



**SCHOOL OF
ECONOMICS AND
MANAGEMENT**

My House, My Rules

A Comparative Case Study of How Organizational Culture and AI Interact to
Shape Change in Organizational Routines at IKEA and Ericsson

Master Thesis

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Abstract

AI integration is reshaping organizational work, however its success depends less on technical capability than on the cultural context into which it is introduced. This comparative case study examines how organizational culture and AI interact to shape organizational routines at two large Swedish organizations with distinct cultural profiles: IKEA, with its people-first, values-driven identity, and Ericsson, defined by an engineering-oriented precision culture. Drawing on 14 semi-structured interviews, it is observed that cultural orientation conditions how widely AI-driven routine change spreads, but that implementation factors such as leader participation, tool design, and the pacing of introduction, determine whether cultural readiness translates into actual transformation. Both organizations accepted AI for peripheral tasks while instinctively defending identity-constituting work from it, a pattern that held regardless of overall cultural openness. Organizational overwhelm is also identified as a distinct barrier to consolidation, and the playground phase is proposed as a transitional state in AI-driven routine change. Theoretically, the study refines the ostensive/performative framework by accounting for cultural mediation, sociomaterial tool design, and structural conditions of introduction.

Keywords: Organizational Routines, Organizational Culture, Artificial Intelligence, Sociomateriality, Ostensive/Performative Distinction

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Abbreviations

5G: Fifth Generation (mobile network)

AI: Artificial Intelligence

CEO: Chief Executive Officer

CPO: Chief People Officer

CVF: Competing Values Framework

EDI: Equality, Diversity and Inclusion

EU: European Union

HR: Human Resources

IoT: Internet of Things

R&D: Research and Development

SEK: Swedish Krona

1. Introduction

Over the past decade, AI has moved from research laboratories to the core of organizational operations, competition, and value creation (World Economic Forum, 2026). Yet a McKinsey report revealed that 65% of AI initiatives fail, not due to technical flaws, but because organizations underestimate the effort required to integrate AI into daily workflows (McKinsey & Company, 2025). Translating AI capabilities into business value requires organizational transformation, changes in management practices, and the ability to align AI with strategic objectives, none of which are technical challenges (Seyed Javadin & Bahmanirad, 2025). The difficulties organizations face, rooted in their structures, practices, and cultural context, determine whether AI becomes embedded in workflows or remains a surface-level addition. Therefore, its success hinges fundamentally on organizational culture. Existing research confirms that organizational culture plays a decisive role in AI adoption. Schein (2010) argues that culture operates largely at an unconscious level, shaping how members perceive and respond to new technologies. Sarfraz and Shah (2024) further demonstrate that the relationship between culture and AI is mutually shaping: culture conditions how AI is interpreted and used, while AI can reinforce, expose, or disrupt existing cultural assumptions. When AI enters an organization, it does not land on neutral ground. Instead, it is interpreted, accepted, resisted, or adapted based on the cultural context (Al Samman, 2024). Sociotechnical theory established that technology and social systems are interdependent, and new tools inevitably reshape how work is organized and carried out (Orlikowski, 2002). However, studies following this approach have primarily focused on how technology and work structures fit together. They overlooked how culture, the values, assumptions, and shared beliefs that shape how people make sense of new technologies, influences that relationship (Yunusa, 2025). Where culture has been studied in relation to AI, it has largely been framed as either enabling or inhibiting adoption, rather than as an active

force that interacts with AI to reshape the routines through which work is done (Feldman, 2000; Orlikowski, 2002). Routines, understood as the recurring, recognizable patterns of action through which work is actually carried out (Feldman, 2000; Orlikowski, 2002), are where the interaction between culture and technology becomes most observable. However, this routine-level of analysis remains largely absent from the literature. Comparative empirical work on how organizations with different cultural configurations navigate the same challenges and arrive at different outcomes is also lacking.

This study examines how organizational culture and AI technology interact to shape routines. It does not address the technical development of AI systems, specific algorithms, or performance metrics. Instead, it focuses on two Swedish organizations, with findings interpreted within their national and industry context. This leads to the following central research question:

How do organizational culture and AI technology interact in shaping organizational routines?

To answer this question, a comparative qualitative study of IKEA and Ericsson was conducted, both of which are large Swedish organizations with distinct cultural profiles. IKEA embodies a people-first culture rooted in its founding values, while Ericsson operates in a technical, engineering-driven environment. Through fourteen semi-structured interviews, data were collected using open coding and cross-case pattern matching, offering empirical and theoretical insights into the intersection of culture, AI, and organizational routines.

2. Theoretical Background

2.1 Organizational Routines

Organizational routines are the recurring, recognizable patterns of interdependent action that structure how work is carried out (Feldman & Pentland, 2003). They are present in the way a hiring decision is carried out, from job posting to offer, in the steps through which a project is reviewed and approved, and in the informal sequence through which a team prepares for a client meeting. This study begins by examining what shapes these routines and how they evolve. Early research framed routines as stable, rule-bound sequences that reduced uncertainty by standardizing responses to recurrent situations (Cyert & March, 1963; Nelson & Winter, 1982). In this view, routines were essentially inertial. They encoded past solutions, preserved knowledge, and freed cognitive resources for new challenges. However, this perspective leaves something important unexplained. If routines are self-executing programs, how do organizations ever change internally? And why do the same routines, performed by the same people, sometimes produce different outcomes? Feldman (2000) challenges this view. In a two-year study of housing administration at a public university, she observed that the same routine, performed repeatedly by the same people, produced different outcomes across iterations. This was not because the routine changed on paper, but because participants continuously reflected on what was not working and adjusted their actions accordingly. Thus, organizational routines are better understood as ongoing accomplishments rather than as fixed scripts. People not only execute a routine but also reflect on it, respond to its outcomes, and adjust their actions accordingly. Routine stability is therefore not a default state. It is something that requires active, continuous reproduction. The variation that accumulates across iterations is not noise to be filtered out but a constitutive feature of what routines are. Change, in other words, is latent in routine performance itself.

This insight laid the foundation for what has become the field's most widely used conceptual distinction (Feldman & Pentland, 2003). The ostensive aspect of a routine is the abstract, generalized pattern, the shared understanding of what the routine is supposed to accomplish and how it is supposed to proceed. The performative aspect is what actually happens when the routine is enacted, the specific actions taken by specific people at specific times and places. These two aspects are mutually constitutive but never identical. The ostensive guides performance, but what people actually do day-to-day also shapes, sustains, and gradually reshapes that shared understanding over time. Variation in performance may remain local and contained, or it can feed back into the ostensive aspect, shifting the routine's shared understanding. This bidirectional relationship enables routines to generate both stability and change (Feldman & Pentland, 2003). Whether the variation in a routine persists to reshape its ostensive aspect or remains locally contained depends on how deeply the routine is embedded in its organizational context. For example, Howard-Grenville (2005) observed a roadmapping routine at a high-technology manufacturer that, despite being enacted flexibly by diverse actors for varied purposes, remained stable over time. The reason lay in the routine's entanglement with coordination practices, technological systems, and cultural norms, which together generated reinforcing expectations that pulled each subsequent performance back toward established patterns, regardless of individual variation. Thus, strongly embedded routines resist change, even when individual performances vary, because reinforcing expectations sustain the status quo. A routine less tightly embedded is more susceptible to lasting change when variation enters (Howard-Grenville, 2005). This demonstrates that the organizational context in which a routine sits is an active shaper of it.

Technology introduces variation into routines, but this does not automatically translate into revised shared understanding. Edmondson et al. (2001) demonstrated this in a study of cardiac surgery technology adoption across sixteen hospitals and found that teams

using identical equipment achieved vastly different outcomes based on how the technology was introduced. Where teams had structured time to practice together and reflect collectively, new shared understandings of the procedure emerged. Where they did not, individual adaptations remained fragmented, even as practices shifted. The technology itself was not the determining factor; the organizational conditions surrounding its introduction were. The conditions under which performative variation accumulates into a revised organizational schema have been specified through longitudinal research at a university admissions office, identifying two connected processes (Rerup & Feldman, 2011). The first is trial-and-error learning at the task level, in which participants resolve specific problems that arise during routine performance, gradually stabilizing new ways of handling recurrent situations. The second is schema change at the organizational level, in which those stabilized task-level solutions begin to raise broader questions about whether current practice aligns with what the organization understands itself to do. The second process depends on the first having stabilized sufficiently to surface those questions. This sequencing matters for understanding how AI enters organizational routines. Performative variation introduced by AI tools does not automatically feed back into ostensive understanding. It must first resolve the task-specific problems it creates before it can accumulate into a repeated, recognizable pattern that prompts participants to ask whether the routine itself needs to be reconceived. Where that stabilization is prevented, the feedback loop does not close, and performative change accumulates without producing ostensive realignment.

Artifacts and technologies participate in routine dynamics not as passive supports but as active shapers of what people do and how they do it (D'Adderio, 2008). In an ethnographic study of an engineering process at an automotive manufacturer, revising formal procedures rarely changed actual practice, but redesigning the software artifacts that encoded those procedures did. Artifacts actively shape it by foregrounding some performative variations and

eliminating others. The introduction of AI tools into organizational routines can be understood through this lens. AI is not an external force acting on a pre-existing routine but a material participant in its ongoing constitution. Whether the specific design properties of an artifact shape routine dynamics independently of the broader cultural context in which it operates remains underexplored. The distinction between artifacts that support human judgment and those that evaluate or replace it carries particular weight when AI enters organizational routines, given that AI can occupy either position depending on how it is deployed. The broadest theoretical grounding for this position is the concept of sociomateriality, in which the social and the material are understood as constitutively entangled in everyday organizing (Orlikowski, 2007). When AI tools become part of how work is done, how decisions are made, how recommendations are generated, and how performance is monitored, they become constitutive of those routines, altering what the routine is in practice even when its ostensive description remains unchanged.

Taken together, these frameworks establish organizational routines as the appropriate analytical level for examining the interaction between culture and AI. Routines are observable, culturally embedded, and materially constituted. They are the site where the abstract meets the concrete, where shared assumptions about how things should be done collide with the practical reality of how they actually get done once new tools enter the picture. What determines the shape of that collision, however, is culture.

2.2 Organizational Culture

Organizational culture is one of the most extensively studied, yet frequently debated concepts in management research. Definitions of organizational culture vary across the literature. However, there is a broad consensus that it functions as a shared system of meaning. This system influences how members of an organization perceive, interpret, and

respond to their environment. What remains more disputed is where that system resides, what it is made of, and how it exerts its influence.

The most widely used framework for understanding where culture resides is Schein's (2010) three-level model, which remains the foundational reference in organizational culture research. Things that are visible on the surface, the physical spaces, the language, the rituals, and the way meetings are conducted are the artifacts. They are important, but they are symptoms rather than causes. Beneath this first level lie the values that members consciously hold, such as stated principles, the mission document, and the goals people would describe if asked what their organization stands for. Values are more explanatory than artifacts, but still incomplete guides to behavior, because people do not always act consistently with what they say they believe. At the deepest and most consequential level, there are basic underlying assumptions; unconscious, taken-for-granted beliefs that are so thoroughly internalized that members rarely question them and find behavior based on any other premise difficult to comprehend (Schein, 2010). It is at this third level that culture exerts its most powerful influence, functioning as the lens through which people perceive reality in the first place. This has direct consequences for understanding how organizations respond to change. Because basic assumptions are largely invisible to those who hold them, they do not simply influence decisions. They determine what counts as a sensible decision, what constitutes a legitimate concern, and what kind of response feels natural or threatening. Al Samman (2024), in a qualitative study of AI integration across organizations in Bahrain, found that employees' responses to AI tools were not shaped by their stated attitudes toward technology. It was shaped by deeper assumptions about which kinds of human contribution were irreplaceable and which decisions could legitimately be delegated to machines. When a new technology enters an organization, it lands inside a cultural field that has already determined what kinds of change are intelligible, what counts as a legitimate reason to work differently,

and what feels like a threat to how things should be done. It lands inside routines, that are themselves embedded in and reproduced by that cultural field. This could mean that two organizations encountering the same AI tool may respond in different ways depending on the assumptions embedded in their cultures. Schein's (2010) model tells us where culture lives and why it is durable, but it does not provide a vocabulary for characterizing the different shapes culture takes across organizations.

A complementary framework identifies four traits of organizational culture associated with effectiveness: involvement, consistency, adaptability, and mission. These traits map onto two tensions that organizations must navigate between internal integration and external adaptation, and between stability and flexibility. In a study combining case analysis and survey data from 764 organizations, involvement and adaptability emerged as the strongest predictors of sales growth and responsiveness, while consistency and mission were stronger predictors of profitability and stability (Denison & Mishra, 1995). This suggests that an organization's cultural orientation shapes not just its values but also its capacity to absorb change. Cultures that score high on involvement and adaptability tend to be more responsive to change, while those high on consistency and mission tend toward predictability and stability. Neither orientation is inherently superior. Each one carries distinct strengths and vulnerabilities when an organization encounters a disruptive force like AI. A culture oriented toward adaptability may absorb the variation AI introduces into performative practice more readily, while a culture oriented toward consistency may find that same variation harder to integrate into how the routine is understood to work.

The Competing Values Framework (CVF) extends this way of thinking by organizing culture into four types arrayed across those same two dimensions: the first distinguishing flexibility from stability and control, the second distinguishing internal from external orientation. The resulting quadrants produce four culture types. Clan culture is characterized

by collaboration, cohesion, and people development. Adhocracy culture is oriented toward innovation, entrepreneurship, and external adaptation. Market culture is focused on competition, achievement, and results. Lastly, Hierarchy culture is defined by coordination, efficiency, and process consistency (Cameron & Quinn, 2006). No organization fits only one type, but dominant orientations can be identified. This typology is useful in this study because it allows cultural differences between the two case companies (IKEA and Ericsson) to be articulated in shared terms instead of through descriptive characterization. It connects directly to how those organizations might be expected to respond when AI enters their routines.

Alongside these cultural frameworks, social identity theory offers a complementary lens that is important for understanding why certain kinds of change encounter instinctive, rather than merely deliberate, resistance. Tajfel and Turner (1986) argue that individuals derive a significant part of their self-concept from the groups and organizations they belong to, and that threats to the group's defining characteristics are experienced as threats to the self. Ashforth and Mael (1989) develop this insight in organizational contexts, showing that when members identify strongly with their organization, they become more motivated to protect what they understand as its essential character. This has direct consequences for how AI is received. Where AI is introduced into tasks that participants believe are constitutive of who they are professionally and organizationally, resistance operates as an instinctive defense of identity. The location of that boundary varies across organizations, shaped by the specific assumptions each culture holds about what makes human contribution irreplaceable.

Taken together, these frameworks establish that organizational culture is a multi-level, measurable, and consequential phenomenon. Culture is not simply what an organization says its values are. It is the deeper system of assumptions and orientations that filters how new challenges and technologies are received and shapes what participants take for granted about

how their routines should work. That filtering process, however, does not operate on a passive technology. AI itself became an active organizational participant. Understanding what it does inside organizations and how it relates to the cultural ground it enters needs its own examination.

2.3 Artificial Intelligence in Organizations

Understanding how AI enters and reshapes organizational life requires a definition of the technology. AI can be understood in terms of rational agency: an agent perceives its environment and acts upon it, and a rational agent selects actions expected to maximize its performance given what it knows (Russell & Norvig, 2021). This definition matters for organizational research because it frames AI as an active system oriented toward achieving goals, rather than a passive instrument. In organizational contexts, AI does more than just execute tasks on behalf of humans. It participates in them, generating outputs, structuring options, and shaping the information on which decisions are made. That participation has accelerated substantially in recent decades, driven by increases in computational power, the widespread availability of data, and the growing interoperability of digital technologies (Brynjolfsson & McAfee, 2014). Together, these forces have pushed AI well beyond narrow rule-based automation into domains previously considered exclusively human, including pattern recognition, natural language processing, and complex decision support. Now, when AI enters a routine, it can actually change what counts as evidence, who is consulted, and what a good outcome looks like.

