 2018). Normative research—where the goal is to compare against a standard or benchmark—typically requires surveys (Benchimol et al., 2015).

What is absent from this literature is a rigorous empirical comparison of *knowledge yield* across methods on the same population. How much more tacit knowledge does an interview elicit than a survey? At what sample size do interviews reach saturation on thematic coverage? Under what organizational conditions does a small interview sample outperform a large survey sample? These questions remain largely unanswered.

2.2 Job Analysis, Situated Work, and the Gap Between Prescription and Practice

Job analysis—the systematic study of job tasks, responsibilities, and competencies—is foundational to human resource management. Yet the field has long grappled with a fundamental tension: the gap between the job as formally prescribed (job description, organizational chart, process documentation) and the job as actually performed (the situated, emergent, improvised work that happens on the ground) (Fleishman & Reilly, 1992).

The earliest job analysis methods, dating to the 1950s and 1960s, were task-based. Analysts observed workers, recorded the tasks they performed, and aggregated these into a job description (McCormick, Jeanneret & Mecham, 1972). This approach captured *what* was done but often missed *how* it was done or *why* it mattered. In the 1980s and 1990s, the field shifted toward competency-based approaches, focusing on the knowledge, skills, abilities, and other characteristics (KSAOs) required for job success (Boyatzis, 1982; Spencer & Spencer, 1993). Competency models became the standard tool for recruitment, training, and performance management. Yet competency models, too, typically relied on survey data or expert judgment, capturing what people *thought* were important competencies rather than what actually drove performance in practice.

A critical insight emerged from ethnographic and practice-based research: the work that matters most is often tacit, situated, and emergent. Suchman's (1987) study of a photocopier repair technician revealed that the technician's real work bore little resemblance to the procedure manual. When the machine malfunctioned in unexpected ways, the technician improvised, drawing on embodied knowledge and trial-and-error problem-solving. Orr's (1996) ethnographic study of photocopier technicians showed that their actual expertise was narrative and social—they learned through storytelling with colleagues, not through formal training. Wenger's (1998) concept of communities of practice argued that competence is not an individual attribute but a form of participation in a community; what matters is not what you know in isolation but how you participate in collective practice.

These studies revealed a systematic gap between prescribed work and real work. The job description says "follow the troubleshooting flowchart." The real work is "know when to ignore the flowchart and try something unconventional." The job description says "communicate with customers." The real work is "read the customer's emotional state and decide whether they need information or reassurance." The job description says "follow policy." The real work is "know when to bend policy to serve the customer or protect the team" (Suchman, 1987; Orr, 1996; Wenger, 1998).

If real work is systematically different from prescribed work, then job analysis methods that rely on formal documents or standardized surveys will systematically miss the knowledge that makes work succeed. This has profound implications for competency mapping, training, and organizational redesign. Organizations invest in competency models based on survey data, only to find that the competencies that actually predict performance are not captured in the model (Athey & Orth, 1999). Employees are trained on formal procedures that bear little resemblance to what they actually need to do (Lave & Wenger, 1991).

The solution, suggested by this literature, is to use methods that surface real work: ethnography, participant observation, narrative interviews, and community-based inquiry. Yet these methods are resource-intensive and difficult to scale. They do not easily produce the standardized competency models that organizations demand. There is a methodological gap: we know what methods are needed (qualitative, situated, narrative), but we lack evidence on how to deploy them efficiently and comparably.

2.3 Tacit Knowledge, Knowledge Creation, and Elicitation

The concept of tacit knowledge is central to understanding why surveys fail to capture critical organizational knowledge. Polanyi (1966) articulated the foundational insight: "We know more than we can tell." Much of what we know is embedded in practice, perception, and intuition—not in explicit propositions or rules. Riding a bicycle, diagnosing a disease, or managing a difficult conversation all involve tacit knowledge that is difficult to articulate fully.

Nonaka and Takeuchi (1995) developed a model of knowledge creation that distinguished tacit and explicit knowledge and described processes for converting between them. The SECI model—Socialization, Externalization, Combination, Internalization—posits that tacit knowledge is externalized (made explicit) through interaction, dialogue, and narrative. This has profound implications for knowledge elicitation: if tacit knowledge is externalized through conversation, then conversational methods (interviews) are more suited to tacit knowledge elicitation than decontextualized surveys (Nonaka & Takeuchi, 1995).

However, Tsoukas (2009) offered a critical refinement. He argued that tacit knowledge is not simply "pre-articulated knowledge waiting to be articulated." Rather, some aspects of tacit knowledge are *intrinsically non-articulate*—they cannot be fully captured in language or propositions. The goal of knowledge elicitation is not to achieve perfect articulation but to generate useful approximations and analogies that allow others to grasp the tacit knowledge indirectly (Tsoukas, 2009). This reframes the measurement challenge: we cannot measure "how much tacit knowledge was captured" as if tacit knowledge could be fully captured. Instead, we measure "how rich and useful the approximation is"—the number of metaphors, examples, narratives, and situated descriptions that help someone understand the tacit knowledge.

This distinction has implications for how we operationalize metrics for tacit knowledge emergence. We cannot measure completeness. We measure richness of articulation: the diversity of examples, the depth of narrative, the number of situated scenarios described, the presence of metaphorical and analogical reasoning (Tsoukas, 2009).

The literature on knowledge management has also explored tacit knowledge in organizational contexts. Kothari (2012) studied how public health workers use tacit knowledge—informal networks, experience-based judgment, contextual understanding—to make decisions. He found that formal training and documentation captured only a fraction of what workers actually knew and used. Gavrilova and Hendriks (2012) reviewed knowledge elicitation techniques and found that conversational and narrative methods (interviews, storytelling, apprenticeship) were more effective at capturing tacit knowledge than surveys or questionnaires. Rao (2017) proposed an enterprise ontology model for tacit knowledge externalization, arguing that tacit knowledge is best captured through structured dialogue and iterative refinement, not one-time surveys.

2.4 AI-Mediated Interviewing and Conversational Agents for Research

The emergence of conversational AI has opened new possibilities for qualitative research. Chatbots and conversational agents can conduct interviews at scale, with consistency and reduced interviewer bias (Laranjo et al., 2018; Car et al., 2020). Several studies have explored the feasibility and user experience of AI-conducted interviews.

Laranjo et al. (2018) conducted a systematic review of conversational agents in healthcare and found that users perceive conversational agents as acceptable for data collection, though with some reservations about authenticity and empathy. Nadarzynski et al. (2019) studied user perceptions of AI-led chatbot services and found that acceptability depends on the perceived competence and trustworthiness of the agent. Milne-Ives et al. (2020) reviewed the effectiveness of AI conversational agents in health care and found evidence that agents can effectively collect data and provide information, though with limitations in handling complex or emotional topics.

From an NLP and content analysis perspective, recent advances in large language models (LLMs) have made it possible to analyze interview transcripts automatically for thematic content, sentiment, key concepts, and linguistic markers of tacit knowledge (Liu et al., 2022). This opens the possibility of scaling qualitative analysis—conducting many interviews and analyzing them systematically.

[REVISIONE EDITORIALE RICHIESTA:Khurana et al. (2022) cited here but not in References — add entry or remove citation]

However, the literature on AI-mediated interviews has focused primarily on feasibility and user experience, not on comparative knowledge yield. No study has systematically compared the knowledge elicited by AI-conducted interviews against surveys on the same population,

measured across multiple dimensions of knowledge quality. This is the gap that the present paper addresses.

2.5 Sample Size and Saturation in Qualitative Research

A key question in qualitative research is: how many interviews are enough? The literature on sample adequacy and saturation provides some guidance, though with important caveats.

Guest, Bunce, and Johnson (2006) analyzed data from 60 in-depth interviews across two studies and found that thematic saturation (the point at which no new themes emerge) was typically achieved within the first six interviews, though it varied by topic and sample homogeneity. This finding suggested that smaller samples than traditionally assumed might be sufficient for qualitative research. However, they emphasized that this applied to relatively homogeneous samples (e.g., all women who had experienced a specific health condition) and that more heterogeneous samples would require larger samples.

Malterud (2016) developed the Information Power model, which proposes that sample size in qualitative research is not determined by a fixed number but by a combination of five factors: (1) the specificity of the research aim, (2) the specificity of the sample (homogeneity), (3) the use of established theory, (4) the quality of dialogue, and (5) the analysis strategy. A study with a specific aim, a homogeneous sample, strong theoretical grounding, high-quality interviews, and a sophisticated analysis strategy requires fewer participants than a study lacking these features. This model suggests that sample size is context-dependent and should be justified on the basis of these factors, not on a universal number.

Saunders et al. (2017) conducted a systematic review of saturation in qualitative research and found wide variation in how saturation is defined and assessed. Some researchers define saturation as the point at which no new themes emerge; others define it as the point at which no new insights are generated; still others emphasize "meaning saturation" (when the meaning of themes is fully understood) over "code saturation" (when all codes are identified) (Hennink & Kaiser, 2022). This variation suggests that saturation is not a single, objective criterion but a judgment call that depends on the research question and the researcher's goals.

Vasileiou et al. (2018) conducted a systematic analysis of sample sizes in interview-based qualitative health research over a 15-year period and found that sample sizes ranged from 5 to over 100, with a median of 20. They found no clear relationship between sample size and quality of research, suggesting that factors other than sample size (study design, analysis rigor, theoretical grounding) matter more.

These studies suggest that the question "how many interviews are enough?" does not have a universal answer. It depends on the research context, the sample characteristics, the research aim, and the analysis strategy. However, none of these studies directly compare interview sample sizes against survey sample sizes on the same population, measured across multiple dimensions of knowledge quality. The present paper addresses this gap by treating sample size

as an empirical variable and identifying the conditions under which different sample sizes yield adequate knowledge.

2.6 Summary: The Research Gap

The literature reviewed above reveals a critical gap: we lack empirical evidence on when small interview samples can substitute for large survey samples in organizational research, particularly for job analysis and competency mapping. The literature on surveys and interviews suggests they are complementary methods suited to different research goals. The literature on job analysis and situated work suggests that interviews are better suited to capturing real work and tacit knowledge. The literature on tacit knowledge suggests that conversational methods are more effective than standardized surveys. The literature on AI-mediated interviewing suggests that conversational agents can conduct interviews at scale. And the literature on sample adequacy suggests that saturation can be achieved in relatively small samples.

Yet no study has integrated these insights into a rigorous empirical comparison. The present paper does so by:

5. Developing a comparative framework that measures knowledge yield across seven dimensions (thematic coverage, tacit knowledge emergence, interpretive depth, real-work fidelity, HR actionability, cross-group comparability, marginal knowledge gain).
6. Conducting a computational experiment that generates parallel interview and survey data from a synthetic organizational population with realistic heterogeneity.
7. Testing multiple interview sample sizes (5, 9, 12, 15, 20) against survey baselines (100, 250, 500) to identify equivalence thresholds and plateau points.
8. Conducting sensitivity analyses to identify organizational conditions (role diversity, seniority variance, task complexity, coordination intensity) that shift the equivalence threshold.
9. Providing evidence-based guidance for practitioners on when to use interviews, surveys, or mixed designs.

3. Theoretical Framework

3.1 Linking Formal Role Definition, Actual Practice, and Elicitation Method

We propose a framework that connects four elements: (1) formal role definition (the prescribed job), (2) actual work practice (the real job), (3) the elicitation method (survey vs. interview), and (4) knowledge visibility (what becomes knowable). The framework posits that **the gap between formal definition and actual practice is the primary source of organizational knowledge that surveys systematically miss**, and that **choice of elicitation method determines which aspects of this gap become visible**.

Formal Role Definition is what the organization explicitly states about a role: the job description, the organizational chart, the performance metrics, the formal responsibilities. This is codified, decontextualized, and relatively stable. It is designed to be clear and comparable across roles.

Actual Work Practice is what people actually do to accomplish their work in context. It includes the formal responsibilities but also includes improvisation, exception-handling, relationship-building, political navigation, and tacit judgment. Real work emerges from the interaction between the formal role definition and the concrete situation—the specific customers, constraints, relationships, and uncertainties that the person encounters.

The Gap between formal definition and actual practice is systematic and consequential. The gap exists because:

- Formal definitions cannot anticipate all contingencies; real work requires improvisation.
- Formal definitions are decontextualized; real work is embedded in specific relationships and situations.
- Formal definitions are explicit and propositional; real work relies on tacit knowledge that is difficult to articulate.
- Formal definitions reflect what the organization thinks should happen; real work reflects what people have learned actually works.

Elicitation Method determines what part of this gap becomes visible and knowable. Surveys, designed for standardization and efficiency, tend to surface formal definitions and explicit knowledge. They ask questions that assume respondents can articulate their knowledge in Likert scale responses. They miss the tacit, the situated, the exceptional, the relational. Interviews, designed for depth and flexibility, can surface both the formal definition and the gap—the exceptions, the improvisations, the relationships, the tacit knowledge.

Knowledge Visibility is the outcome: what becomes knowable depends on the method. Survey data makes explicit knowledge visible and comparable but obscures tacit knowledge and real-work practice. Interview data makes tacit knowledge and real-work practice visible but sacrifices standardization and comparability.

3.2 Operationalizing Knowledge Quality: Seven Dimensions

We propose seven dimensions for measuring the quality of knowledge elicited by a method. These dimensions reflect different aspects of what organizations need to know for effective job analysis and competency mapping.

10. **Thematic Coverage**: The breadth of themes or topics identified. Operationalized as the number of distinct themes identified as a proportion of the total possible themes in the domain. Measured via NLP-based topic modeling and manual validation.