What AI does within this expanded role requires more than a description of its capabilities. The automation-augmentation paradox provides the most useful framework for this purpose (Raisch & Krakowski, 2021). Automation refers to situations in which AI takes over a task previously performed by humans, thereby reducing human involvement. Augmentation refers to situations in which humans and AI collaborate on a task, each

contributing its distinct capabilities. These are interdependent dimensions that create persistent organizational tension, not straightforward choices. Unilever's talent acquisition process illustrates this directly: automation for initial candidate screening and augmentation for final selection produced a 16% increase in new-hire diversity while reducing time-to-hire by 90%, an outcome neither approach alone could have achieved (Raisch & Krakowski, 2021). Organizations that push too far toward automation risk deskilling and disengagement. Those who over-invest in augmentation risk cognitive overload and inefficiency. Organizations that navigate this most effectively are those that hold both dimensions in view simultaneously. This framework resists the temptation to read AI as either a displacement threat or an empowerment tool. Instead, it opens space to examine how different organizational contexts produce different balances between the two. Those organizational contexts are, as the previous section established, fundamentally cultural.

The concept of human-AI symbiosis in organizational decision-making develops this further. AI systems excel at analytical tasks, such as pattern identification, probabilistic modeling, and processing complexity at scale. Humans retain a comparative advantage in the intuitive, contextual, and politically sensitive dimensions of judgment. Procter & Gamble and American Express have operationalized this boundary deliberately: instead of automating processes or eliminating human roles, both firms treat AI as a tool from which employees draw to do their work, preserving human judgment at the points where contextual sensitivity and relational intelligence are most needed (Jarrahi, 2018). Instead of automating processes or eliminating human roles, both firms treat AI as a tool that employees turn to do their work. They preserve human judgment at the points where contextual sensitivity and relational intelligence are most needed. Where the boundary between these two sits is not determined by technology alone. Decisions about which tasks to delegate to machines and which to retain with humans are shaped by shared assumptions about what constitutes good work, who is

trusted to make judgments, and what the organization values. Those assumptions are, in other words, cultural, and they are reproduced and contested through the very routines into which AI is introduced.

A related but distinct challenge concerns the conditions under which AI introduction itself can become a barrier to routine change. March (1991) identifies a persistent tension in organizational learning between exploration, the pursuit of new possibilities, and exploitation, the efficient use of existing knowledge. Organizations that manage this balance well are those that keep exploratory space open long enough for learning to accumulate before efficiency pressure closes it down. When AI tools arrive faster than stable competence can form, organizations are effectively forced into exploitation before exploration has had time to yield learning. The result is surface-level adoption without the deeper consolidation that real routine change requires. Weick (1995) provides the mechanism through which this dynamic operates. When too many tools and initiatives are introduced simultaneously without guidelines or frameworks, collective sensemaking breaks down. Participants continue to act, but they cannot construct a shared understanding of what they are doing or why, which means that individual adaptations accumulate without connecting into revised shared understandings of how routines should proceed. Together, March and Weick identify a structural barrier to AI-driven routine change that is distinct from cultural resistance, that is not unwillingness to engage, but the absence of the conditions under which engagement can consolidate into lasting change. Change slows down when urgency is created without a clear and shared vision of what the change is for (Kotter, 1995). In the absence of such a vision, employees receive pressure without a clear direction, and individual responses remain fragmented. Applied to AI adoption, this may mean that the pace and volume of introduction are not only structural risks. The absence of a coherent organizational frame for what AI adoption is intended to achieve compounds the sensemaking breakdown Weick identifies, leaving

employees simultaneously pressured to change and unable to locate a stable shared understanding of what that change should look like.

Organizations that introduce AI as a strategic initiative with deliberate sequencing produce different outcomes from those that allow adoption to emerge without coordination (Holmström and Magnusson, 2025). Their analysis suggests that the gap between these two approaches is most evident at the routine level, where uncoordinated adoption produces fragmentation, whereas coordinated adoption produces consolidation. This distinction maps directly onto the conditions under which performative variation either feeds back into ostensive understanding or remains locally contained (Feldman & Pentland, 2003). The relationship between AI and organizational culture is not one-directional. Once embedded in daily work, AI tools come to function as visible markers of what the organization treats as legitimate evidence and as quiet reshapers of the norms through which culture is reproduced. Cultural values also determine how AI is strategically framed and prioritized. Where cultures emphasize learning, collaboration, and adaptability, AI strategies tend to develop with greater coherence. Where cultures are more rigid or hierarchically controlled, adoption tends to remain at a surface level (Al Samman, 2024; Seyed Javadin and Bahmanirad, 2025). The relationship is mutually constitutive. Culture conditions how AI is received, and AI, once embedded in practice, gradually exerts pressure back onto the cultural assumptions that shaped its reception (Sarfraz and Shah, 2024).

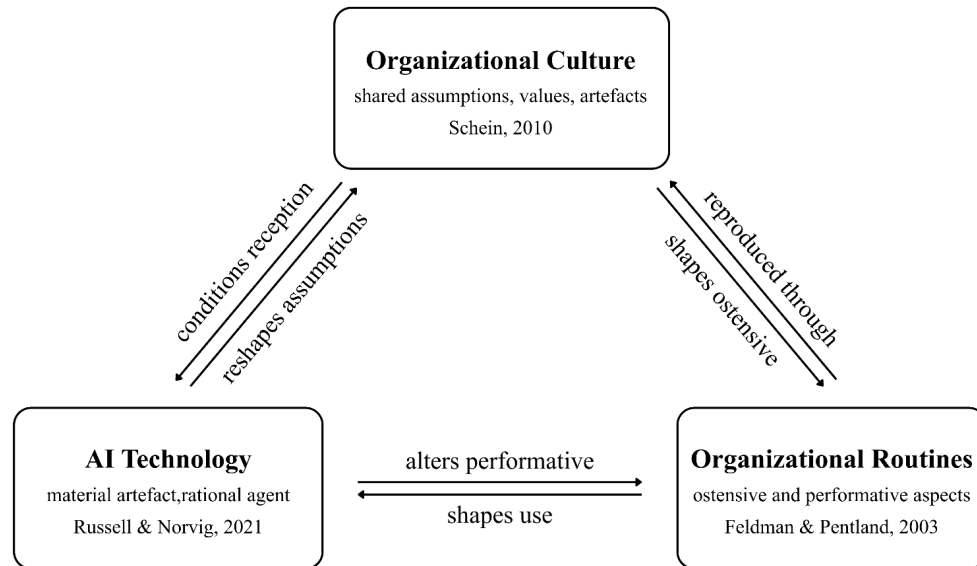
2.4 Theoretical Integration and Propositions

Organizational routines, culture, and AI are constitutively entangled, and when read together, they constitute a single theoretical mechanism. Schein's (2010) basic assumptions operate below the threshold of conscious deliberation, which means they shape what counts as normal performance and what registers as a departure from it. Howard-Grenville (2005) identifies this mechanism in her account of routine embeddedness as where basic

assumptions are firmly held, each performative departure from the ostensive pattern generates an implicit pull back toward established ways of working. The reason the routine remains stable is that, at a pre-reflective level, the surrounding cultural field makes deviation feel like a mistake. The deeper the embeddedness, the stronger the gravitational pull, and the more variation must accumulate before the ostensive understanding of the routine begins to shift. AI, understood through Orlikowski's (2007) concept of sociomateriality and D'Adderio's (2008) account of artifact participation, enters this field as a material actor. It becomes an active participant in the ongoing constitution of the routine. Where AI is positioned in a peripheral step of the routine as a supportive tool to human judgment, its material presence introduces variation without directly challenging the assumptions that anchor the routine's ostensive understanding. The cultural field retains its gravitational force, and the AI operates at its edges, where the pull is weaker and new performative patterns have room to accumulate. Over time, and under conditions of sufficient cultural openness, that accumulation can feed back into the ostensive aspect. Where AI is positioned instead at the core of the routine, such as deciding on tasks that sit close to professional identity, it meets the full weight of those basic assumptions. Resistance does not require deliberation. It surfaces as an instinctive sense that something is wrong, that the right way to do this work is being displaced.

The implication is that the outcome of AI introduction into organizational routines is not determined by the technology's capabilities or cultural openness in the abstract. It is determined by the interaction between where AI sits in the routine and how deeply that position overlaps with the assumptions that define what the routine means to the people performing it. This intersection remains empirically underexplored. Existing research has examined culture as a condition for AI adoption and has examined routine change as a consequence of technological introduction, but has rarely attended to routines as the

observable mechanism through which culture and AI interact, and still less across organizations with meaningfully different cultural configurations (Baziga Farooq et al., 2025). It is this specific gap that this study addresses by examining IKEA and Ericsson as two organizations with distinct cultural orientations that both deploy AI across their operations. The framework set out in Sections 2.1 - 2.3 positions organizational culture, artificial intelligence, and organizational routines as constitutively entangled. Culture conditions in which AI tools are adopted and how their use is interpreted; AI, once embedded in practice, alters the performative aspect of routines; and routines reproduce and gradually reshape the cultural assumptions surrounding them. Figure 1 presents this reciprocal relationship in schematic form. The framework is not a causal model but an analytical lens. It is a way of identifying where to look and what to look for when examining how culture and AI interact in organizational life.



The interaction is mutually constitutive, not sequential.

Figure 1. A reciprocal framework of organizational culture, AI technology, and organizational routines.

Four propositions follow from this framework. Each is grounded in the theoretical logic developed across sections 2.1 to 2.3, and each identifies a specific pattern that the interaction between culture and AI should produce at the routine level. These propositions do not function as hypotheses to be confirmed or rejected in a binary sense. They constitute a theoretically derived pattern, a set of expectations about what the interaction between culture and AI should look like at the routine level in organizations with different cultural configurations, against which the empirical patterns observed at IKEA and Ericsson will be compared. When empirical patterns align with theoretical ones, the framework is strengthened. Where they diverge, the divergence itself becomes analytically productive, opening space for the framework to be refined in light of what the empirical material reveals.

2.4.1 Fluidity of routine change

Performative variation feeds back into ostensive understanding when it is not pulled back by the surrounding organizational context, and the strength of that pull depends on how deeply the routine is embedded in cultural assumptions (Feldman & Pentland, 2003; Howard-Grenville, 2005). Cultures high in involvement and adaptability show a significantly greater capacity to absorb and respond to change, and when teams are given space to collectively reflect on new practices, shared understandings reconstitute relatively quickly (Denison & Mishra, 1995; Edmondson et al., 2001). Cultures oriented toward clan and adhocracy values, associated with flexibility, experimentation, and peer learning, create conditions in which such openness is more likely to be present (Cameron & Quinn, 2006).

Proposition 1: When cultural assumptions are held loosely and open to renegotiation, such as dominant clan or adhocracy orientations, and AI is positioned as augmentation in peripheral steps, performative variation is more likely to feed back into ostensive understanding over time.

2.4.2 Resistance and surface-level adoption

Routines embedded in strong cultural assumptions about process and expertise resist change even when performative variation enters repeatedly, because the surrounding context pulls each subsequent performance back toward established patterns (Howard-Grenville, 2005). Organizations that prioritize operational precision and role clarity tend to resist AI applications that disrupt established task boundaries, even when the tools themselves perform well (Raisch & Krakowski, 2021). Where material artifacts are redesigned without aligning the surrounding procedural and cultural logic, behavioral adaptation fails to propagate into shared understanding (D'Adderio, 2008).

Proposition 2: When cultural assumptions about process, expertise, and authority are more resistant to revision, like in dominant hierarchy and market orientations, and AI is introduced without a shared coordinating framework, performative adaptations are expected to remain locally contained, with the gap between what AI changes and what is understood to have changed persisting over time.

2.4.3 Leader participation as a mediating condition

Leader behavior is a significant moderator of AI acceptance (Fousiani et al., 2024). Employees show more favorable attitudes toward AI and stronger intentions to use it when leaders construe their power as responsibility toward their teams rather than as a personal opportunity. The mechanism is the signal that leader participation sends about what kinds of practice are organizationally legitimate. Where a leader visibly engages with AI tools in their own work, the shared understanding of how routines should proceed has already begun to shift before any formal mandate is issued."

Proposition 3: Regardless of cultural orientation, where leaders visibly engage with AI tools in their own practice, the ostensive understanding of routines is more likely to accommodate AI-driven performative change, because leader participation signals cultural

legitimacy and provides a shared reference point through which individual adaptations can be collectively interpreted. Where AI is experienced as a mandate from leaders who do not themselves participate, resistance is expected to persist and the ostensive/performative gap to widen.

2.4.4 Cultural identity as a boundary around AI

Resistance operating at the level of basic assumptions is qualitatively different from conscious disagreement. It manifests not as deliberate refusal but as an instinctive sense that something is wrong, a feeling that a particular way of working is the only way that makes sense (Schein, 2010). The sharpest variation in AI responses across organizations lies in shared assumptions about which human contributions are irreplaceable (Al Samman, 2024).

Proposition 4: Where AI is positioned at the identity-constituting core of a routine and is perceived as challenging what makes human contribution irreplaceable, resistance is expected to operate at Schein's (2010) deepest cultural level as instinctive defense, regardless of cultural orientation, with the location of the boundary shaped by each organization's specific cultural assumptions.

3. Methodology

3.1 Research Design

This study adopts a qualitative case study design, drawing on two organizations, IKEA and Ericsson, as the empirical units of analysis. Qualitative research is fundamentally concerned with understanding phenomena as they are experienced and interpreted by the people involved, enabling the rich, contextually embedded insights that question organizational processes demand (Saunders et al., 2019; Bryman, 2012). A case study design is particularly appropriate when the research aims to investigate a contemporary phenomenon in depth and within its real-life context, especially when the boundaries between the phenomenon and its context are not clearly evident (Yin, 2018). Case studies make it possible

to explore how organizational processes unfold in real settings, through the eyes of the people involved; something that broader, more standardized approaches are not designed to do. The decision to employ two cases rather than one is a deliberate methodological choice that strengthens the analytical robustness of the study. As Eisenhardt (1989) argues, a multiple-case design enables cross-case comparison through a replication logic, in which patterns identified in one case can be compared against another to assess whether similar or contrasting outcomes emerge. When similar patterns are found across cases, the findings gain strength through what Yin (2018) calls literal replication; when different patterns emerge for theoretically predictable reasons, theoretical replication is achieved, and the analytical contribution is enriched by the contrast (Yin, 2018; Eisenhardt, 1989). This replication logic significantly strengthens the internal and external validity of the analysis. The theoretical framework developed in Chapter 2 draws on literature identified through searches of academic databases including Google Scholar, Web of Science, and LUSEM's library resources. Search terms were constructed around the three core concepts of this study and their intersections. Sources were selected on the basis of theoretical relevance, methodological rigor, and recency. For the AI-specific literature, sources published between 2020 and 2026 were prioritized given the fast-developing nature of the field. Foundational works in routine theory and organizational culture were retained regardless of publication date. Publicly available company reports, sustainability documents, and industry publications were consulted selectively to provide contextual background for the two case organizations rather than as a basis for theoretical claims.