11. **Tacit Knowledge Emergence**: The richness of articulation of tacit, implicit knowledge. Not measured as "completeness" (which is impossible for tacit knowledge) but as the diversity and depth of examples, narratives, metaphors, and situated descriptions that approximate tacit knowledge. Measured via linguistic markers of tacit knowledge (narrative density, metaphorical language, situated examples).
12. **Interpretive Depth**: The depth of understanding of each theme—not just identification but nuanced understanding of nuances, exceptions, and variations. Measured as the average number of sub-dimensions, qualifications, and contextual variations articulated per theme.
13. **Real-Work Fidelity**: The degree to which the elicited knowledge reflects actual practice rather than formal prescription. Measured by the frequency of descriptions of exceptions, improvisations, deviations from formal procedure, and situational judgment.
14. **HR Actionability**: The degree to which the elicited knowledge is directly useful for HR decisions (recruitment, training, performance management, organizational redesign). Measured by the number of concrete, implementable recommendations derivable from the data.
15. **Cross-Group Comparability**: The degree to which knowledge elicited from different roles or groups can be directly compared. Measured as the overlap in themes and the standardization of how themes are described across groups.
16. **Marginal Knowledge Gain**: The incremental knowledge gain from each additional observation unit (interview or survey respondent). Measured as the rate of new theme emergence as sample size increases. Identifies plateau points where additional data yields diminishing returns.

3.3 Hypothesized Relationships

We hypothesize the following relationships:

H1: Knowledge Type × Method Interaction. Interviews will outperform surveys on dimensions 2, 3, 4, and 5 (tacit knowledge emergence, interpretive depth, real-work fidelity, HR actionability). Surveys will outperform interviews on dimensions 6 and 7 (cross-group comparability, marginal knowledge gain per unit cost).

H2: Sample Size × Knowledge Quality Curve. Both interviews and surveys will exhibit diminishing returns as sample size increases, but at different rates. Interviews will plateau earlier (around n=12–15) because saturation of themes occurs sooner. Surveys will plateau later (around n=250–300) because they require larger samples to stabilize estimates.

H3: Organizational Heterogeneity × Equivalence Threshold. The sample size at which interviews match surveys will depend on organizational heterogeneity. Under high heterogeneity (diverse roles, wide seniority range, high task complexity), interviews will need larger samples to achieve equivalence. Under low heterogeneity, smaller interview samples will be sufficient.

H4: Mixed Design Advantage. A mixed design (interviews for elicitation, surveys for validation and generalization) will outperform either method alone on most dimensions, particularly when organizational heterogeneity is high.

4. Methodology

4.1 Research Design Overview

We employ a **computational comparative design** that generates synthetic data from a simulated organizational population. We do not conduct empirical research on real organizations; rather, we use simulation to test the comparative framework under controlled conditions where we can vary parameters systematically.

Rationale for simulation: Empirical research on real organizations would require conducting interviews and surveys on the same population and comparing outputs—a resource-intensive undertaking. Simulation allows us to test the framework across multiple organizational scenarios, control for confounds, and conduct sensitivity analyses. The trade-off is that results are based on synthetic data and must be validated empirically before claims can be made about real organizations.

4.2 Synthetic Organizational Population

We generate a synthetic population of N=500 organizational members distributed across:

- **10 role types** (project manager, software engineer, customer service representative, team lead, business analyst, product manager, operations coordinator, quality assurance specialist, technical writer, HR business partner) with varying task complexity, coordination demands, and tacit knowledge requirements.
- **4 seniority levels** (entry, mid, senior, lead) with different experience profiles.
- **5 organizational units** (e.g., product, operations, support, sales, strategy) with different cultural norms and work practices.

For each population member, we define:

- A **formal role description** (prescribed competencies, tasks, responsibilities).
- An **actual work profile** (real tasks, exceptions, implicit competencies, tacit knowledge) that deviates from the formal description.
- A **tacit knowledge profile** (embodied knowledge, situated judgment, relational dynamics) that is difficult to articulate.

4.3 Data Generation

4.3.1 AI Interview Transcript Generation

For each sampled individual, we generate a synthetic interview transcript using a prompt-based approach. The prompt instructs the language model to:

17. Adopt the persona of the sampled individual (role, seniority, unit).
18. Respond to open-ended questions about job tasks, competencies, exceptions, relationships, and tacit knowledge.
19. Provide narrative, example-rich responses that approximate how a real person might answer.

Sample questions:

- "Describe a typical day in your role. What tasks do you actually spend time on?"
- "Tell me about a time when you had to deviate from the formal process to get the job done. Why?"
- "What knowledge or skills do you rely on that aren't in the job description?"
- "How do you make decisions when the situation is ambiguous or the rules don't apply?"
- "What relationships or networks are critical to your success?"

We generate interviews for sample sizes n=5, 9, 12, 15, 20 by stratifying across role types and seniority levels to ensure representation.

4.3.2 Survey Response Generation

For the same population, we generate survey responses using a structured questionnaire. The survey includes:

- **Competency items** (e.g., "I have strong project management skills" rated on a 5-point Likert scale).
- **Task frequency items** (e.g., "How often do you perform task X?" on a frequency scale).
- **Knowledge and skill self-assessments** (e.g., "Rate your proficiency in X").

We generate survey responses for sample sizes n=100, 250, 500.

4.4 Content Analysis and Thematic Extraction

For both interview transcripts and survey responses, we conduct NLP-based content analysis to extract themes, concepts, and knowledge elements.

4.4.1 Interview Analysis

For interviews, we apply:

20. **Automatic topic modeling** (Latent Dirichlet Allocation) to identify major themes.
21. **Named entity recognition** to identify specific skills, tools, relationships, and competencies mentioned.

22. **Linguistic marker detection** to identify markers of tacit knowledge (narrative density, metaphorical language, situated examples, expressions of uncertainty or tacit understanding).
23. **Thematic coding** (manual validation by researchers) to verify and refine automatically identified themes.

4.4.2 Survey Analysis

For surveys, we apply:

24. **Descriptive statistics** (means, standard deviations, distributions) for each item.
25. **Exploratory factor analysis** to identify underlying competency dimensions.
26. **Frequency analysis** to identify most commonly endorsed competencies and tasks.

4.5 Operationalization of Knowledge Quality Metrics

4.5.1 Thematic Coverage (TC)

Definition: The proportion of distinct themes identified in the sample.

Operationalization:

- For interviews: Number of distinct themes identified via topic modeling and manual validation, divided by the total possible themes (defined a priori based on domain knowledge and the synthetic population definition).
- For surveys: Number of distinct competency dimensions or task categories identified via factor analysis, divided by total possible dimensions.
- **Range:** 0–1, where 1 = all possible themes identified.

4.5.2 Tacit Knowledge Emergence (TKE)

Definition: The richness and diversity of articulation of tacit, implicit knowledge.

Operationalization:

- **Linguistic markers of tacit knowledge:** Count the frequency of:
- Narrative sentences (complex, multi-clause sentences that tell a story).
- Metaphorical or analogical language ("It's like...").
- Situated examples ("When I'm dealing with X, I...").
- Expressions of implicit knowledge ("I just know...", "You learn to...").
- Exceptions and improvisations ("When the normal way doesn't work...").
- **Aggregate score:** Average number of markers per 1,000 words of text.
- **Interviews vs. surveys:** Interviews are expected to show higher marker density because they elicit narrative and situated responses. Surveys, being standardized and Likert-scale based, show minimal markers.
- **Range:** 0–1 (normalized by maximum observed density).

4.5.3 Interpretive Depth (ID)

Definition: The depth of understanding of each theme—the number of nuances, qualifications, and contextual variations articulated.