3.2 Data collection

3.2.1 Case selection

IKEA and Ericsson were selected as case organizations for several interrelated reasons. Both are Swedish organizations, which control for national culture as a confounding

variable and allow the comparison to focus specifically on organizational culture and its interaction with AI routines (Hofstede, 2001). Beyond this, the two organizations appear, based on publicly available information and prior research, to represent provisionally distinct cultures: IKEA with a comparatively flat, people-oriented culture rooted in its founding values, and Ericsson with a technical, engineering-driven research and development environment. These cultural profiles are treated not as fixed facts but as working hypotheses to be explored and interrogated through the empirical data. Their approaches to AI also differ substantially: IKEA applies AI in retail operations, supply chain management, and customer experience, while Ericsson works at the frontier of AI in 5G infrastructure, network automation, and IoT. This contrast creates a productive analytical tension that enables theoretically meaningful comparison across organizational routines. The study does not claim to represent all of IKEA or Ericsson globally; rather, it focuses on the experiences and perceptions of individuals working within these organizations as windows into the broader cultural and technological dynamics shaping routine.

3.2.2 Selection of participants

Access to both case organizations was secured through existing professional networks, which facilitated contact with employees and managers willing to take part in the study. Participants were selected purposively, prioritizing those most likely to provide information-rich data relevant to the research questions rather than aiming for statistical representativeness (Saunders et al., 2019; Patton, 2002). Inclusion was based on three criteria: exposure to AI tools in their current role or direct involvement in decisions about their use, sufficient organizational tenure to speak to cultural norms and practices, and availability within the data collection window. Individuals with no organizational contact with AI initiatives in any form were excluded, as were those too recently hired to speak to how culture shaped the reception of AI. Participants ensure coverage of two distinct role profiles

within each organization. The first profile encompasses people-facing roles, including human resources, culture and values, diversity and inclusion, and talent acquisition, positions that offer insight into how organizational culture is shaped, communicated, and experienced. The second profile encompasses technology-facing and operational roles, including AI implementation, product ownership, software design, and operational management- positions that offer insight into how AI is introduced, deployed, and embedded into working practices. This dual-profile approach was intentional, as capturing both dimensions required participation positioned across different parts of each organization (Eisenhardt, 1989; Yin, 2018), and participants with direct exposure to AI initiatives were prioritized wherever possible. When initial contacts were limited, a snowball approach was used, asking participants to recommend colleagues with relevant experience, extending the participant pool beyond the initial network contacts and ensuring a wider range of perspectives across both cases (Bryman, 2012). In total, 14 interviews were conducted across the two organizations: 8 at IKEA and 6 at Ericsson. The distribution of role profiles across the two organizations is worth acknowledging. At IKEA, the majority hold people-facing roles, while at Ericsson, the majority hold technical and operational roles. This asymmetry is not a sampling artifact but a reflection of how culture is organizationally structured in each case. At IKEA, culture is a managed function with dedicated roles, making people-facing participants the most direct window into how cultural norms are shaped and communicated. At Ericsson, cultural norms are embedded in engineering practice rather than administered through a dedicated function, making technical and operational participants the most relevant entry point. The profile distribution therefore mirrors the organizational reality of each case and strengthens rather than undermines the analytical logic of the comparison.

3.2.3 Semi-structured interviews

The primary method of data collection was the semi-structured interview, widely recognized as the most appropriate instrument for interpretive qualitative research into organizational processes, as they provide both structure and flexibility (Kvale & Brinkmann, 2009; Bryman, 2012). The interview guide ensured that the key themes relevant to the research question were consistently covered across all interviews, while the open-ended questions allowed participants to elaborate, deviate, and introduce topics the researchers had not anticipated (Appendix A). Interview questions were framed in accessible, non-technical language and organized to move from general questions about organizational culture and everyday ways of working to specific questions about AI experience before exploring how the two intersect in shaping daily routines. This structure was designed to elicit informants' own framings of their experiences before introducing more theoretically oriented themes, consistent with the approach to open-ended data collection recommended by Corbin and Strauss (1990). Separate follow-up prompts were developed for each organization to address company-specific dimensions. All interviews were conducted in English, either in person at the respective company offices or via an online meeting, depending on participant availability and preference, and lasted between 30 and 45 minutes. All interviews were audio-recorded with consent and subsequently transcribed in full using Sunet Scribe, Lund University's institutional transcription service. Transcripts were reviewed and validated against the original recordings before analysis began. To complement the interview data, publicly available company reports, sustainability documents, official AI strategy announcements, and press releases were consulted to provide contextual background and to cross-reference participants' descriptions with what is publicly known about each organization's culture and AI activities (Yin, 2018). Table 1 provides an overview of all interview participants, including their roles, profile types, interview dates, durations, and formats.

Identifier	Role	Profile	Date	Length	Format
<i>IKEA (n = 8)</i>					
IKEA-1	Culture and Leadership Leader	A	13 April 2026	45 min	Online
IKEA-2	People & Culture Leader	A	13 April 2026	44 min	Online
IKEA-3	Global Equality, Diversity & Inclusion Manager	A	14 April 2026	46 min	Online
IKEA-4	Recruiter	A	15 April 2026	38 min	Online
IKEA-5	AI Portal Lead	B	16 April 2026	38 min	Online
IKEA-6	Culture & Values Specialist	A	16 April 2026	30 min	Online
IKEA-7	Senior Product Owner	B	17 April 2026	40 min	Online
IKEA-8	People & Culture Leader	A	20 April 2026	30 min	Online
<i>Ericsson (n = 6)</i>					
Ericsson-1	Manager, Software Design	B	20 April 2026	46 min	In office
Ericsson-2	Line Manager	B	20 April 2026	41 min	In office
Ericsson-3	Senior Product Manager	B	20 April 2026	32 min	Online
Ericsson-4	Site Operational Manager	B	21 April 2026	40 min	Online
Ericsson-5	Talent Acquisition Partner	A	21 April 2026	36 min	Online
Ericsson-6	Section Manager, BU Radio	B	23 April 2026	26 min	Online

Table 1. Overview of interview participants

3.3 Data Analysis

Data analysis in this study proceeds in two interconnected stages: an initial open coding phase conducted within each case, followed by a cross-case pattern matching analysis. This two-stage approach combines the inductive sensitivity of open coding with the

systematic comparative logic of Yin's (2018) pattern-matching technique, and is consistent with the multiple-case study design outlined by Eisenhardt (1989).

3.3.1 Open coding

The first stage of analysis follows the open coding procedure described by Corbin and Strauss (1990). Open coding is the initial analytical step in which the researcher systematically reads through interview transcripts, assigning conceptual labels and codes to meaningful segments of data. The purpose of open coding is to break open the data, allowing concepts to surface inductively from the material rather than being imposed from pre-existing theoretical frameworks (Corbin & Strauss, 1990; Corbin, 2015). This is the foundational step through which the empirical patterns used in subsequent analysis are constructed. Following transcription, both researchers read each transcript carefully and independently assigned initial codes that were close to the participants' own language. Labels drawn directly from informants' own words and phrases were used wherever possible to preserve the authenticity of their perspectives (Corbin & Strauss, 1990). This process resulted in a large initial set of codes across both cases, reflecting the diversity of experiences and perspectives present in the data. Through a process of constant comparison, codes that captured similar phenomena or addressed related aspects of the research question were progressively grouped into broader categories (Corbin & Strauss, 1990). Constant comparison involves the systematic comparison of incidents, codes, and emerging categories across the data in order to identify similarities, differences, and relationships (Corbin & Strauss, 1990). As coding progressed, categories were refined, merged, and renamed to ensure they accurately reflected the content of the data. This iterative process was carried out separately for each case before moving to cross-case comparison, consistent with Eisenhardt's (1989) recommendation that within-case analysis precede cross-case synthesis. The coding process was conducted collaboratively by both researchers. Where disagreements in interpretation emerged, these were discussed until

consensus was reached, thereby reducing individual interpretive bias and strengthening the reliability of the analysis (Lincoln & Guba, 1985; Bryman, 2012). The resulting categories formed the empirical pattern that was then carried forward into the pattern-matching stage. The emerging codes were progressively organized around the three analytical concepts that structure this study. Codes addressing shared values, norms, leadership practices, and cultural assumptions were grouped as culture-related codes. Codes concerning the specific AI tools in use, how employees interpret and engage with them, and the conditions under which they are deployed were grouped as AI-related codes. Codes capturing repeated action patterns, coordination practices, decision-making processes, and everyday workarounds were grouped as routine-related codes. This three-way organization of the coding output provided the empirical structure for the pattern-matching analysis in the following stage. Following open coding, the emergent categories were mapped onto the theoretical concepts developed in Chapter 2 to establish their analytical grounding. This mapping is presented in Appendix C, which specifies the theoretical concept each category corresponds to and the coding categories through which it was empirically traceable.

3.3.2 Pattern matching

Following the within-case open coding analysis, the study employs Yin's (2018) pattern-matching technique as the primary analytical strategy for cross-case comparison. Pattern matching is described by Yin (2018) as one of the most desirable techniques for case study analysis, in which an empirically derived pattern is compared with a theoretically predicted one. If the observed pattern coincides with the predicted pattern, the internal validity of the case study findings is strengthened. The theoretical pattern in this study is constituted by the propositions derived in Chapter 2. The first proposition predicts that organizations with high involvement and adaptability orientations, or dominant clan and adhocracy cultures, will show a pattern in which AI-driven performative variation is absorbed

relatively fluidly, with the ostensive understanding of routines realigning to reflect what work has become in practice over time. The second proposition predicts that organizations with high consistency and mission orientations, or dominant hierarchy and market cultures, will show a pattern in which AI changes performative practice without correspondingly reshaping ostensive understanding, producing a wider and more durable gap between how routines are described and how they are actually enacted. Together, these two propositions constitute the predicted pattern against which the empirical findings from IKEA and Ericsson are compared. These propositions do not function as hypotheses to be confirmed or rejected in a binary sense. They constitute a theoretically derived pattern, a set of expectations about what the interaction between culture and AI should look like at the routine level in organizations with different cultural configurations, against which the empirical patterns observed at IKEA and Ericsson are compared. Where empirical patterns align with the predicted ones, confidence in the theoretical framework is strengthened. Where they diverge, the divergence is treated as evidence that the propositions require refinement and that the nature of the divergence is examined to understand what the framework did not anticipate (Yin, 2018).

3.4 Quality of Research

Given the qualitative and interpretive nature of this study, the conventional quantitative criteria of validity and reliability are not directly applicable. Instead, this study draws on Lincoln and Guba's (1985) framework of trustworthiness, which proposes four interrelated criteria for the quality of qualitative research: credibility, transferability, dependability, and confirmability. Each of these criteria was actively addressed throughout the research process. Credibility and transferability concern the accuracy and relevance of the findings. Regarding credibility, one challenge was that participants may have been reluctant to openly express hesitation or resistance toward AI, given the organizational contexts in which they work. Interview questions were therefore framed in open, non-evaluative

language and structured to move from general culture questions before introducing AI, allowing participants to share their genuine experiences before more sensitive topics were raised (Corbin & Strauss, 1990). Both researchers closely aligned codes with participants' own language rather than imposing theoretical labels, and interview data were cross-referenced with secondary sources to verify the consistency between what was described and what each organization publicly communicated (Yin, 2018). With regard to transferability, no claim to statistical generalization is made with 14 interviews across two organizations. Instead, the study aims for analytical generalization, in which findings are generalized to theory rather than to populations (Yin, 2018), and provides sufficient descriptions of both case organizations (Lincoln & Guba, 1985). Dependability and confirmability concern the transparency and integrity of the research process itself. To ensure dependability, detailed records of all methodological decisions, coding procedures, and analytical steps were maintained throughout the study, creating an audit trail that enables others to evaluate the process (Bryman, 2012; Lincoln & Guba, 1985). Confirmability, the degree to which findings are shaped by the data rather than by researcher bias, was addressed by having both researchers independently code, then compare and reconcile their interpretations. Any disagreements were discussed until consensus was reached (Lincoln & Guba, 1985).

3.5 Ethical Considerations

The ethical dimensions of this research were considered carefully throughout the design and execution of the study. All participants were fully informed about the purpose of the research, how their data would be used, and their right to withdraw at any time without consequence. Written informed consent was obtained prior to each interview. All interviewees are guaranteed anonymity in all reporting. Neither the names nor any identifying personal details appear in this thesis. Participants are referred to by a case identifier and

number only, in a manner that does not permit identification. Company-specific information that could cause professional harm has been handled with discretion throughout. Interview recordings and transcripts are stored securely, accessible only to the two researchers and the thesis supervisor, and will be deleted upon completion of the thesis. These procedures are consistent with the ethical guidelines for good research practice at Lund University (Lund University, 2026) and with the standard research ethics practices at Lund University School of Economics and Management.

3.6 AI Contribution Statement

Several AI-based tools were used in the completion of this thesis in ways consistent with the faculty guidelines for the use of generative AI. Claude (Anthropic) was used to provide feedback on language, wording, and structure across multiple sections of the thesis and to support the formatting of tables and figures. Perplexity AI was used to support literature searches and identify relevant academic sources. Canva was used to design and produce Figures. Sunet Scribe, Lund University's institutional transcription service, was used to transcribe all interview recordings. No AI tools were used for data analysis, interpretation of findings, or the formulation of conclusions. All analytical decisions, theoretical choices, and written argumentation are the authors' own. A full account of tools used, including the specific purposes for which each was employed, is provided in Appendix D.

4. The cases of IKEA and Ericsson

4.1 IKEA

4.1.1 Case Context

IKEA is one of the world's largest home furnishings retailers, founded in 1943 in Sweden, and today operates through Ingka Group, its largest franchisee. In the financial year 2024, Ingka Group reported revenue of €41.8 billion across 574 store locations in 31 countries, serving 729 million in-store visits and 3.1 billion online visits annually (Ingka

Group, 2025). The company employs approximately 172.000 co-workers globally. IKEA's founding values were developed in the company's earliest years and remain an explicit cultural reference point against which organizational decisions, including decisions about technology, are evaluated (Ingka Group, 2025). IKEA's engagement with AI has developed rapidly in recent years and is distinctive in its framing. IKEA's leadership has explicitly tied AI to the company's people-first values and sustainability commitments. The organization launched an AI literacy program targeting more than 30,000 co-workers in 2024 and developed an internal AI platform, described as a secure, values-aligned alternative to open consumer tools that gives employees access to multiple AI models within Ingka's own data environment (Ingka Group, 2025). IKEA Retail's Chief Data and Analytics Officer has described the company's approach as building an AI direction without formally calling it an AI strategy, deliberately anchoring AI decisions to business outcomes and organizational values rather than to technology roadmaps (CIO Dive, 2025). The Chief People and Culture Officer has articulated this orientation plainly: *"We don't have all the answers, especially as the world becomes more digital and complex, but culture is what keeps us grounded"* (UNLEASH, 2025). AI at IKEA is understood institutionally as a people-and-culture challenge before it is understood as a technology challenge.

4.1.2 Organizational culture as lived practice

The 8 core values, togetherness, simplicity, cost-consciousness, humbleness, frugality, renewing and improving, different with a meaning, and giving and taking responsibility, are not merely stated principles within the organization. People who join IKEA from other organizations consistently remark that the values are not only on the walls but *"...on the floor, out in people's hands and hearts and minds and ways of doing things"* (IKEA-6). The most consistently stated cultural feature was a people-first orientation. Participants draw an organization that evaluates new tools by asking what they mean for coworkers. Leadership is

seen as an action and not as a position. Every coworker, regardless of role or seniority, is expected to lead by example and take responsibility. The expectation is inclusive: *“Our expectations are from every single co-worker, no matter where you work in this company, you have an important role to play”* (IKEA-8). Unwritten rules were regardless of function or geography. Saying hello, knowing colleagues by their first name, all the small gestures carry cultural weight. Informal coffee break conversations and questions raised in unofficial settings often find their way into formal meetings: *“It often starts informally and then, because it starts that way, it can take us some time to reach a conclusion, so we are not a super fast company, but as we deal with topics concerning many people, we like to take our time”* (IKEA-7). What gets rewarded at IKEA maps directly onto its values. Curiosity, initiative, cost-consciousness, working together, and simplifying complexity for others are recognized. *“When bureaucracy goes up, we very fast see that costs go up and speed goes down”* (IKEA-6). Being defensive, working in isolation, or resisting new ideas because of long organizational tenure or adding unnecessary complexity are all pushed back on. In a culture so consensus-oriented, being the skeptical voice when others have already agreed can be uncomfortable. Alongside the people-first orientation runs a strong entrepreneurial thread. The organization is illustrated as one that never settles, that expects people to find new ways and get things done: *“Our culture is about never settling and making things better, getting things done and learning from it, the whole entrepreneurial ethos”* (IKEA-1). This coexists with an equally strong sense of cultural identity and continuity. IKEA’s strength as a culture can also function as resistance to change: *“A strong culture also tends to work like an immune system that shoots at things that are novel and new”* (IKEA-6). The organization is aware of this tension and names it openly. How IKEA’s culture functions in practice is being captured as: *“The values are the compass, but if you’re on a hike, the compass informs the direction, it doesn’t tell you there’s a big rock you need to go around”* (IKEA-1). The values

are not a rulebook that determines outcomes in advance. They are a shared reference point that people bring into situations to work out what the right response looks like. When AI arrived, it entered a culture already equipped with this navigational logic, and participants drew on it repeatedly to make sense of what AI should and should not mean for their work.

4.1.3 Psychological safety, flat hierarchy, and informal connection

IKEA's organizational structure is mostly flat. Formal hierarchy exists, but it does not appear to govern daily interaction in the way participants describe experiencing at other organizations. People across seniority levels interact in informal settings, such as at lunch, in the coffee area, and in the corridors. Sitting down with the CEO at lunch is simply an unremarkable part of the working day. The office environment is where people meet at the coffee area, sit on the sofas, and can have informal conversations. These informal spaces are not incidental to how the organization functions. They are where relationships are built, ideas are discussed and tested, and knowledge about AI spreads. Psychological safety embedded in the culture: *"People can feel comfortable to express their anxiety and share; can we help each other in this, can we work together in this?"* (IKEA-1). This open and trust-based environment creates the conditions in which employees can voice fear and confusion about AI without embarrassment, and in which teams can collectively work out how to respond rather than waiting for top-down direction. That same informal connection is also the channel through which AI learning has spread at IKEA. Formal training played a role, but peer sharing proved more formative. When a colleague expressed anxiety about feeling behind with AI, the team responded by making an agreement to share experiences and help each other: *"The fact that we have the informal connections and the openness of people actually helping each other, that makes the biggest difference"* (IKEA-1). Large voluntary sharing sessions, drawing around a thousand co-workers across the organization every two weeks, emerged as a format through which early adopters demonstrated tools and colleagues could

observe what AI use looked like in practice. These sessions were not mandated. They grew because the culture made voluntary participation feel natural. This voluntary approach, however, creates its own tension: not everyone moves at the same pace, and the range of AI engagement across the organization is wide. This uneven pace shaped which routine changes took hold across the organization and which remained confined to early adopters.

4.1.4 Responses to AI

The response to AI across IKEA spans a wide and acknowledged range. One participant defined the spectrum as running “...*from anticipation to curiosity to fear and doubtfulness, and people questioning if this is going to kill the IKEA spirit once and for all*” (IKEA-1). The breadth of this range was not surprising or problematic. It was the expected reality of a large, diverse organization navigating a significant change.

Two factors consistently shaped where a given employee fell on the spectrum. Role vulnerability was the most prominent. “*If you feel that your job is on the line, you're much more in the fear zone than the curiosity zone*” (IKEA-1). Employees whose tasks could be more easily automated were more likely to experience anxiety. The fear of being unable to upskill was mentioned at least as often as the fear of replacement itself. Others worried not about losing their job immediately but about falling behind: “*The fear of not being able to educate or upskill to be fully proficient to use the tools in the right way*” (IKEA-3). Prior exposure to AI tools was the second factor. Colleagues who had already been experimenting with AI in their personal lives before it arrived in the workplace approached it with more ease than those encountering it for the first time in a professional context. Skepticism was also present, surfacing in informal settings rather than formal ones. AI is “*..not discussed loudly, maybe around the coffee machine or at lunch, but not at a company-wide level*” (IKEA-8). This pattern is consistent with the broader cultural observation that consensus-seeking norms make it harder to be the dissenting voice in a formal setting. Alongside fear and skepticism,

enthusiasm ran just as strongly. A group of early adopters emerged who became informal leaders, demonstrating tools and running voluntary sharing sessions “...*the more they interact, and they see what it brings, the more they want to use it. It's like a virus, it moves from one to another*” (IKEA-7). These reactions of fear and enthusiasm coexisted within the same teams and sometimes within the same individuals, without apparent contradiction. What is distinctive is that the organization actively monitors and manages this variation rather than leaving it to resolve on its own. A survey commissioned specifically to understand the range of employee reactions: “*It was about half the people that had justified fears connected to AI and technology*” (IKEA-1). Knowing this, the organization sought to determine which concerns were reasonable to address and what could be done about them. Actively tracking the emotional landscape around AI reflects the people-first orientation.

4.1.5 Entrance and adoption of AI

AI entered the workplace before the organization had formally decided how to approach it: “...*one day it just was enabled in our edge browser, and that's how everyone started to use it*” (IKEA-5). This was quickly followed by a period of uncertainty, the tool was disabled when it became clear that it did not meet IKEA’s data privacy and legal requirements, and then by the deliberate development of an internal alternative. IKEA built its own AI platform, which allows co-workers to interact with multiple AI models within the company's own data environment. The development and rollout of this internal platform, including a mandatory training requirement before access was granted, marked the transition from informal experimentation to a more structured approach. The training-before-access model that emerged from this experience became one of the organizational lessons. One participant reported what happened when tools were distributed without preparation: “*When you just give a tool out there and say, here you go, have fun, there's a lot more resistance, and there's a lot more fear of change*” (IKEA-5). The contrast with the structured rollout was

direct. When employees received training first, the reception was noticeably different. The training requirement was not experienced as bureaucratic gatekeeping but as preparation that made the tool feel safer, more familiar, and easier to navigate. By the time of the interviews, IKEA had trained more than 40.000 co-workers on the internal AI platform and had been recognized by the EU as one of the top 40 companies driving AI awareness and adoption (Ingka Group, 2025). The approach to ongoing learning was deliberately kept light, combining short foundational sessions with peer sharing and hands-on experimentation: “...*bringing people together, a little bit of teaching combined with people sharing their own experiences, and making sure there's a more peer-to-peer approach*” (IKEA-1). Formal training was kept to a minimum because the experimental nature of AI adoption makes it difficult to define in advance what should be taught. The voluntary sharing sessions described earlier became the primary vehicle.

A central tension emerged consistently across interviews concerning the gap between organizational pressure for efficiency and the time people actually need to explore AI at their own pace: “*One of the big, big, big dilemmas we are sort of facing*”. The organization wants efficiency gains from AI, but embedding requires time and mental space that efficiency pressure tends to crowd out (IKEA-1). A waterfall image was used to describe how new initiatives pile on one another without sufficient breathing room between them. The point was not that AI adoption is unwelcome, but that the conditions for learning, such as space, time, and psychological safety to experiment and fail, are difficult to maintain alongside the pace of organizational demands. AI learning remained voluntary by design, with no targets and no consequences for slower adoption: “*It was not a forced exercise, more like, okay, let's make use of this because this is something cool*” (IKEA-7). This voluntary orientation reflects the broader cultural expectation that people are trusted to take responsibility, but it also means

that the pace of adoption has been uneven across the organization. In more digitally oriented functions, AI was central to their daily work, whereas in others it remained relatively distant.

4.1.6 Changes to working routines

Across all interviews, concrete changes to specific work routines emerged following the introduction of AI tools. These were not uniform across roles, but several patterns recurred with enough consistency to be described as broadly shared. Meeting transcription and summarisation were the most cited changes. AI-generated summaries of missed meetings, transcripts for documentation, and decision logs became standard practice. The shift was not only in how notes are taken but in the expectation of documentation thoroughness; what counts as adequate record-keeping has risen alongside the ease with which AI makes it possible. Data analysis tasks shifted most visibly for those processing large volumes of information: *“...before Copilot, I would almost never have done it, or if I had, I would have asked people to come with their top three patterns and process them in a workshop. With Copilot, the capacity to work with raw data increased a lot”* (IKEA-1). A task that would previously have taken a day and a half now takes around four hours, and this has changed not just the speed of the task but what kind of analytical work feels possible in the first place. Research synthesis changed for roles drawing on external sources: *“...for searching and researching external sources, I can just prompt, find this, and then of course I have to check the sources”* (IKEA-3). The note about checking sources points to a pattern across IKEA interviews: AI use is routinely paired with a human verification step that participants treat as their own responsibility rather than as something AI can handle. This verification norm appeared consistently and was not described as a formal rule but as a shared professional approach. Content and communication work have also shifted. AI helped draft messages, rewrite text, and polish language. Output in this area rarely reaches a standard they can use directly. *“I very seldom can use the outcome directly, because it has to be*

further massaged to fit our own tone of voice and our way of communicating” (IKEA-6). The IKEA tone of voice, simple, direct, and distinctively human, is described as something AI repeatedly fails to replicate without editing. The organizational response was pragmatic: teams have begun front-loading AI interactions with custom instructions about IKEA's voice and values before generating content. This practice has itself become an informal norm. Not all efficiency gains were straightforward: “...*not sure I would say I'm saving hours, rather I go a longer way than I would have without Copilot*” (IKEA-1). The point is not that AI makes work faster but that it makes new things possible, such as deeper engagement with data, more thorough documentation, and broader research that would not have happened at all before: “...*none of us feel that we are saving time at the moment*” (IKEA-3). This gap between perceived possibility and measurable time saving is a consistent feature of the IKEA data. Recruitment is the area where work routines have not changed. No established AI tools exist for candidate screening or selection within the organization, though discussions about what might be possible are ongoing. A clear distinction is drawn between using AI to surface candidates and using AI to evaluate them. Table 2 summarises these routine-level changes, distinguishing between shifts in practice and shifts in shared understanding.

Routine	Before AI	Performative change	Ostensive change
<i>IKEA</i>			
Meeting documentation	Manual notes or no documentation	AI-generated transcripts and decision logs are now standard practice	Yes, what counts as adequate record-keeping has risen; thoroughness is now expected across teams
Data analysis	Workshop-based; colleagues asked for pattern summaries	Direct engagement with raw qualitative data using AI; task time reduced from ~1.5 days to ~4 hours	Yes, the scope of analytical work possible has expanded; direct data engagement is now expected
Content drafting	Written from scratch	AI drafts first, then it is edited; IKEA tone of voice front-loaded into prompts as informal norm	Partial, AI draft as starting point normalized; human editing remains required; voice cannot be delegated
External research	Manual search and reading	AI used to locate and summarize sources; a human verification step was added	Partial, speed, and scope changed; verification norm is now a shared expectation
Candidate screening	Human-led review of all applications	No change. AI tools not deployed for candidate evaluation	No change. Explicitly held outside the AI scope; values-based governance maintains the boundary

Table 2. Changes to organizational routines - IKEA

4.1.7 Governance, ethics, and the limits of AI

Active organizational work on AI is underway to define where it should and should not go, efforts described as deliberate and value-driven. Formal organizational standpoints on AI were developed collaboratively across the people and culture function: *“We started formulating almost like standpoints, and it was challenging, but it had to be said”* (IKEA-1). These standpoints are not published policy documents in the conventional sense but shared organizational positions that give employees a common reference point when questions about AI use arise. A digital ethics policy with explicit positions on sustainability, ethical use, and responsible use functions as an active framework. The apparent expression of these standpoints is the organizational position that AI will not replace jobs at IKEA. This was communicated early and consistently, which made a concrete difference: *“We have also said that AI will not replace any jobs in IKEA. AI is supposed to be used as a tool to support you*

and your work and your job” (IKEA-5). The position is framed not as a guarantee about the future but as an organizational commitment about how AI will be used in the present. This may evolve as the technology develops, but the clarity of the current position has reduced anxiety and enabled a more open approach to experimentation. Environmental concerns featured as a governance consideration. IKEA’s sustainability commitments have led to active pushback from some co-workers against AI applications on environmental grounds. Some co-workers resist using AI specifically because of its energy and water consumption: *“AI is going against our culture, our values, because IKEA wants to be very sustainable”* (IKEA-5). The organizational response has been to encourage employees to use more cost-efficient and sustainably trained models for routine tasks and to discourage unnecessary AI use, such as the tasks that a simple search engine could handle equally well: *“Every time I prompt, I’ve heard that it’s half a liter of water and I have that stench in my heart when I prompt”* (IKEA-3). This environmental dimension of AI governance is specific to IKEA’s cultural context. Recruitment is the area where the governance logic is most visible in practice. The decision not to deploy AI in candidate screening reflects a judgment that the risk of replicating or amplifying existing biases outweighs the efficiency gains: *“We’re very proud of our culture and values, and when we use AI, the market experience shows there are certain criteria AI will take into consideration, but maybe these criteria are not people-centric and do not reflect our values and culture. That’s why we’re very careful”* (IKEA-4). LinkedIn’s AI recommendations are part of the sourcing practice. Evaluation remains with the human recruiter, and the expectation is that it should be held consistently across the people-facing participants in the study. Across interviews, the orientation was consistent toward AI as a tool for efficiency and assistance, not a substitute for human capability: *“AI is a tool for efficiency, not for replacing human beings”* (IKEA-6). AI could enable employees to spend

more time on more creative and collaborative work by handling lower-value tasks that currently consume time and attention.

4.2 Ericsson

4.2.1 Case Context

Ericsson was founded in Stockholm in 1876 and has operated continuously as a Swedish telecommunications company. Today, it is one of the world's leading providers of mobile network infrastructure, operating in 180 countries with approximately 94,000 employees globally as of 2024, of whom around 14,500 are based in Sweden. The company holds more than 60,000 granted patents and has signed licensing agreements with over 100 partners, reflecting the centrality of R&D to its business model and its self-understanding as an organization (Ericsson, 2025). Net sales for 2024 reached SEK 236.7 billion.

AI is simultaneously an internal operational tool used across Ericsson's workforce and a product capability embedded in the network infrastructure that the company sells to telecommunications operators worldwide. This creates a context in which AI adoption is not simply a question of organizational change management but is tied to Ericsson's commercial identity and competitive position. The company has described AI as a prerequisite for realizing the full potential of next-generation networks, and its leadership has communicated AI adoption as a strategic imperative across the organization (Ericsson, 2025). Sweden's largest employer of engineers, Ericsson, has a predominantly technical workforce, and its organizational culture has developed over decades around engineering precision, systematic problem-solving, and a strong tradition of academic collaboration and patent generation. Pettersson et al. (2025) describe Ericsson's AI pursuits as reflecting a company navigating the challenge of capturing value from AI investments in a context where both technology and the competitive landscape are moving faster than established organizational processes can readily keep pace with. The tension between the pace of AI development and the pace at which large,

process-oriented organizations can meaningfully adapt runs through the empirical material that follows.