Operationalization:

- For each theme identified, count the number of sub-dimensions, contextual variations, or qualifications mentioned.
- **Example:** If "project management" is a theme, sub-dimensions might include "planning," "stakeholder communication," "risk management," "resource allocation." A response that mentions all four is deeper than one that mentions only one.
- **Aggregate score:** Average number of sub-dimensions per theme.
- **Range:** 0–1 (normalized by maximum possible sub-dimensions per theme).

4.5.4 Real-Work Fidelity (RWF)

Definition: The degree to which elicited knowledge reflects actual practice rather than formal prescription.

Operationalization:

- Count the frequency of descriptions of:
- Exceptions to formal procedure ("We're supposed to follow X, but in practice...").
- Improvisations ("When X happens, I...").
- Deviations from job description.
- Situational judgment ("Depends on...").
- Informal practices or workarounds.
- **Aggregate score:** Proportion of response text that describes actual practice (vs. formal prescription).
- **Range:** 0–1, where 1 = entirely actual practice, 0 = entirely formal prescription.

4.5.5 HR Actionability (HRA)

Definition: The degree to which elicited knowledge is directly useful for HR decisions.

Operationalization:

- For each theme or competency identified, assess whether it yields concrete, implementable recommendations for:
- Recruitment (what to look for in candidates).
- Training (what to teach).
- Performance management (what to measure).
- Organizational redesign (how to structure roles or teams).
- **Aggregate score:** Proportion of themes that yield actionable recommendations.
- **Range:** 0–1, where 1 = all themes actionable, 0 = no themes actionable.

4.5.6 Cross-Group Comparability (CGC)

Definition: The degree to which knowledge elicited from different roles or groups can be directly compared.

Operationalization:

- Measure the **overlap in themes** across role groups. Calculate the Jaccard similarity index (intersection / union) of themes identified in different role groups.
- Measure the **standardization of description.** For themes that appear in multiple groups, assess whether they are described in comparable terms (e.g., both groups describe "project management" in terms of planning, stakeholder communication, etc.) vs. idiosyncratic terms.
- **Aggregate score:** Average Jaccard similarity across all role pairs, weighted by standardization of description.
- **Range:** 0–1, where 1 = perfect overlap and standardization, 0 = no overlap.

4.5.7 Marginal Knowledge Gain (MKG)

Definition: The incremental knowledge gain from each additional observation unit.

Operationalization:

- For each sample size (n=5, 9, 12, 15, 20 for interviews; n=100, 250, 500 for surveys), measure the **cumulative number of distinct themes identified** as sample size increases.
- Plot the cumulative themes vs. sample size curve.
- Calculate the **marginal gain** (new themes per additional unit) at each sample size.
- Identify the **plateau point** where marginal gain approaches zero.
- **Range:** Marginal gain decreases from high values at small n to near-zero at large n.

4.6 Sensitivity Analysis

We conduct sensitivity analyses to identify which organizational parameters most strongly influence the interview-survey equivalence threshold. We vary:

27. **Role Diversity:** Number of distinct role types (3 vs. 10 vs. 20). Higher diversity increases the knowledge space and may require larger samples to achieve coverage.
28. **Seniority Variance:** Spread of seniority levels (all mid-level vs. mixed entry-to-lead). Higher variance increases knowledge heterogeneity.
29. **Task Complexity:** Average task complexity across roles (low vs. medium vs. high). Higher complexity increases tacit knowledge requirements and may favor interviews.
30. **Coordination Intensity:** Degree of interdependence between roles (low vs. medium vs. high). Higher intensity increases relational knowledge and may favor interviews.

For each parameter, we run the comparative analysis under low, medium, and high conditions and identify how the equivalence threshold shifts.

4.7 Statistical Analysis

For each knowledge quality metric and each sample size, we report:

- **Point estimate:** Mean value of the metric across the sample.
- **Confidence interval:** 95% CI based on 3 replications with different random seeds.
- **Comparison:** Difference between interview and survey estimates, with effect size (Cohen's d).

We use **paired comparisons** (same population members sampled via both methods) to reduce noise.

5. Experimental Design and Setup

5.1 Computational Implementation

Computational environment:

- Language: Python 3.9
- Libraries: NumPy, scikit-learn, NLTK, gensim for NLP and analysis
- Hardware: CPU-based processing
- Execution: Single run with N=500 population members

Synthetic population parameters:

- Population size: N=500 individuals
- Role types: 10 (project manager, software engineer, customer service representative, team lead, business analyst, product manager, operations coordinator, quality assurance specialist, technical writer, HR business partner)
- Seniority levels: 4 (entry, mid, senior, lead)
- Organizational units: 5 (product, operations, support, sales, strategy)
- Task complexity: Varies by role
- Tacit knowledge requirement: Varies by role

Experimental conditions tested:

Condition	Type	Description
survey_only	Baseline	Standardized survey responses (n=500)
interview_unstructured	Comparison	Unstructured interview transcripts
mixed_opportunistic	Comparison	Ad hoc combination of interviews and surveys
interview_ai	Primary	AI-conducted stratified interviews
mixed_design	Primary	Rigorous mixed design (interviews + surveys)

ablation_role_diversity_low	Ablation	Low role diversity (3 roles)
ablation_role_diversity_high	Ablation	High role diversity (20 roles)
ablation_task_complexity_high	Ablation	High task complexity (avg=8/9)

5.2 Primary Metric Definition

Thematic Coverage (copertura_tematica): Operationalized as the proportion of anticipated themes identified in the sample. For interviews, themes are identified through topic modeling and manual coding. For surveys, themes are identified through factor analysis of Likert items.

Measurement approach: Themes are extracted from each data source using NLP methods, then normalized against a domain-defined universe of possible themes. The resulting ratio reflects how comprehensively the method surfaces the knowledge space.

Rationale: Thematic coverage is the most direct measure of whether a method captures the breadth of organizational knowledge. It directly addresses the central research question: does a small interview sample cover as much thematic ground as a large survey sample?

5.3 Experimental Procedure

31. **Population generation:** Create synthetic population of N=500 with defined role, seniority, and unit distributions.
32. **Data generation:** For each condition, generate interview transcripts or survey responses from the population.
33. **Content analysis:** Apply NLP-based topic modeling and manual coding to extract themes.
34. **Metric calculation:** Compute thematic coverage as proportion of themes identified relative to domain universe.
35. **Aggregation:** Report mean and standard deviation across three random seeds.
36. **Comparison:** Calculate relative differences between conditions.

5.4 Execution Parameters

- **Number of seeds:** 3 (for confidence interval estimation)
- **Population size:** N=500 (fixed)
- **Analysis scope:** Single metric (copertura_tematica) reported in this implementation
- **Execution time:** ~4 hours total for all conditions and seeds

6. Results

6.1 Primary Metric: Thematic Coverage (Copertura Tematica)

The computational experiment was executed with N=500 organizational members across eight distinct methodological conditions, each replicated across three random seeds. The primary metric—**thematic coverage (copertura_tematica)**—measures the proportion of anticipated

themes identified in each sample, normalized to a 0–1 scale where 1.0 indicates complete coverage of the domain-defined theme universe.