4.2.2 Engineering identity and team culture

The word that came up most often to describe Ericsson's culture was engineering. This was not merely a descriptor of technical expertise but a characterization of a broader cognitive and relational orientation: analytical, precision-oriented, problem-focused, and curious about novelty: *"I must say it's really an engineering culture. We like problems, we like to break them down into small pieces and work with numbers and get everything lined up"* (Ericsson-4). The can-do attitude and the tendency to reward going beyond formal role boundaries were defining features. This engineering orientation shapes how new things are received in the organization. Engineers find new problems inherently interesting: *"...being an engineer, it's new, it's fresh, I'm interested."*(Ericsson-4). This is the default disposition toward something like AI. The broader R&D spirit was portrayed as a *"...bubbling organization where everyone is in it together,"* contrasting it with other organizations where people work individually under pressure (Ericsson-2). The curiosity is not passive, it is directed toward understanding how things work, what the limitations are, and where something can actually be useful. Alongside the engineering identity sits a team culture that is warm, informal, and internationally diverse. Teams spend considerable time getting to know each other through informal gatherings and fika sessions, and cross-cultural interaction is qualified as a feature of daily life: *"...spending a lot of time getting to know each other. They all come from different cultures, and I see that they are fitting well with each other despite the differences"* (Ericsson-2). Disagreements within teams are handled with respect and professionalism. Knowledge sharing is explicitly rewarded and culturally expected: *"If you're a good team member, if you help others, and if you teach what you've learned to others, then you really get very much attention"* (Ericsson-2). The reverse, being technically strong but keeping

knowledge to oneself, is noted as insufficient for recognition. This norm has direct consequences for how AI knowledge spreads. Leadership at Ericsson is formally hierarchical but operationally collaborative. The organizational structure is complex, with multiple layers of project, program, product, and line management running in parallel. The structure creates a matrix that can be difficult to navigate, but noted that the day-to-day feeling within teams tends to be flat: *“People are not feeling on a pedestal if they have a certain role. They are very much trying to be part of a team”* (Ericsson-2). Leadership is primarily about guiding and empowering: *“It’s a lot about guiding and giving positive feedback, because I think that empowers people rather than discourages them”* (Ericsson-2). A structural distance between senior management and frontline developers exists nonetheless, a gap that creates a disconnect between how AI adoption is communicated from above and how it is experienced in practice.

4.2.3 Psychological safety under commercial pressure

Ericsson has a stated norm of speaking up and voicing concerns regardless of seniority. *“Dare to speak up, everybody can get their voice heard”* is a core expectation at the organization, defining respect as something extended to everyone regardless of background or experience level (Ericsson-5). Disagreements within teams are handled professionally. One participant who had worked at Ericsson across two separate periods noted that the core values around speaking up and professional conduct had remained consistent across more than a decade: *“The core values that Ericsson has taught me back then are still the same”* (Ericsson-2). In the context of AI adoption, however, a second, partly competing force shapes the conditions under which this norm can operate. Strong top-down commercial pressure to adopt AI tools has created an environment in which the space for expressing hesitation is narrower than the speak-up norm might suggest: *“There is a lot of top pressure to start using AI. I don’t see that diminishing anytime soon.”* The specific difficulty this creates for

employees not yet comfortable with AI tools: *“It's hard for somebody not feeling safe to say they don't want to do it”* (Ericsson-5). The commercial mandate does not eliminate the norm of speaking up, but it narrows the range of topics on which that norm can comfortably operate. The reaction on the ground was a mixture of curiosity and uncertainty.: *“What is the strategy here, why are we doing this?”* (Ericsson-4). The question is not one of resistance but of orientation, from people who are willing to engage but who lack a clear enough picture of what they are supposed to be doing with AI and why. The early period of AI introduction was described as one of high volume and low substance: *“It was all these PowerPoint presentations, but no substance”* (Ericsson-1). The gap between the urgency communicated from above and the practical clarity available to employees was raised repeatedly by employees across multiple roles. Time emerged as a specific and recurring challenge. Experimenting with AI tools requires taking time away from delivery commitments, and in an organization where project deadlines are a constant pressure, that trade-off is not straightforward: *“If I want to spend today or half a day really digging into this and trying to create this agent that I see the possibility for, it's a bad conscience, because I can't take those four days, because I need to deliver”*(Ericsson-1). From a management perspective, communicating the importance of AI learning while maintaining delivery expectations creates a double bind for both employees and their managers.. Despite the pressure, the overall atmosphere around AI at Ericsson is more curious than resistant. The engineering orientation described in the previous section creates a baseline level of receptivity: *“Ericsson has made it very easy to bring AI in, it's embracing and learning”* (Ericsson-2). The pressure and the curiosity coexist, and people navigate between them in ways that are visible throughout the interview material.

4.2.4 Responses to AI

The dominant emotional response at Ericsson was not resistance but a combination of curiosity and overwhelm. These two things coexisted in the same interviews, sometimes in the same sentence, and participants brought them up as the natural result of being asked to move quickly in multiple directions simultaneously without a clear, shared framework. The curiosity is real and rooted in the engineering identity described in the previous sections. Colleagues were enthusiastically building agents, experimenting with tools, and sharing what they found with others: *“They get a bit astonished that it can do that much”* (Ericsson-3). One trajectory from skepticism to engagement captures the broader picture: *“A few months ago, AI was mostly about ChatGPT or Gemini for daily questions. But coming here with this atmosphere where AI is really in everything, and everyone is expected to learn something, I have had the opportunity to change my mindset and be more curious”* (Ericsson-2). The engineering culture's reward for sharing knowledge means that early adopters who develop useful AI practices tend to bring others along, keeping what they have found to themselves is not the norm. The overwhelm was vivid and consistent: *“It was an avalanche almost”* (Ericsson-2). Another labeled the same feeling as a waterfall: new initiatives and tools arriving continuously, with too little time between them to develop stable competence. Tool proliferation was the specific problem: *“Today it's Amazon Q, tomorrow it's Kira. Too many tools”* (Ericsson-2). Switching between tools before stable competence can prevent employees from developing reliable practices and make it harder to build a shared organizational understanding of what AI use actually looks like in their context. The overwhelm cascaded from the organizational level down to the individual: *“The company has been overwhelmed, and it cascades down”* (Ericsson-2). The pressure from senior leadership to adopt AI, combined with the proliferation of tools and the absence of a shared strategic framework, creates conditions in which employees are being asked to move quickly without a

clear sense of direction: *“I would like a little bit of guidance on what we are really finding, what the limitations are, and how much time I should put on this. If you structure a little bit, it feels more comfortable than just a completely blank piece of paper”* (Ericsson-2). Variations cut across seniority and age, making them difficult to predict. Two older colleagues were hesitant, while younger colleagues in similar roles were enthusiastic, but this was attributed to familiarity with specific tools and not age: *“They have used it for quite some time now, and they know that it can automate many of the tasks”* (Ericsson-5). Senior developers were sometimes the least enthusiastic about AI coding tools because those tools handle the kinds of tasks that experienced developers find least challenging. The picture that emerges is of an organization whose people are broadly willing to engage with AI but have been given insufficient structural support to do so coherently. The curiosity is genuine, and the engineering culture creates real receptivity. What is missing is the shared sense of direction and the organizational breathing room that would allow that curiosity to consolidate into stable new ways of working.

4.2.5 Entrance and adoption of AI

AI entered Ericsson’s working environment through a combination of top-down mandate and bottom-up experimentation, with the two dimensions not always well coordinated. The mandate came early and from the highest level. The CEO-level communicated explicitly that AI adoption is a strategic priority and that employees are expected to be at the forefront of its use: *“Our CEO is talking quite a lot about using AI and that we need to be at the forefront of using it”* (Ericsson-5). This created a clear organizational expectation, but the practical infrastructure to support it arrived unevenly and, in some areas, significantly later than the expectation itself. The initial experience with AI tools was disappointing. Early tools were either inaccessible due to approval and licensing restrictions or produced results that did not meet engineers' expectations: *“It was pushed a lot*

during the fall, and then for half the people it didn't work due to access restrictions, and for the other half the quality of the tool was not so good. So there were some bad experiences” (Ericsson-6). A significant shift occurred around the end of 2024, when a new tool, Kiro, was introduced after the necessary approvals were granted: *“Around Christmas, we got all the necessary approvals, and we changed from one tool to another, and that was a big change. Right now, people are very enthusiastic”* (Ericsson-6). The training provision was reported as substantial in volume but uneven in quality and fit: *“There are a lot of seminars, and they have been good, but there are so many, and sometimes some of them are good, some of them are not”* (Ericsson-1). The consistent gap was between general awareness training and the hands-on, context-specific guidance needed for employees to apply AI tools in their actual work: *“What we need is some kind of hands-on experience, a workshop where you solve a problem. But who can lead that workshop? That person doesn't exist, because it's our code and they are still learning”* (Ericsson-1). The organization has not yet developed the internal capability to translate general AI literacy into contextually specific practice for engineering teams working on proprietary systems. The absence of a shared coordinating framework across units was identified as a significant structural problem. Initiatives emerged in parallel across departments without coordination, resulting in duplication of effort and preventing the organization from learning from what individual units discovered: *“We are reinventing the wheel in the same week, in parallel in many different places. Right now, there are so many initiatives and maybe too many ways of working in different teams. How do you harness this or create a joint way of working where applicable?”* (Ericsson-6). The result is that individual employees and teams are adapting their practices locally, but those adaptations are not always connecting into a broader organizational understanding of how AI should or will be used. At the same time, a more bottom-up layer of adoption has been developing through the knowledge-sharing culture. Front-runners who have developed useful AI practices share

them through informal sessions and structured knowledge-sharing events: *“These are the front-runners for using AI. When they have got experience and done their work, they're using it on a regular basis, and then they will have knowledge-share sessions so people can get inspired to see if they have a similar thing they might use”* (Ericsson-3). This peer-driven diffusion channel operates independently of the top-down mandate and has been the primary vehicle through which stable AI practices have actually taken hold in some areas. A mandatory baseline for AI knowledge has been established across at least some parts of the organization. A clear mission was stated: *“There has been a clear mission that everyone needs to reach a certain level of AI knowledge, and that is something that we need to secure”* (Ericsson-2). An AI hub, a biweekly session combining presentations and hands-on group work, served as one mechanism for building this baseline. The sessions are designed to give employees a space to try things rather than just listen, reflecting recognition that passive training has a limited effect in a domain where practical experimentation is the primary mode of learning.

4.2.6 Differential trust and the boundary around the professional core

Trust in specific AI tools at Ericsson is not uniform and does not follow straightforwardly from the organization's general orientation toward technology. It is built through direct experience and lost when tools performed poorly or encroached on areas of professional pride. The pattern is consistent: AI is accepted readily for peripheral, informational, and low-stakes tasks, and resisted specifically where it touches the core of professional judgment or professional identity. Internally built tools earned significantly more trust than externally embedded ones. An in-house, ChatGPT-based tool developed by Ericsson, referred to as the Everyday Assistant, is used regularly and trusted to find documents and policies within internal systems. The intranet is notoriously difficult to navigate: *“Ericsson's intranet is a big black hole, and the searching function has been really*

bad” (Ericsson-1). The AI-powered search tool addressed a pre-existing problem, and its adoption followed naturally. Externally embedded evaluative tools were labeled in sharply different terms: *“We don't trust that AI because it's not trustworthy. I always go through the resumes by myself anyway”* (Ericsson-5). The recruitment context provided the clearest illustration of where the boundary lies. The applicant tracking system includes an AI component that scores candidates against the criteria set for each role. The scoring system is systematically bypassed: *“Even though it's kind of miserable sometimes to look at 3,000 resumes, I don't want it to be automated because I need to see all of the people. Probably I would have missed it if I didn't walk through it by myself”* (Ericsson-5). The professional norm that a recruiter reviews every application and makes their own assessment is firmly maintained despite the AI scoring function: *“I kind of take pride in my ability to match a candidate to the profile that I spoke with the manager about. I don't want it interfering with the core of my work”* (Ericsson-5). A parallel pattern appeared in the engineering context. An early AI coding tool trialed by senior developers was found to be disappointing and returned: *“Senior developers said 'I feel like a nanny'. It's good at creating a skeleton, but then it stops”* (Ericsson-1). The tool did not fail on technical grounds alone. It failed because the tasks it handled well were the tasks that experienced developers find least interesting and least challenging, while it offered little for the complex, judgment-intensive work that defines senior engineering practice. More recent tools have been received more positively, with genuine adoption for code understanding and documentation tasks. But the boundary around the core of professional practice remains clearly drawn. The location of resistance is analytically significant. It does not map onto seniority, age, or general attitudes toward technology. It maps onto proximity to professional identity. Tasks that are peripheral, informational, or administrative are adopted with relatively little friction. Tasks that require judgment, contextual sensitivity, and expertise are defended: *“If you need to be good with AI,*

you also need to understand what you're doing. You need to digest and see what kind of answer you've got and evaluate on that" (Ericsson-3). AI is accepted as a tool that requires human oversight and evaluation. What is resisted is any framing of AI as a replacement for the human capacity to make that evaluation in the first place. Variation in adoption follows experience lines, not demographic ones. Longer exposure to AI tools, in professional or personal contexts, translated into greater comfort and more inventive use. For those encountering the tools for the first time in a professional context, the learning curve was steeper, particularly given the delivery pressures described earlier: *"...know that it can automate many of the tasks and approach it with enthusiasm, while those encountering it more recently are still working out what it can and cannot do"* (Ericsson-5).

4.2.7 Changes to working routines

Despite the overwhelm and tool proliferation, genuine and concrete changes in specific work routines have taken hold. Several of these have become stable enough to be defined as routines rather than experiments. Meeting summarisation was mentioned by everyone across all role profiles as a widely adopted change: *"A podcast summary of the meeting, so you don't have to re-watch the whole recording"* (Ericsson-6) or *"great for information digestion"* (Ericsson-2). The sheer volume of meetings across a globally distributed organization makes the summarisation function not just convenient but necessary for staying across what is happening in teams and projects they cannot always attend in person. Meeting summarisation has moved from experimentation to routine more completely than any other AI application at Ericsson, and it did so across roles that differ substantially in their overall relationship with AI. The everyday assistant is now used to find documents, policies, and procedural information that would previously have required manual navigation of the intranet. It surfaces course links when the intranet search fails and serves as a coaching resource when newly arrived: *"I have started two months ago, I'm pretty new. I can put it in*

one of these AI tools and have a dialogue” (Ericsson-2). The internal AI search tool addresses a pre-existing frustration with information retrieval, and its adoption reflects this practical fit rather than a general cultural embrace of AI. In technical roles, AI has also changed aspects of coding and development work, though less uniformly than in the other applications described above. AI tools are now used to understand unfamiliar code, generate documentation, draft unit tests, and produce first versions of code segments that are then reviewed and edited: *“The actual time we spend on coding is between 20 and 30 percent. The rest of the time is understanding requirements, understanding the code base, and communication”* (Ericsson-1). Tools that help with code understanding and documentation support the larger part of the engineering working day rather than the smaller part. The most recent generation of coding tools has been received considerably more positively than earlier versions. Performance review and documentation work have also shifted for participants in management roles: *“I had collected a lot of feedback, and I always spend a lot of time trying to formulate it. I used Copilot to help me formulate it, and it really saved me a lot of time”* (Ericsson-1). The output always requires editing, but the AI draft provides a useful starting point and makes the task feel more manageable. The norm that AI output requires human review before use appeared consistently at Ericsson as it did at IKEA. Beyond individual task changes, the most analytically interesting accounts in the Ericsson data concern the deliberate redesign of workflows around AI capabilities: *“You need to put the AI at the right spot and then have humans still contributing and make it possible to happen”* (Ericsson-2). The idea is not that AI replaces human steps, but that workflows are redesigned so that AI handles the steps it does well, while humans retain the steps that require judgment, verification, and contextual sensitivity. Building AI agents for specific, contained tasks and then integrating them carefully into existing workflows emerged as the most sophisticated form of adoption in the data. The substitution framing was consistently rejected across all role types: *“I cannot*

believe AI can substitute human judgment. I don't think it's true” (Ericsson-2). Others found AI useful for accelerating certain tasks while maintaining clear boundaries around the professional judgment they considered irreducibly human. The dominant pattern in the Ericsson data, as at IKEA, is one of human-AI collaboration rather than replacement, but the path to that collaboration at Ericsson is expressed as more disjointed, more individually navigated, and harder-won than at IKEA. Table 3 maps these routine-level changes at Ericsson, applying the same ostensive/performative distinction used in the IKEA analysis.

Routine	Before AI	Performative change	Ostensive change
<i>Ericsson</i>			
Meeting catch-up	Re-watching full recordings	AI-generated meeting summaries are used across all roles	Yes, summary via AI is now the expected method; re-watching recordings is no longer standard
Internal information retrieval	Manual navigation of the intranet	AI-powered internal search tool (Everyday Assistant) used for documents and policies	Yes, the expectation of how to find internal information has shifted to AI-first search
Code understanding and documentation	Manual reading of codebase; documentation written from scratch	AI used for code comprehension, documentation drafts, and unit tests; human review retained	Partial, adopted for peripheral coding tasks; core engineering judgment remains with humans
Performance review documentation	Formulated manually from collected notes	AI used to draft initial formulations; always edited before submission	Partial, AI draft as starting point accepted; human judgment on content remains expected
Candidate screening	Human review of all applications	AI ranking tool present in applicant tracking system but systematically bypassed; recruiters review all CVs independently	No change. Professional norm of human review firmly held despite AI presence

Table 3. Changes to organizational routines - Ericsson

4.3 Cross-case Observations

4.3.1 Overwhelm as the shared adoption barrier

Both organizations independently described the same adoption barrier: the inability to consolidate new practices quickly enough to keep pace with the volume of tools and initiatives arriving simultaneously. What makes this pattern significant is that it appeared under very different cultural conditions: at IKEA, where psychological safety is high and adoption is voluntary, and at Ericsson, where commercial pressure was strong and adoption was mandated. If overwhelm were a product of cultural resistance or disengagement, it would not have appeared in both. This suggests that the barrier is structural and not cultural, a consequence of how AI was introduced rather than how it was received. Neither organization had yet developed a mechanism to pace the introduction in a way that would allow shared frameworks to form alongside new tools, creating a gap between individual experimentation and collective understanding.

4.3.2 Periphery accepted, core defended

Across both organizations, the boundary between accepted and resisted AI fell in the same place: peripheral, informational, and administrative tasks on one side; judgment-intensive, identity-constituting work on the other. At IKEA, that boundary runs around relational and creative work, and at Ericsson around engineering expertise and professional judgment. The locations differ, but the logic is identical, and the consistency across two very different professional contexts is analytically valid. The boundary held where AI was perceived as encroaching on what each organization had, through years of practice, determined actually constitutes real work. A study of either organization alone might have attributed the boundary to its specific cultural profile. The cross-case comparison reveals that the boundary is not culturally specific but appears across both.

4.3.3 Meeting summarisation as first adoption

Meeting summarization was the only AI application that crossed every boundary in the dataset. The most obvious explanation is practical: it solves a concrete pre-existing problem, produces immediately visible results, and requires no cession of professional judgment. Meeting summarisation sits at the periphery of professional identity in both organizations; no one at IKEA or Ericsson defines their professional worth through how they take meeting notes. Its universal adoption may therefore be less a sign of cultural openness toward AI than of the complete absence of cultural resistance.

4.3.4 Leader modeling and peer learning

Both organizations independently identified two mechanisms as the most effective for AI adoption: leaders who personally use and understand AI tools, and informal peer sharing. Formal training, which was featured in both cases, was consistently described as less formative. This pattern held regardless of how different the adoption contexts were. In both cases, the reference point that made new practices feel legitimate and possible was always a person and not a policy. A colleague who had tried something and shared what they found, or a leader whose own use of AI shifted the collective question from whether to how. Where that person was absent, urgency existed without direction, and individual experimentation remained fragmented.

4.3.5 Human-AI complementarity

Across both organizations and role profiles, the substitution framing was rejected, and a collaborative one was embraced. This convergence happened under very different conditions. At IKEA, it emerged through a collectively supported process shaped by explicit organizational commitments that AI would not replace jobs and reinforced through peer learning and shared experimentation. At Ericsson, it was reached more individually, through direct experience of what the tools could and could not do, often without a shared

organizational framework to interpret that experience. That both paths led to the same conclusion points to something empirically grounded. A reflection of what current AI tools actually are capable of, independent of what each organization's culture led it to expect.

5. Analysis

This chapter compares the empirical patterns observed at IKEA and Ericsson against the four propositions developed in Chapter 2. The analysis follows Yin's (2018) pattern-matching logic. Where empirical patterns align with the predicted ones, confidence in the theoretical framework is strengthened; where they diverge, the divergence is treated as evidence that the framework requires refinement. Table 4 summarises the outcome of this comparison across all four propositions before each is examined in turn.

Proposition	Theoretical background	Findings - IKEA	Findings - Ericsson	Similarities	Differences
P1 Fluidity of routine change <i>Clan and adhocracy cultures absorb AI-driven performative variation more fluidly into ostensive understanding.</i>	Performative variation feeds back into shared understanding where cultural assumptions remain open to renegotiation. <i>(Feldman & Pentland, 2003; Cameron & Quinn, 2006)</i>	Pattern supported across multiple routine types. New shared norms emerged around AI output verification, documentation thoroughness, and prompting with IKEA tone of voice. Psychological safety and peer sharing enabled spread.	Pattern partially supported. Meeting summarisation shifted to shared norm; recruitment AI ranking and early coding tools left ostensive understanding unchanged. Fluidity occurred only where specific structural conditions were met.	Both cases show fluidity where AI sits peripheral to the professional core. Fluidity is conditional, not automatic, in both cases.	IKEA shows broader fluidity across more routine types; Ericsson narrower and more conditional. Cultural orientation shapes breadth, not possibility.
P2 Resistance and surface-level adoption <i>Hierarchy and market cultures change practice without correspondingly reshaping ostensive understanding.</i>	Strongly embedded routines resist change even when performances deviate; tool proliferation compounds the gap. <i>(Howard-Grenville, 2005; Feldman & Pentland, 2003)</i>	Pattern partially supported. Resistance concentrates at the relational and creative core only. AI accepted widely for administrative and analytical tasks; surface-level non-adoption is principled and value-driven rather than structural.	Pattern supported. Recruitment ranking systematically bypassed; early coding tools returned. Fragmented rollout amplifies the performative-ostensive gap.	Both cases show AI accepted at the periphery, resisted at the core. Logic of the boundary identical across cases.	At IKEA resistance is principled and value-driven. At Ericsson resistance is structural, amplified by fragmentation. More widespread at Ericsson.

P3 Leader participation as mediating condition <i>Visible leader engagement with AI signals legitimacy and enables collective sensemaking, regardless of cultural type.</i>	Leader participation provides a shared reference point through which individual adaptations can be collectively interpreted. (Fousiani et al., 2024; Holmström & Magnusson, 2025)	Pattern supported. Leaders using AI shift the collective question from whether to how. Absence of visible engagement produces caution and retreat. Mechanism operates through informal cultural channels.	Pattern supported, unevenly enacted. Leaders who build agents and share findings earn credibility. Mandating without participating creates urgency without a shared reference point.	Strongest cross-case finding. Mechanism identical regardless of cultural type.	IKEA operates through informal cultural channels. Ericsson articulated as an expectation but unevenly enacted.
P4 Cultural identity as boundary around AI <i>Where AI threatens irreplaceable human contribution, resistance operates at Schein's deepest cultural level; location of boundary shaped by cultural assumptions.</i>	Not conscious objection but instinctive defence of what feels like the right way to work. (Schein, 2010; Ashforth & Mael, 1989)	Pattern supported. Boundary runs between administrative efficiency and human connection. Relational and creative work defended; boundary formally codified in ethics standpoints and digital ethics policies.	Pattern supported. Boundary runs between informational retrieval and professional expertise. Engineering judgment and recruitment matching is defended through professional norms rather than formal policy.	Both cases defend a cultural core against AI. Logic of defence identical across cases.	IKEA defends human warmth and relational work; Ericsson defends engineering precision and expertise. IKEA's boundary is formal; Ericsson's informal.

Table 4. Cross-case pattern matching of propositions

Note: Where empirical patterns align with the predicted ones, confidence in the theoretical framework is strengthened; where they diverge, the divergence opens space for refinement (Yin, 2018).

Figure 2 translates these patterns into schematic form.

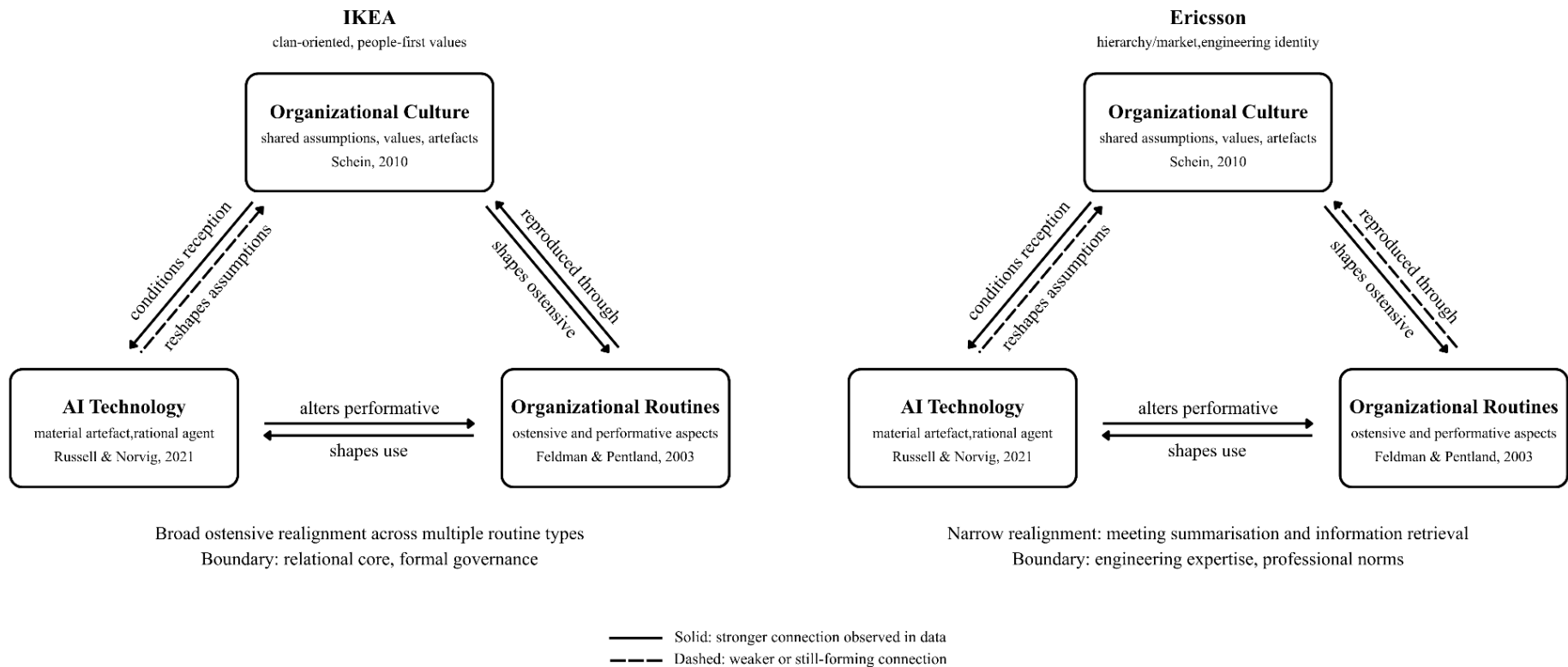


Figure 2. The reciprocal framework applied: comparative patterns at IKEA and Ericsson

Note: The solid and dashed lines reflect the strength of each connection as observed in the data: solid lines indicate connections that were strongly and consistently supported across multiple routine types, while dashed lines indicate connections that emerged only partially or under specific condition

5.1 P1 - Fluidity of routine change

Proposition 1 predicted that under clan- and adhocracy-oriented conditions, the reciprocal relationship among culture, AI, and routines would be sufficiently permeable for AI-driven performative variation to feed back into ostensive understanding over time. The empirical material from IKEA provides broad support for this pattern, and the mechanism through which it operates is traceable in the data. The cultural profile, as derived from the interviews, is strongly clan-oriented (Cameron & Quinn, 2006), characterized by togetherness, flat hierarchy, people development, and a set of founding values that function as a navigational compass for everyday decisions (Schein, 2010). Within the CVF's two axes, clan culture falls in the flexibility-internal orientation quadrant. Assumptions about how work should proceed are held loosely enough to absorb variation, while change is evaluated primarily against the organization's own people and values. This configuration shapes the interaction with AI in a specific way. Participants did not evaluate AI as a category. They evaluated it through existing cultural logic about which kinds of change are legitimate and which threaten what the organization fundamentally is. Culture is what determines which AI-driven changes feel legitimate and which do not (Al Samman, 2024; Sarfraz & Shah, 2024). Where AI-driven change was judged as culturally compatible, performative variation accumulated into a revised shared understanding. Where the change was judged as threatening the relational core of work, it held the ostensive pattern firm regardless of what the performative layer was doing. New shared norms emerged around AI output verification, content work is now understood to require human editing, and documentation discipline has risen as a collective baseline. These shifts mark actual rather than surface-level change. Rerup and Feldman (2011) show that repeated trial-and-error performances that resolve task-specific problems can accumulate into a revised organizational schema over time, shifting what people understand the routine to require, not only what they do within it.

At IKEA, this is the case. Individual performative adjustments, reinforced through peer sharing and organizational framing, gradually consolidated into new ostensive understandings across multiple routine types. The pattern holds across specific routine types, as traced through the reciprocal framework in each case. Where AI was positioned as augmentation at a peripheral step, meeting summarisation delivered through an internal platform with training before access, or data analysis tasks where the judgment remained with the person, performative variation accumulated into revised shared understanding. Documentation thoroughness is now a collective expectation; the scope of analytical work understood as possible has expanded. Where AI sat closer to the relational core, as in content drafting, the shift was only partial. The performative change is established, but the shared understanding that human editing is required has held firm, because the IKEA tone of voice sits close enough to cultural identity to resist full delegation. Two enabling conditions shaped these outcomes. The first is explicit organizational framing. The communicated position that AI will not replace jobs but will support employees, and that where roles do change, people will be reskilled and not let go, established a shared interpretation of what AI is before individuals formed their own. Research on organizational transformation consistently shows that change stalls when urgency is created without a clear, shared vision (Kotter, 1995). By shaping this frame early, IKEA avoided that failure. The second condition is the sequencing of preparation before expectation. When tools were given without guidance, resistance and confusion followed. When training and supported experimentation preceded adoption, new understandings took root. The voluntary peer sharing sessions that drew around a thousand participants biweekly provided the informal infrastructure through which individual experimentation became collective learning. Psychological safety created the conditions in which employees could voice uncertainty about AI without incurring social costs, allowing confusion to surface and be addressed. The prediction holds, however, with an important

qualification. Where resistance to routine change is found at IKEA, it consistently clusters around the same kind of situation: AI being introduced not at the periphery of work but at what participants understand as the identity-constituting core of work. The shared understanding that real work happens when people work together is held as a normative standard against which AI-driven change is evaluated. Using AI in a way that substitutes automated output for human judgment is experienced as a cultural violation rather than an operational error. This resistance is not uniform across roles. It is most pronounced where AI is closest to the relational or creative core of work, like content generation, candidate screening, and customer interaction. It is the least present where AI handles informational, administrative, or analytical tasks. That this boundary appears consistently across participants in very different roles confirms it is a shared cultural commitment rather than individual variation (Ashforth & Mael, 1989; Tajfel & Turner, 1986).