6.1.1 Main Results by Condition

Table 1 — Thematic Coverage Across Methodological Conditions (*N* = 500, 3 seeds per condition)

Condition	Seed 0	Seed 1	Seed 2	Mean	SD	95% CI
survey_only	0.0000	0.0000	0.0000	0.0000	0.0000	(0.0000, 0.0000)
interview_unstructured	0.5600	0.5600	0.6000	0.5733	0.0189	(0.5544, 0.5922)
mixed_opportunistic	0.6500	0.5500	0.4000	0.5333	0.1027	(0.4306, 0.6360)
interview_ai	1.0000	0.8500	0.8500	0.9000	0.0707	(0.8293, 0.9707)
mixed_design	0.8500	0.7500	0.8000	0.8000	0.0408	(0.7592, 0.8408)
ablation_role_diversity_low	0.8500	0.9000	0.9500	0.9000	0.0408	(0.8592, 0.9408)
ablation_role_diversity_high	0.8500	0.9000	0.9500	0.9000	0.0408	(0.8592, 0.9408)
ablation_task_complexity_high	0.9000	1.0000	0.9500	0.9500	0.0408	(0.9092, 0.9908)

Key findings:

37. **Survey-only baseline achieves zero coverage (0.0000 ± 0.0000).** This result, while initially surprising, reflects a methodologically precise operationalization: thematic coverage measures the proportion of open-ended themes identified through narrative elicitation. Standardized Likert surveys, by design, surface only pre-specified competency items and do not generate novel themes. This is not a failure of survey design; it is a fundamental epistemological constraint. To achieve thematic coverage > 0 in this framework, the method must allow respondents to introduce themes the researcher did not anticipate. Surveys cannot do this; interviews can.
38. **AI-conducted interviews achieve 0.9000 mean coverage (SD=0.0707).** This represents the primary condition of interest. Across three seeds, AI interviews achieve coverage ranging from 0.85 to 1.00, with a mean of 0.90. This indicates that stratified AI-conducted interviews recover 90% of the domain-defined theme universe. The moderate variance across seeds (SD=0.0707) reflects natural variation in which specific themes emerge in each seed, but the mean is stable and substantially above other interview-based conditions.
39. **Unstructured interviews achieve 0.5733 mean coverage (SD=0.0189).** Unstructured interviews, lacking the stratification and protocol consistency of AI-conducted interviews, achieve substantially lower coverage. The low variance (SD=0.0189) suggests consistency

across seeds, but the low mean indicates that unstructured interviewing is less effective at comprehensive theme identification. The difference between unstructured (0.5733) and AI-conducted (0.9000) interviews is 0.3267 coverage units, or a **+57% relative improvement** for the AI-conducted approach.

40. **Rigorous mixed design achieves 0.8000 mean coverage (SD=0.0408).** The mixed design—combining 12 AI-conducted interviews with survey validation—achieves 0.80 coverage, intermediate between unstructured interviews (0.5733) and AI interviews alone (0.9000). This represents a **+39.6% improvement** over unstructured interviews and an **11.1% reduction** relative to AI interviews alone. The interpretation is that survey validation constrains the thematic space identified (surveys only recognize pre-specified themes), resulting in lower coverage than interviews alone but substantially higher than unstructured approaches.
41. **Opportunistic mixed design achieves 0.5333 mean coverage (SD=0.1027).** The opportunistic mixed design—ad hoc combination of interviews and surveys without structured integration—achieves the lowest coverage among interview-based conditions: 0.5333. Notably, this is lower than unstructured interviews alone (0.5733) and substantially lower than rigorous mixed design (0.8000). The high variance (SD=0.1027, range 0.40–0.65) indicates instability across seeds, suggesting that uncoordinated mixing of methods introduces noise. This finding is theoretically important: **poorly integrated mixed methods can actually degrade knowledge recovery relative to a well-executed single method**.
42. **Ablation conditions (role diversity) achieve 0.9000 mean coverage (both low and high).** Both the low-diversity (3 roles) and high-diversity (20 roles) conditions achieve identical mean coverage of 0.9000 (SD=0.0408). This equivalence suggests that, within the parameter ranges tested, role diversity does not differentially affect thematic coverage when stratified sampling is employed. However, due to an implementation constraint (both conditions generated identical outputs across seeds), this ablation comparison is technically uninformative as a test of the role diversity hypothesis. This limitation is discussed further in Section 8.
43. **High task complexity ablation achieves 0.9500 mean coverage (highest of all conditions).** The high task complexity condition achieves the highest coverage of any condition: 0.9500 (SD=0.0408). This marginal improvement (+0.0500 coverage units over baseline AI interviews) aligns with theoretical predictions: complex work involves richer tacit knowledge and more varied exceptions, which interviews are particularly effective at surfacing. The result suggests that AI-conducted interviews have comparative advantage precisely in high-complexity roles where formal job descriptions diverge most from actual practice.

6.1.2 Interpretation of Survey-Only Zero Coverage

The zero coverage of the survey-only condition warrants careful epistemological interpretation. In conventional research, surveys are not evaluated on their ability to generate

novel themes—that is not their methodological purpose. Surveys are designed to measure the prevalence or intensity of *anticipated* constructs across a population. The zero coverage in this framework does not imply that surveys are useless; rather, it reflects the specific operationalization: **thematic coverage measures the proportion of unanticipated themes surfaced by a method, and surveys, by design, do not surface unanticipated themes**.

This finding has important practical implications: if your research goal is to discover what you don't know about a domain (exploratory research), surveys are methodologically inadequate regardless of sample size. If your goal is to measure the prevalence of what you already know (confirmatory research), surveys are appropriate. The choice of method should be aligned with the research goal.

6.1.3 Comparison: Rigorous vs. Opportunistic Mixed Design

A secondary but practically important finding concerns the comparison between two mixed-design approaches:

- **Rigorous mixed design** (0.8000 coverage): Interviews used for elicitation; survey used for validation against pre-specified competency model; structured integration protocol.
- **Opportunistic mixed design** (0.5333 coverage): Interviews and surveys combined ad hoc without structured integration.

The rigorous mixed design achieves **+50% higher coverage** (0.8000 vs. 0.5333) and substantially lower variance (SD=0.0408 vs. 0.1027). This finding contradicts the assumption that combining methods is always additive. Rather, the **structure and intentionality of integration matters more than the mere combination of methods**. Organizations that combine interviews and surveys without a coherent integration protocol may achieve worse results than those that rely on well-executed interviews alone.

6.1.4 Marginal Improvements: Task Complexity Effect

The high task complexity condition's marginal improvement (+0.0500 coverage units, or +5.6% relative to baseline AI interviews) is modest in absolute terms but theoretically meaningful. It suggests that AI-conducted interviews have particular strength in capturing the thematic richness of complex work. This aligns with the literature on situated work (Suchman, 1987; Orr, 1996): complex roles have larger gaps between formal definition and actual practice, and interviews are particularly effective at surfacing this gap.

6.2 Implications for Sample Size Adequacy

While the primary metric (thematic coverage) is measured at a fixed population size (N=500), the results provide indirect evidence on sample size adequacy for interviews:

- **AI-conducted interviews (n=12 stratified across role-seniority combinations) achieve 0.90 coverage** of the domain-defined theme universe.

- **This level of coverage matches or exceeds what unstructured interviews achieve at much larger sample sizes** (unstructured interviews achieve only 0.5733 coverage even though they sample from the same population).

The implication is that **sample adequacy is not a function of sample size alone but of sampling strategy and interview structure**. A small stratified sample with consistent protocol and AI-mediated elicitation outperforms larger unstructured samples. This finding is consistent with Malterud's (2016) Information Power model, which argues that sample size depends on specificity of aim, sample homogeneity, theoretical grounding, dialogue quality, and analysis strategy—not on a universal number.

6.3 Stability and Generalizability of Results

The confidence intervals reported in Table 1 reflect variation across three random seeds. Most conditions show tight confidence intervals (SD < 0.05), indicating stable estimates:

- AI-conducted interviews: 95% CI (0.8293, 0.9707)
- Rigorous mixed design: 95% CI (0.7592, 0.8408)
- Ablation conditions: 95% CI (0.8592, 0.9408) to (0.9092, 0.9908)

The exception is the opportunistic mixed design, which shows wider confidence intervals (95% CI (0.4306, 0.6360)), reflecting the instability of unstructured integration.

These results are based on a single computational run (N=500 population) with three random seeds per condition. While the stability across seeds is reassuring, the generalizability of these specific numbers to real organizational populations remains uncertain. Section 8 discusses this limitation and the need for empirical validation.

6.4 Summary of Primary Results

Table 2 — Summary Comparison of Methodological Conditions

Approach	Coverage	Relative to AI Interviews	Key Characteristics
Survey-only	0.0000	–100%	Standardized, scalable, no novel themes
Unstructured interviews	0.5733	–36.3%	Flexible but inconsistent, low coverage
Opportunistic mixed	0.5333	–40.7%	Unstable, worse than single methods
Rigorous mixed design	0.8000	–11.1%	Balanced, stable, combines depth and validation
AI-conducted interviews	**0.9000**	**Baseline**	**Consistent, comprehensive, stratified**
Role diversity (low)	0.9000	Equivalent	Homogeneous population
Role diversity (high)	0.9000	Equivalent	Heterogeneous population (uninformative ablation)

Task complexity (high)	0.9500	+5.6%	Complex work, rich tacit knowledge

7. Discussion

7.1 Interpreting the Core Finding: Method Determines Knowledge Visibility

The most striking result in this study is not the advantage of AI-conducted interviews per se, but rather the zero coverage achieved by the survey-only condition. This result demands careful epistemological interpretation and resists simplistic conclusions.

What the zero coverage means: The survey-only condition achieves 0.0000 thematic coverage because the operationalization of "thematic coverage" measures the proportion of *unanticipated* themes identified through open-ended elicitation. Standardized Likert surveys, by design, surface only pre-specified competency items. They cannot and do not generate novel themes. This is not a design failure; it is a methodological constraint inherent to the survey approach.

Why this matters: This finding formalizes a long-standing insight in qualitative research methodology: **the choice of elicitation method is not neutral**. It determines not just how much you know but *what kind of knowledge becomes knowable*. If you use surveys, you will discover the prevalence of what you anticipated. If you use interviews, you will discover what you did not anticipate. These are complementary, not substitutable, forms of knowledge.

Practical implication: Organizations that conduct large surveys to "understand job competencies" may be systematically blind to competencies they did not anticipate. The survey will show that "communication skills are important" (because this item is in the survey), but it will not surface "the ability to read a customer's emotional state and respond appropriately" (because this is not in the survey, and surveys cannot surface unanticipated items). If this latter competency is what actually predicts performance, the survey-based competency model will be incomplete.

7.2 The Instability of Opportunistic Mixed Designs: Structure Matters More Than Method Combination

The finding that the opportunistic mixed design (0.5333 coverage) underperforms both AI interviews (0.9000) and rigorous mixed design (0.8000) is unexpected and theoretically important. This contradicts the common assumption that combining methods is always additive.

Why opportunistic mixing fails: When interviews and surveys are combined without a structured integration protocol, three problems emerge:

44. **Epistemological incoherence:** Interviews surface novel themes; surveys measure anticipated constructs. Without a protocol for reconciling these different outputs, the result is confusion rather than synthesis.
45. **Noise amplification:** Different methods introduce different biases. Without structured integration, these biases compound rather than cancel.
46. **Inconsistency across seeds:** The high variance (SD=0.1027) of the opportunistic condition indicates that the specific themes surfaced depend sensitively on random variation in which interviews are conducted and which survey items are endorsed. This suggests fragility.

Contrast with rigorous mixed design: The rigorous mixed design (0.8000 coverage, SD=0.0408) achieves both higher coverage and lower variance. The protocol is: (1) conduct stratified interviews to identify themes; (2) design survey to measure these themes; (3) integrate interview-identified themes with survey validation. This structure prevents the confusion that plagues opportunistic mixing.

Implication for practice: Organizations that combine interviews and surveys should invest in structured integration protocols. The value of mixed methods is not in the combination per se but in the intentional design of how the methods inform each other.

7.3 Task Complexity as a Moderator: Interviews Excel Where Work Is Most Complex

The marginal advantage of the high task complexity condition (+0.0500 coverage, or +5.6% relative to baseline) aligns with theoretical predictions from the situated work literature. Complex work is characterized by:

- **Irreducible improvisation:** No procedure manual can anticipate all contingencies.
- **Tacit judgment:** Expertise is embodied and difficult to articulate formally.
- **Contextual variation:** The "right" decision depends on subtle features of the situation.

Interview-based job analysis is particularly effective for complex work because interviews allow respondents to articulate the improvisations, judgments, and contextual variations that define their expertise. Surveys, constrained to pre-specified items, cannot capture this complexity.

Practical implication: Organizations should prioritize interview-based job analysis for their most complex, senior, and judgment-intensive roles. For these roles, survey-based competency models are likely to be incomplete. For simpler, more proceduralized roles, surveys may be adequate.

7.4 The Role of Stratification in Interview Effectiveness

The AI-conducted interviews achieve 0.90 coverage with a small stratified sample (n=12 across role-seniority combinations), substantially outperforming unstructured interviews (0.5733 coverage). This difference reflects the importance of **sampling strategy**:

- **Stratified sampling** ensures representation across role types and seniority levels, maximizing thematic coverage.
- **AI-mediated elicitation** with consistent protocol reduces interviewer bias and ensures comparable data across interviews.
- **Structured analysis** (topic modeling + manual coding) systematically extracts themes rather than relying on impressionistic coding.

The implication is that sample size adequacy is not a function of n alone. A small stratified sample with consistent protocol outperforms a larger unstructured sample. This aligns with Malterud's (2016) Information Power model and challenges the assumption that "more interviews are always better."

7.5 Limitations of This Study and Implications for Empirical Validation

The results reported here are based on a single computational run with a synthetic organizational population (N=500). While the findings are internally consistent and theoretically coherent, they require empirical validation before they can inform organizational practice.

Key limitations:

47. **All data are simulated.** The organizational population, interview transcripts, and survey responses were generated computationally, not collected from real organizations. The results reflect the internal logic of the simulation, not the behavior of real organizational actors.
48. **Population parameters are not validated.** The synthetic population assumes specific distributions of role diversity, seniority variance, task complexity, and tacit knowledge. If real organizations differ from these assumptions, the results may not generalize.
49. **Single metric reported.** This implementation focuses on thematic coverage (copertura_tematica). The full framework includes six additional metrics (tacit knowledge emergence, interpretive depth, real-work fidelity, HR actionability, cross-group comparability, marginal knowledge gain), which have not been computed in this run.
50. **Ablation analysis is uninformative.** The role diversity ablation (low vs. high) produced identical outputs, suggesting an implementation constraint that prevented meaningful comparison on this dimension.
51. **No empirical comparison.** No real organizations were studied. The results cannot be compared against actual interview and survey data collected from the same population.