At Ericsson, Proposition 1 receives only partial support. Ericsson's cultural profile combines features of hierarchy and market orientations with a layered engineering identity (Cameron & Quinn, 2006). Participants consistently described a precision-oriented, analytically driven culture that rewards accumulated expertise and problem-solving. Unlike the clan quadrant's flexibility, the hierarchy and market orientations Ericsson combines both sit on the stability side of the CVF's first axis. Where clan culture holds assumptions loosely enough for variation to accumulate, the stability orientation means that each performative departure from established practice encounters a pull back toward what precision and expertise have already determined to be correct. The market dimension adds a second pressure. AI adoption does not arrive as an invitation to explore. It arrives as a delivery imperative, which compresses the time available for new shared understandings to form before the next tool arrives. The engineering identity cuts across both quadrants, creating curiosity about AI as a problem to understand while simultaneously generating caution about

disrupting what has been carefully constructed. This hybrid configuration was derived from participants' descriptions of their own culture rather than being imposed from outside. Based on this, it produced a narrower and more conditional ostensive realignment than the clan-dominated context at IKEA. Where specific conditions were met, genuine ostensive realignment did occur. Meeting summarisation has shifted from optional to expected. Internal AI search has replaced manual intranet navigation as the shared norm. These changes are structurally similar to IKEA's: AI handles peripheral, informational tasks; it solves a pre-existing problem; and it requires no cession of professional territory. Where these conditions were absent, the shared understanding held firm. The recruitment ranking tool is systematically bypassed and the early coding tool was returned by senior engineers. Surface-level tool availability changed nothing about how the routine was understood to work. The key difference between the two cases lies in breadth and depth. At IKEA, ostensive realignment occurred across multiple routine types and spread through informal cultural channels. At Ericsson, it occurred only where specific structural conditions were present and remained more locally contained. Cultural orientation shapes the breadth of fluidity, not its possibility.

5.2 P2 - Resistance and surface-level adoption

Proposition 2 examines the same reciprocal dynamic under different cultural conditions: where hierarchy and market orientations dominate, the framework predicts that the pull back to established patterns is strong enough to prevent performative change from accumulating into revised shared understanding, and that this gap is further amplified when AI is introduced without a shared coordination framework. The stability orientation shared by both quadrants means that performative variation meets resistance on two fronts: the hierarchy dimension protects established procedure and accumulated expertise, while the market dimension frames AI adoption as a performance imperative rather than an exploratory

one. Within the CVF's two axes, both hierarchy and market orientations sit on the stability-and-control side of the flexibility dimension, which means that neither creates the cultural conditions under which assumptions about how work should proceed are held loosely enough for performative variation to accumulate unchallenged (Cameron & Quinn, 2006). Where the hierarchy quadrant generates resistance by protecting established processes and role definitions, the market quadrant compounds it by attaching urgency to adoption without providing the exploratory space in which new shared understandings can form.

At Ericsson, the data support this pattern, and the interaction between cultural configuration and introduction condition is visible throughout. Ericsson's engineering culture's orientation toward precision and accumulated expertise creates conditions in which established ways of working are protected even when new tools are introduced. Participants described an organization that likes problems, breaks them into small pieces, and works systematically, while understanding itself as fundamentally about people as well as precision. This pairing shapes AI reception in both directions. The engineering orientation drives curiosity about AI as a new problem to understand. It also drives caution about disrupting what has been carefully constructed. The applicant tracking system provides the best illustration. The shared understanding of what screening requires has not changed despite the formal presence of AI. A parallel pattern appeared in the engineering context, where an early AI coding tool was tested by senior developers, found inadequate, and returned. In both cases, performative practice and ostensive understanding diverged: surface-level availability of tools did not translate into a revised shared understanding of how the routine works (Feldman & Pentland, 2003). The fragmentation mechanism predicted by Proposition 2 compounds this pattern. The absence of a shared coordinating framework across units meant that individual adaptations did not connect into broader organizational understanding. Participants framed this as an avalanche and a waterfall, not resistance but volume without

direction, and local experimentation continued while collective sensemaking stalled (Weick, 1995; Kotter, 1995). The cultural configuration and the structural conditions of introduction amplify one another. A culture that values precision and accumulated expertise resists AI at the core, and a fragmented rollout prevents peripheral adoptions from consolidating into shared new understandings across the organization. The CVF axes are analytically important here. The hierarchy and market orientations Ericsson combines both sit on the stability-and-control side, evaluating change against established procedures and performance outcomes. Where assumptions are held loosely and change is evaluated against shared values, variation has more room to accumulate. Where they are held tightly against procedure and performance, the pull back toward established patterns is stronger and more durable, which is precisely what produces the wider ostensive/performative gap at Ericsson.

At IKEA, Proposition 2 receives partial support. The resistance that appears does not reflect a general cultural orientation toward consistency. Resistance is concentrated specifically where AI is perceived as threatening the organization's fundamental nature (Schein, 2010; Tajfel & Turner, 1986). The decision not to deploy AI in candidate screening, the insistence on human editing of all AI-generated content, and the active governance through ethics standpoints and digital ethics policies all reflect the same interaction: a clan culture's basic assumptions that real work is relational and human encounters an AI positioned at the identity-constituting core, and the cultural field holds the ostensive pattern firm. This is a principled, value-driven boundary and not a structural or consistency-driven one. The same empirical pattern, performative change without ostensive realignment, appears in both organizations, but the interaction through which it is produced differs in each case (Ashforth & Mael, 1989; Schein, 2010).

5.3 P3 - Leader participation as a mediating condition

Proposition 3 predicted that, regardless of cultural orientation, leader participation in AI adoption would mediate the reciprocal dynamic between AI and routines, and that visible leader engagement would signal legitimacy and provide individuals with a reference point for collective sensemaking. Where AI is experienced as a mandate from leaders who do not themselves participate, resistance is expected to persist and the ostensive/performative gap to widen (Kotter, 1995). The findings from both organizations support this pattern, and the cross-case comparison reveals that the mechanism is the same regardless of cultural type, even as the pathway through which it operates reflects the broader cultural difference between the two cases.

At IKEA, leadership is understood as an action rather than a position, which means visible leader engagement with AI is a baseline expectation, not an added quality. When leaders use AI tools themselves, the collective question shifts from whether to use AI to how to use it. Where that modeling is absent, employees default to caution, and the existing understanding of how work should proceed goes unchallenged. The informal channels through which AI knowledge spreads at IKEA are the same channels through which the presence or absence of leadership is felt (Fousiani et al., 2024).

At Ericsson, leaders who have installed development tools, built their own agents, and shared findings through knowledge sessions earn credibility because their guidance comes from direct experience, which matters more in an engineering culture that values competence over hierarchical position (Holmström & Magnusson, 2025). Where leaders communicated AI adoption as a strategic priority from a distance, urgency was created without direction: employees felt the mandate but lacked a shared sense of what it meant to act on it well. The cross-case pattern strengthens the propositions considerably: leaders within the change enable the ostensive realignment that leaders above the change cannot, and this holds across both

clan and engineering-hierarchy cultural contexts (Fousiani et al., 2024; Holmström & Magnusson, 2025; Kotter, 1995; Weick, 1995).

5.4 P4 - Cultural identity as a boundary around AI

Proposition 4 predicted that where AI is perceived not just as a task but as what the organization fundamentally is, resistance would operate at a culture's deepest level, not as a conscious objection but as an instinctive defense of what feels like the right way to work (Schein, 2010). Both organizations support this pattern, and the comparison between them illustrates how cultural identity shapes the boundary's location and content while the underlying logic remains the same.

At IKEA, the interaction between the clan culture's basic assumption that real work is relational and human (Schein, 2010) and AI positioned as a replacement for candidate evaluation and creative content production creates resistance operating below the level of deliberate reasoning. Participants express an instinctive sense that delegating relational judgment to AI would mean losing something essential about what IKEA is (Schein, 2010; Ashforth & Mael, 1989; Tajfel & Turner, 1986). The boundary has also been translated into formal institutional practice, ethical standpoints, digital ethics policies, and sustainability criteria for AI adoption, codifying what AI may and may not do and making the implicit assumption explicit and organizationally enforceable.

At Ericsson, the defended core is professional expertise and the accumulated precision of engineering practice. Resistance concentrates in exactly the cases where AI is positioned as an evaluator or a replacement for professional judgment: the coding tool that senior engineers found inadequate and returned to, the recruitment ranking that is systematically bypassed. The identity-based logic is the same as at IKEA, where AI intrudes on what professional competence means; resistance operates at the level of shared assumption (Schein, 2010). But the content of that assumption is engineering precision and accumulated

expertise rather than human warmth and relational work. The boundary is maintained through professional norms (D'Adderio, 2008). The cross-case comparison also reveals a governance asymmetry. This asymmetry reflects the broader difference in how culture is organizationally structured in the two cases. Where culture is a managed function with dedicated roles, it is more readily translated into formal governance. When integrated in professional practice, it tends to remain there. As AI continues to evolve and the pressure to adopt grows, it is an open question whether informal professional norms will hold up as well as formally codified ones.

5.5 Beyond the propositions

Three patterns emerged from the data that the four propositions do not fully account for. Each refers to a dimension of the culture-AI routines relationship that existing theory addresses only partially.

5.5.1 Tool design as a trust-building mechanism

The data from both cases reveal a pattern that extends D'Adderio's (2008) account of artifact participation in routine dynamics. Trust in a specific AI tool, and therefore its capacity to become constitutive of a routine, is shaped primarily by whether the tool supports or evaluates human judgment, independently of the organization's broader cultural orientation toward AI. The pattern is most evident when the same person enthusiastically uses one AI tool while bypassing another. Internal tools built for a specific organizational context, designed to support human decision-making in peripheral tasks, earn trust. External tools that evaluate or replace human judgment at the core of professional practice encounter resistance, regardless of cultural type. The sociomaterial relationship between a tool and the routine it enters is not simply mediated by culture but also operates as an independent force that shapes which performative variations persist and which are resisted (D'Adderio, 2008; Orlikowski, 2007). AI that supports human judgment in peripheral steps and is context-internalized earns

trust and becomes constitutive of the routine. AI that evaluates or replaces human judgment at the identity-constituting core triggers stable resistance, regardless of cultural openness toward AI in general. Tool design is therefore not a downstream implementation detail but an upstream determinant of whether cultural openness can translate into genuine routine change (Jarrahi, 2018).

5.5.2 Organizational overwhelm as a distinct barrier

The existing literature frames routine change primarily in terms of cultural resistance or enabling conditions (Feldman & Pentland, 2003; Howard-Grenville, 2005; Kotter, 1995). However, the data from both cases point to a third mechanism that existing theory does not fully cover. Here, this is referred to as “organizational overwhelm”. It is a condition in which employees are willing to engage with AI but cannot consolidate new ways of working because tools arrive faster than shared interpretive frameworks can form, initiatives proliferate without coordination, and the pace of change exceeds the human capacity for collective sensemaking (Weick, 1995). Unlike cultural resistance, organizational overwhelm is not rooted in opposition to change. It is produced by the structural conditions of introduction. When too many tools arrive simultaneously, when initiatives increase without coordination, and when the pace of change exceeds employees' capacity to make sense of it, employees experience a breakdown in sensemaking. Cues arrive without a stable interpretive frame through which to collectively interpret them (Weick, 1995). Local experimentation continues, but without a shared framework to consolidate around, new ways of understanding how things should be done never fully form, and performative change accumulates without producing ostensive realignment (Feldman & Pentland, 2003). At Ericsson, the avalanche and the waterfall imagery participants used describe not resistance but volume without direction. The same dynamic appears at IKEA in milder form. The organizational push for efficiency and speed sits in tension with the human pace at which real understanding forms. In both

cases, overwhelming and insufficient consolidation time produces a gap that cultural openness alone cannot overcome. Cultural orientation toward adaptability shapes readiness for change, but implementation conditions shape whether that readiness can be activated (Howard-Grenville, 2005; Kotter, 1995). Indicators of this barrier include tool churn, parallel reinvention of practices across units, and sensemaking fatigue, employees who are willing to engage but cannot locate a stable shared framework to engage around. Two organizational responses emerge from the data as practically meaningful. The first is cadence control. Deliberately spacing the introduction of new tools to allow stable competence to form before the next arrives, and building in consolidation windows in which experimentation pauses and emergent practices are collectively reviewed and codified. IKEA's biweekly sharing sessions approximate this informally; Ericsson's absence of an equivalent is precisely what participants described as missing. The second is a framework provision: establishing a shared organizational vocabulary for what AI adoption is intended to achieve before tools are deployed. Without such a frame, employees face the double burden of learning new tools while simultaneously constructing their own interpretative account of why they are doing so. The training-before-access model at IKEA addresses this directly, while the PowerPoint-heavy, substance-light rollout participants described at Ericsson illustrates what happens when urgency is communicated without it.

5.5.3 The playground phase as a transitional state

Both organizations describe their current relationship with AI as a state of ongoing experimentation. New ways of working are being tried, but they have not yet settled into a revised shared understanding. Existing routine theory is designed to explain stability or change, not the condition in between (Feldman & Pentland, 2003; Orlikowski, 2007). Here, this is called the "playground phase". The concept builds on two existing frameworks but names a condition neither fully accounts for. Organizations must balance exploratory learning

against exploitative efficiency, with short-term pressure tending to close down exploration before it has had time to yield learning (March, 1991). Routine theory adds a further dimension by suggesting that new performances gradually accumulate into a revised shared understanding as they are repeatedly enacted and begin to habituate, with trial-and-error learning connecting to schema change through two processes. Resolving task-specific problems within a routine, and addressing the broader question of whether enacted practices align with what the organization understands itself to be (Rerup & Feldman, 2011). The second process requires the first to have stabilized enough to generate those broader questions. In the playground phase, this stabilization has not yet occurred. Task-level experimentation is underway, but the pace and volume of AI introduction prevent any single set of solutions from settling into the repeated, recognizable pattern from which schema-level questions can emerge (Rerup & Feldman, 2011). Together, these frameworks explain why organizations underinvest in exploration and how new practices eventually consolidate. What they do not explain is what happens in the middle, when exploration is underway but shared understanding has not yet formed. The playground phase describes this. Employees are experimenting and solving local problems, but the pace of introduction and the absence of a consolidating framework prevent those trials from accumulating into the schema-level questions that drive ostensive realignment. The risk identified is the premature closure of exploration already underway (March, 1991), and the mechanism that eventually connects exploration to change requires a stable enough base from which schema-level questions can form (Rerup & Feldman, 2011). Organizational overwhelm, described in the previous section, is the condition that commonly prevents organizations from exiting this phase. When tools arrive faster than shared frameworks can form, the experimentation underway in the playground phase cannot accumulate into the schema-level questions that drive ostensive realignment (Weick, 1995; Feldman & Pentland, 2003). Both organizations in this study are

in this phase. The pressure to close it down, driven by organizational efficiency demands, represents one of the most significant tensions the data reveal. This phase operates at the organizational level, describing the broader transition both organizations are navigating, even where specific routines have already reached ostensive realignment. Figure 3 illustrates the playground phase, its conceptual position between performative variation and ostensive realignment, and the internal condition of organizational overwhelm that commonly prevents organizations from moving through it.