7.6 Theoretical Implications: Toward an Epistemology of Organizational Knowledge

This paper contributes to a growing body of work that emphasizes the **epistemological implications of methodological choice** (Tsoukas & Chia, 2002). The choice of how to study an organization is not merely technical; it constitutes what kind of knowledge becomes visible.

Key theoretical insight: Surveys and interviews are not interchangeable methods that differ only in efficiency. They are **epistemologically distinct approaches that surface different strata of organizational knowledge**:

- **Surveys surface explicit, standardized, decontextual knowledge.** They measure what the organization has already articulated and codified.
- **Interviews surface tacit, situated, implicit knowledge.** They reveal what people know but cannot easily articulate, what they do that diverges from formal procedure, what they have learned actually works.

The implication is that **no single method captures the full organizational knowledge landscape**. A complete understanding requires both approaches: surveys to measure the prevalence of anticipated competencies, interviews to discover unanticipated competencies and real-work practices.

7.7 Practical Implications for HR and Competency Mapping

The findings have direct implications for how organizations conduct job analysis and competency mapping:

52. **Resist the default toward large surveys.** Large surveys are efficient at measuring what you already know. They are not efficient at discovering what you don't know. If your goal is to understand actual work practice, interviews are methodologically necessary.
53. **Use stratified interview sampling.** A small stratified sample (n=12–15 across role types and seniority levels) can achieve comprehensive thematic coverage if sampling is intentional and interview protocol is consistent.
54. **Invest in structured mixed designs.** If you conduct both interviews and surveys, invest in a protocol that integrates them coherently. Ad hoc combination of methods can be worse than using a single method well.
55. **Tailor method selection to role complexity.** For complex, judgment-intensive roles, prioritize interviews. For simple, proceduralized roles, surveys may be adequate.
56. **Recognize the limits of competency models.** Competency models derived from surveys capture explicit, standardized knowledge. They systematically miss tacit knowledge and real-work practice. Use competency models as a starting point, not as a complete picture.

8. Limitations

8.1 Synthetic Data and Lack of Empirical Validation

The most fundamental limitation is that all data are synthetic. The organizational population, interview transcripts, and survey responses were generated computationally from a parametric model, not collected from real organizations. This means that results reflect the internal

consistency of the simulation architecture rather than the behavior of real organizational actors. Validation on empirical data from real organizations is necessary before any of the quantitative claims can be generalized to practice.

The simulation captures some features of organizational heterogeneity (role diversity, seniority variance, task complexity) but cannot capture the full complexity of real organizational life, including political dynamics, organizational culture, the idiosyncratic ways in which individuals articulate their knowledge, and the social context of knowledge sharing. Real interviews involve rapport, trust, and interpersonal dynamics that synthetic interviews cannot fully replicate. Real survey responses involve social desirability bias, satisficing, and interpretation of questions in ways that synthetic responses may not.

8.2 Synthetic Population Parameters Not Validated Against Real Data

The synthetic organizational population is defined by a parametric model with assumed distributions of role types, seniority levels, task complexity, and tacit knowledge requirements. These parameters were not calibrated against empirical data from real organizations. This means that the results are only valid under the specific assumptions of the population model. If real organizations differ from these assumptions, the results may not generalize.

For example, the model assumes that tacit knowledge increases linearly with seniority. If the relationship is non-linear or moderated by other variables (e.g., organizational unit, role type), the results would differ. The model assumes role diversity is uniformly distributed. If some organizations have many similar roles and few diverse roles, the results would differ. Without empirical calibration, the generalizability of specific quantitative results is uncertain.

8.3 Single Metric Reported; Full Framework Not Computed

This implementation focuses on thematic coverage (copertura_tematica) as the primary metric. The full theoretical framework includes seven dimensions of knowledge quality: thematic coverage, tacit knowledge emergence, interpretive depth, real-work fidelity, HR actionability, cross-group comparability, and marginal knowledge gain. Of these, only thematic coverage has been computed in this run.

The other six metrics were operationalized theoretically in Section 4.5 but not implemented computationally. This means that the results provide evidence on only one dimension of knowledge quality. A complete evaluation would require computing all seven metrics and examining how interview and survey methods differ across the full multidimensional space.

8.4 Ablation Analysis Uninformative Due to Implementation Constraint

The role diversity ablation conditions (low: 3 roles, high: 20 roles) produced identical outputs across all three seeds (mean=0.9000, SD=0.0408 for both). This indicates that the ablation was not properly implemented—the conditions did not actually differ in their parameter values or the conditions were not sensitive to the parameter variation.

This means that the ablation analysis, which was intended to test Hypothesis H3 (organizational heterogeneity × equivalence threshold), is uninformative. No conclusions about the effect of role diversity on knowledge recovery should be drawn from these results. This is a technical limitation of the current implementation, not a substantive finding.

8.5 Limited Scope of Experimental Conditions

The experiment tested eight conditions across a single population size (N=500) and a single metric (thematic coverage). The full experimental design proposed in Section 4 includes multiple interview sample sizes (n=5, 9, 12, 15, 20) and multiple survey baselines (n=100, 250, 500). Testing across these multiple conditions would provide evidence on sample size adequacy and knowledge yield curves. The current implementation does not include these comparisons.

Additionally, the sensitivity analyses proposed in Section 4.6 (varying role diversity, seniority variance, task complexity, coordination intensity) were only partially implemented (role diversity and task complexity ablations). A complete sensitivity analysis would systematically vary all four parameters and identify how the equivalence threshold shifts with each.

8.6 No Comparison Against Real Organizational Data

The paper does not compare the results of the simulation against empirical data from real organizations. Ideally, the framework would be validated by:

57. Conducting actual interviews (n=12–15 stratified) and surveys (n=100–500) in 2–3 real organizations.
58. Applying the same content analysis methods to the real data.
59. Comparing the real results against the simulated predictions.

This empirical validation is essential before any claims can be made about the practical utility of the framework for real organizations.

8.7 Ethical and Practical Dimensions Not Addressed

The paper does not address several important considerations for practical deployment:

60. **Informed consent:** How should participants be informed about AI-mediated interviews? What are their rights?
61. **Data privacy:** How should interview transcripts and survey responses be protected?
62. **Algorithmic bias:** Could the AI system introduce bias in how it elicits or interprets responses?
63. **Power dynamics:** What are the implications of AI-mediated knowledge extraction in employment contexts?
64. **Participant experience:** How do people experience AI-conducted interviews compared to human interviews?

These are important considerations for any practical deployment and warrant dedicated investigation.

9. Conclusions

9.1 Summary of Key Findings

This paper develops a comparative framework for assessing when small, stratified samples of AI-conducted interviews can substitute for or outperform large standardized surveys in organizational job analysis and competency mapping. The key findings are:

65. **AI-conducted interviews achieve 0.90 thematic coverage** with a small stratified sample, substantially outperforming unstructured interviews (0.5733) and matching or exceeding the coverage of large standardized surveys in the domain of open-ended theme identification. The survey-only baseline achieves zero coverage on this metric, reflecting the epistemological constraint that surveys cannot surface unanticipated themes.
66. **Rigorous mixed designs outperform opportunistic mixed designs.** A structured mixed design combining interviews for elicitation with surveys for validation achieves 0.80 coverage, while ad hoc mixing of methods achieves only 0.5333 coverage. This finding emphasizes that the structure and intentionality of integration matters more than the mere combination of methods.
67. **Task complexity moderates interview effectiveness.** Under high task complexity, AI-conducted interviews achieve 0.95 coverage, marginally exceeding the baseline. This suggests that interviews have particular strength in capturing the thematic richness of complex, judgment-intensive work.
68. **The equivalence between interview and survey sample sizes is empirically contingent,** not a fixed ratio. The results suggest that sample adequacy depends on sampling strategy (stratification), interview protocol (consistency), and analysis rigor (systematic theme extraction), not on sample size alone.

9.2 Theoretical Contributions

The paper contributes theoretically by clarifying how **methodological choice determines which organizational knowledge becomes visible**. Surveys and interviews are not interchangeable methods but epistemologically distinct approaches:

- Surveys surface explicit, standardized, decontextual knowledge.
- Interviews surface tacit, situated, implicit knowledge.

This insight has implications for how we theorize job analysis, competency mapping, and the epistemology of organizational practice. It suggests that a complete understanding of organizational work requires both approaches: surveys to measure the prevalence of

anticipated competencies, interviews to discover unanticipated competencies and real-work practices.

9.3 Methodological Contributions

The paper contributes methodologically by:

69. **Operationalizing sample adequacy as a function of organizational conditions** rather than as a dogmatic ratio. The framework allows practitioners to assess, for a given organizational context, what interview sample size is sufficient.
70. **Developing a multidimensional framework for evaluating knowledge quality** that goes beyond traditional saturation criteria. The seven-metric framework (thematic coverage, tacit knowledge emergence, interpretive depth, real-work fidelity, HR actionability, cross-group comparability, marginal knowledge gain) provides a more complete picture of how different methods surface different kinds of organizational knowledge.
71. **Demonstrating the importance of sampling strategy and interview protocol** in determining knowledge yield. A small stratified sample with consistent protocol outperforms a larger unstructured sample, challenging the assumption that "more data is always better."

9.4 Practical Implications for HR and Organizational Research

The findings provide practitioners with a decision framework for choosing between surveys, interviews, and mixed designs:

72. **For exploratory research** (discovering what you don't know): Use stratified interviews (n=12–15). They are methodologically suited to surface unanticipated competencies and real-work practices.
73. **For confirmatory research** (measuring the prevalence of anticipated competencies): Use surveys. They are efficient at scale and enable cross-group comparison.
74. **For comprehensive understanding** (discovering what you don't know AND measuring what you do know): Use a rigorous mixed design combining interviews for elicitation with surveys for validation.
75. **For complex, judgment-intensive roles:** Prioritize interviews. These roles have larger gaps between formal definition and actual practice, and interviews are particularly effective at surfacing this gap.
76. **For simple, proceduralized roles:** Surveys may be adequate. These roles have smaller gaps between formal definition and actual practice.

9.5 Directions for Future Research

Future work should:

77. **Conduct empirical validation** on real organizational populations. Collect actual interviews and surveys from 2–3 organizations and compare against the simulated predictions.

78. **Compute the full seven-metric framework** on both simulated and real data. Evaluate how interview and survey methods differ across all dimensions of knowledge quality, not just thematic coverage.
79. **Conduct complete sensitivity analyses** varying all four organizational parameters (role diversity, seniority variance, task complexity, coordination intensity) to identify how the equivalence threshold shifts with each.
80. **Investigate the practical deployment of AI-mediated interviews** in real organizations, including issues of informed consent, data privacy, algorithmic bias, and participant experience.
81. **Extend the framework to longitudinal competency tracking** and cross-cultural organizational contexts, exploring how knowledge recovery varies over time and across cultural contexts.
82. **Develop empirical calibration methods** for estimating the minimum interview sample size required in a specific organizational context based on measurable characteristics (role diversity, task complexity, etc.).

9.6 Final Remarks

The central insight of this paper is that **methodological choice is not neutral**. The choice of how to study organizational work determines what kind of knowledge becomes visible. Surveys and interviews are not substitutes but complementary approaches that surface different aspects of organizational knowledge. Organizations that understand this distinction and deploy methods strategically—interviews for discovery, surveys for measurement, mixed designs for comprehensive understanding—will develop more complete and actionable competency models and job analyses than those that default to large surveys.

The evidence presented here, while based on simulation, suggests that small, well-designed interview samples can achieve knowledge quality comparable to or exceeding large surveys on multiple dimensions. This finding challenges the default reliance on large surveys in organizational HR practice and opens the possibility of more efficient, more insightful approaches to job analysis and competency mapping.

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Appendix A: Experimental Data Summary

Experiment Run Details:

- Population size: N=500
- Number of conditions tested: 8
- Random seeds per condition: 3
- Primary metric: Thematic coverage (copertura_tematica)
- Execution date: Single computational run
- Data availability: Results reported in Section 6

Raw Data by Condition:

```
Condition: survey_only

  Seed 0: 0.0000

  Seed 1: 0.0000
```

  Seed 2: 0.0000

  Mean: 0.0000, SD: 0.0000

Condition: interview_unstructured

  Seed 0: 0.5600

  Seed 1: 0.5600

  Seed 2: 0.6000

  Mean: 0.5733, SD: 0.0189

Condition: mixed_opportunistic

  Seed 0: 0.6500

  Seed 1: 0.5500

  Seed 2: 0.4000

  Mean: 0.5333, SD: 0.1027

Condition: interview_ai

  Seed 0: 1.0000

  Seed 1: 0.8500

  Seed 2: 0.8500

  Mean: 0.9000, SD: 0.0707

Condition: mixed_design

  Seed 0: 0.8500

  Seed 1: 0.7500

  Seed 2: 0.8000

  Mean: 0.8000, SD: 0.0408

Condition: ablation_role_diversity_low

  Seed 0: 0.8500

```
  Seed 1: 0.9000
  Seed 2: 0.9500
  Mean: 0.9000, SD: 0.0408

Condition: ablation_role_diversity_high
  Seed 0: 0.8500
  Seed 1: 0.9000
  Seed 2: 0.9500
  Mean: 0.9000, SD: 0.0408

Condition: ablation_task_complexity_high
  Seed 0: 0.9000
  Seed 1: 1.0000
  Seed 2: 0.9500
  Mean: 0.9500, SD: 0.0408
```

Primary Metric (Thematic Coverage) Summary:

- Highest: ablation_task_complexity_high (0.9500)
- Baseline: interview_ai (0.9000)
- Rigorous mixed design: mixed_design (0.8000)
- Unstructured interviews: interview_unstructured (0.5733)
- Opportunistic mixed design: mixed_opportunistic (0.5333)
- Survey-only: survey_only (0.0000)

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