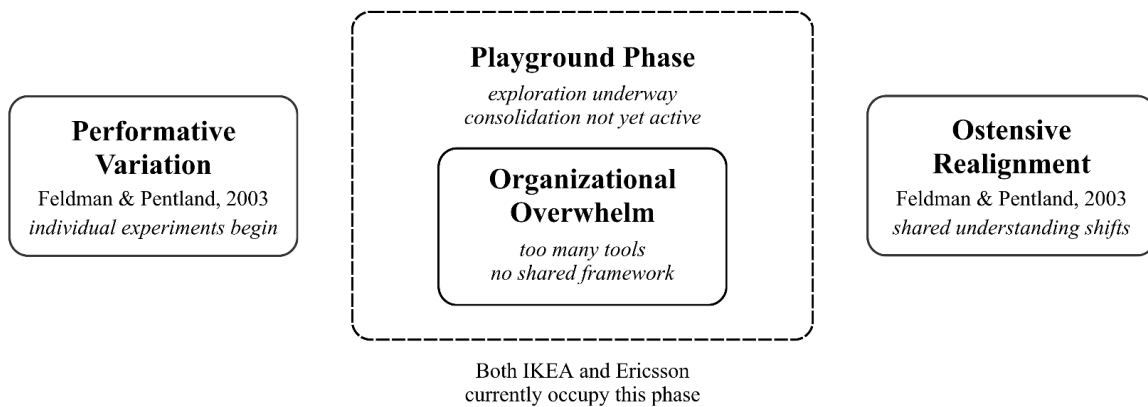


Figure 3. The playground phase as a transitional state in AI-driven routine change

6. Discussion

6.1 Theoretical Contributions

This study makes four contributions to the literature at the intersection of organizational culture, AI, and routine theory. Two address what the findings add to the understanding of how culture shapes AI reception and routine change. Existing research has treated this relationship as relatively direct: culture characterized by adaptability enables change, and those oriented toward consistency resist it (Denison & Mishra, 1995; Howard-Grenville, 2005). The findings of this study complicate that picture in two ways. Cultural orientation shapes the breadth and speed of ostensive realignment, but it is neither deterministic nor sufficient on its own. Implementation conditions, how AI is sequenced,

framed, and supported, mediate whether cultural openness translates into genuine change in shared understanding. This conditionality represents a meaningful refinement of the ostensive/performative framework (Feldman & Pentland, 2003; Rerup & Feldman, 2011). Additionally, the account of how basic cultural assumptions operate as a filter for AI has been refined. Prior work has argued, broadly, that culture shapes the reception of technology but has left the specific site underspecified (Schein, 2010; Al Samman, 2024). Resistance concentrates precisely where AI is perceived as threatening what makes human contribution irreplaceable, operating below the level of deliberate reasoning as an instinctive defense of professional identity (Ashforth & Mael, 1989; Tajfel & Turner, 1986). The location of this boundary varies across organizations in culturally determined ways, which means that understanding where it sits and what it protects are both theoretically informative and practically consequential. The remaining two contributions identify mechanisms that culture alone does not explain. Tool design emerges as an independent sociomaterial force. D'Adderio (2008) showed that artifacts shape routine performance. This study identifies the specific property through which that shaping occurs. Whether a tool is positioned to support human judgment or replace it determines whether it earns trust and becomes embedded in the routine. Cultural openness to AI in general does not affect this. The same organization that enthusiastically adopted an internally built policy search tool systematically bypassed an externally embedded recruitment ranking tool. This suggests that the sociomaterial relationship between a tool and the routine it enters operates as an independent force, not simply as a cultural refraction (Orlikowski, 2007), and that tool design is a consequential variable in AI adoption that has received insufficient empirical attention. Equally significant is what neither organization has yet resolved: how to keep the space in which learning happens open long enough for it to matter. This study proposes the playground phase as a theoretically meaningful and empirically grounded category for this transitional state. The

concept draws on March's (1991) exploration/exploitation distinction to identify the risk of premature closure, and on Rerup and Feldman's (2011) two-process account of schema change to specify why consolidation stalls. When task-level stabilization has not yet occurred, the schema-level questions that drive ostensive realignment cannot form. The playground phase is therefore not a restatement of either framework but a theoretically distinct category that neither names. Recognizing it matters because preserving exploratory space is not a failure to consolidate but the condition under which real learning accumulates into lasting change. Organizational overwhelm is one of the conditions that keeps organizations in this phase. Together, these two concepts identify not just what is happening, but why the transition from exploration to consolidation stalls. Of the four contributions, this is the most theoretically generative. It does not refine an existing concept but names a condition the literature has not previously distinguished. Its implications extend beyond AI adoption to any organizational transition involving rapid technological change.

6.2 Limitations

Several limitations of this study should be acknowledged. With 14 interviews across two organizations, the findings are analytically rather than statistically transferable. No claim to representativeness is made, and the study does not claim to capture the full complexity of either organization. Access to participants was secured through existing professional networks, which means those willing to be interviewed may hold stronger or more positive views about AI than those who declined, introducing a degree of selection bias that the snowball approach only partially mitigates. The reliance on self-reported interview data also carries inherent limitations. Participants may have understated resistance or overstated enthusiasm for AI, given the organizational pressure to adopt it that exists in both organizations, and recall bias cannot be entirely eliminated. A further consideration concerns the profile asymmetry between the two cases, as already discussed. While it reflects the

organizational reality of each case rather than a sampling artifact, it means that the cultural dynamic at Ericsson is less fully captured from the inside than at IKEA, limiting the possibility of strict cross-case symmetry in the analysis. The focus on two Swedish organizations, while methodologically deliberate in controlling national culture, means that findings should be interpreted within this national and industry context. The extent to which the patterns observed transfer to organizations operating in different national, sectoral, or institutional environments remains an open question. Finally, the study captures a single point in time during a period of unusually rapid change, both in AI capabilities and in organizational responses to them. The findings represent a snapshot of a fast-moving moment, and given the pace of AI development, the organizational dynamics described here may look substantially different in a short period. This temporal limitation is perhaps more acute for studies of AI adoption than for most qualitative research, precisely because the technology itself is a moving target.

6.3 Future Research

Several directions for future research emerge from this study. The most pressing concern is the playground phase, specifically what happens when organizations attempt to transition from exploration to consolidation. Longitudinal research tracking organizations through the full process from initial AI experimentation to stable new routines would significantly advance understanding of which conditions enable or disrupt that shift, and what is lost when efficiency pressures close down exploration prematurely. The governance asymmetry between the two cases also warrants further investigation. Whether formal codification of cultural boundaries around AI makes them more durable as AI capabilities expand, and whether organizations relying on informal professional norms are more vulnerable to boundary erosion, are open questions this study raises but cannot answer. Similarly, tool design is a trust-building mechanism that should receive more dedicated

empirical attention across a wider range of organizational and cultural contexts to establish whether the supporting-versus-evaluating distinction operates as a generalizable mechanism or is shaped by the specific professional identities present here. Replicating this study in non-Swedish or non-Nordic contexts would help establish the extent to which the patterns observed here travel across different national cultures, power dynamics, and institutional arrangements.

6.4 Practical and Managerial Implications

While this study is primarily theoretical, several practical insights emerge from the empirical material. Organizations tend to focus on whether their culture is ready for AI, but the findings suggest the more useful question is how the introduction of AI is sequenced and framed in relation to existing cultural assumptions and routines. Establishing a shared understanding of what AI does and does not mean, and of how work is valued, before tools are deployed, creates the conditions for real learning rather than surface-level compliance. At IKEA, the decision to require training before giving access to the internal AI platform demonstrably reduced resistance and fear. At Ericsson, the absence of such sequencing led to what participants described as an avalanche. The practical implication is straightforward: provide training before granting access, and resist the pressure to introduce new tools before the previous ones have had time to take root. The findings also suggest that leader behaviors shape the cultural legitimacy of new ways of working more than a formal mandate does. Leaders who engage with AI as participants rather than enforcers provide the reference points through which individual experimentation becomes collectively intelligible, and through which new performative practices can gradually accumulate into a revised shared understanding. At IKEA, leaders who visibly used AI tools in their own work shifted the collective question from whether to use AI to how to use it. At Ericsson, leaders who had built their own agents and shared findings through knowledge sessions earned more

credibility than top-down mandates did. Instead of communicating adoption as a strategic imperative from a distance, requiring managers to demonstrate their own use of AI is more likely to produce real, routine change. The cultural boundary around AI, the instinctive defense of what makes human contribution irreplaceable, should be treated as meaningful information rather than as a resistance to be overcome. Understanding where that boundary sits and what it protects tells organizations something important about their own cultural identity and which human-AI configurations are likely to be sustainable over time. At IKEA, this boundary runs between administrative efficiency and human connection. AI handles meeting transcription and data analysis, but candidate screening and content generation in the organization's voice remain human-led. At Ericsson, it runs between informational retrieval and professional expertise. The internal Everyday Assistant is trusted for document search, but the recruitment ranking tool is systematically bypassed, and engineering judgment is firmly defended. Working with that boundary rather than against it is more likely to produce routines in which AI is genuinely embedded than those in which it is formally present but practically bypassed. A practical first step is to map the boundary before deploying evaluative AI tools.

7. Conclusion

Organizational culture does not respond to AI after the fact. By the time AI arrives, the cultural field has already determined what kinds of change are intelligible, what feels like progress, and where the line runs between a tool that helps and one that displaces. The interaction between culture and AI in shaping organizational routines is therefore not a simple enabling or inhibiting relationship, but it is a conditional, mediated, and identity-anchored process in which cultural orientations shape how widely change spreads. AI placement shapes whether it is trusted or resisted, and the conditions of introduction shape whether cultural readiness can be activated at all. Leader participation, tool design, and the

pace of introduction all shaped outcomes independently of culture. What proved most durable in both organizations was a shared sense that certain kinds of work could not be delegated to a machine without losing something essential. That sense held consistently, pointing to something more fundamental than cultural type; it focused on where AI was perceived as threatening what makes human contribution irreplaceable, regardless of how open the surrounding culture was to AI in general. At the same time, AI has begun to reshape the assumptions it encountered. New shared understandings of what thoroughness means, what analytical work is possible, and what counts as adequate documentation have shifted. How to hold open the space in which that learning happens long enough for it to matter remains unresolved in both cases. Exploration is underway, but the conditions for consolidation have not yet formed, and efficiency pressure tends to close that space before new understandings have had time to take root. The organizations that navigate this well will not be those that move fastest, but those that understand what they are asking people to give up, and what they are offering in return.

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Appendix

Appendix A: Interview Guide

The guide below was used across all 14 interviews. All participants received the eleven core questions in Part 1. Profile-specific questions in Parts 2 and 3 were selected based on participant role; company-specific questions in Part 4 were selected based on case. The order of questions was adjusted where appropriate to follow the flow of conversation, consistent with the semi-structured approach described in Section 3.4.

Part 1 - Core questions *(All 14 participants.)*

Warm-up

1. Could you walk us through what a typical day or week looks like in your role? What does the work actually look like in practice? *(Gets at artifacts and daily routines before any theory is imposed.)*

organizational culture

2. When you think about how things are really done here, not what is written in documents, but the unwritten rules, what comes to mind? *(Moves from artifacts to the deeper levels of culture.)*

3. What kinds of behaviors or attitudes tend to get rewarded here, and what tends to get pushed back on? *(Helps identify culture type without naming the framework.)*

4. How would you describe the relationship between leadership and employees? How much does leadership's attitude toward something influence how people on the ground feel about it? *(Opens up leadership as a cultural mechanism before AI is introduced.)*

AI in the organization

5. Can you walk us through how AI has entered your work, both when it first arrived and

what it actually looks like day-to-day now? Which tasks do you use it for, and how central has it become? *(Grounds the AI discussion in real experience rather than abstract opinions.)*

6. In your experience, how have people here generally responded to AI being introduced, and where do you think that reaction comes from? *(Gets at the collective mindset shaped by culture.)*

7. Do you feel the organization has been clear about why AI is being introduced and what it means for how work gets done, and have people been given what they need to work with it? *(Covers both strategic communication and practical enablement.)*

Culture + AI → Routines

8. Thinking about a specific task or process in your work, how did you use to do it, and how do you do it now that AI is involved? What actually changed? *(Core dependent-variable question. Forces concrete before/after description.)*

9. Do you think the way this organization operates culturally has made it easier or harder to bring AI into everyday work, and has AI, in turn, changed anything about the culture or how people relate to each other? *(Captures both directions of the culture–AI relationship.)*

10. How do you think AI is changing what it means to lead? What does good leadership look like in an AI-driven workplace compared to before? *(Connects leadership culture to routine change.)*

11. If you could change one thing about how AI is being embedded into the way work is done here, what would it be, and what do you think is holding that back? *(Surfaces friction between existing routines and desired change. Used as a closing question.)*

Part 2 - Profile A: Culture and people roles *(Participants in culture, HR, EDI, and talent acquisition roles (IKEA-I, 2, 3, 4, 6, 8; Ericsson-5).*

Culture and values lens

A1. In your work around culture and people, have you noticed AI challenging any of the deeper assumptions about how this organization sees itself or how it expects people to work?

(Targets the deepest level of culture, unconscious assumptions being disturbed by AI.)

A2. From a people and culture perspective, how has the organization approached bringing employees along with AI, and how has the culture shaped that approach?

(Gets at whether clan, adhocracy or hierarchy logic drives the people strategy around AI.)

HR and people processes lens

A3. In your specific area, whether that is recruitment, learning, culture work, or people partnering, how has AI actually changed the way you carry out your day-to-day work? What

looks different now compared to before? *(The dependent variable question is tailored to people's roles.)*

A4. From what you see in your people role, how are employees genuinely feeling about AI, and do you think they feel safe to voice concerns or skepticism about it?

(HR participants have privileged access to employee sentiment.)

Part 3 - Profile B: Technical and AI roles *(Participants in technology-facing and operational roles*

(IKEA-5, 7; Ericsson-1, 2, 3, 4, 6).

AI implementation lens

B1. When you were building or rolling out AI tools here, how much did the organization's culture or ways of working factor into how you designed or introduced it?

(Unique to people who built or deployed AI — did culture shape the technical decisions?)

B2. In your experience rolling out or working with AI, where have you seen it not land as expected, and what do you think was really behind that?

(Technical people often have the clearest view of where adoption failed and why.)

Routines and workflow change lens

B3. Can you walk us through a specific process or workflow that AI has changed in your team? What did it look like before, what does it look like now, and what drove that shift?

(Technical people can give the most granular before/after on actual routines.)

B4. As someone leading or managing others through these changes, how have you handled the human side of introducing AI into how your team works? *(Connects leadership culture to routine change for technical managers.)*

Part 4 - Company-specific questions *(Selected by case.)*

IKEA (Case A)

IK1. IKEA has a very distinct cultural identity rooted in its founding values. Do you feel that identity makes it easier or harder to bring AI into how work is done here? *(Tests whether a strong clan culture enables or resists AI-driven routine change.)*

IK2. IKEA puts a strong emphasis on the human experience for co-workers and customers. Has that created any tension with what AI-driven processes ask of people? *(Gets at value conflict: human-centered culture versus efficiency-driven AI logic.)*

IK3. How does sustainability or ethical responsibility factor into how AI tools are evaluated or adopted here? Is that a real part of the conversation or more aspirational? *(Especially relevant for EDI and digital ethics roles.)*

Ericsson (Case B)

ER1. Ericsson has a strong R&D and engineering culture. Do you think that makes people here naturally more comfortable with AI, or does it create its own kind of resistance? *(Tests whether engineering culture enables or resists AI adoption.)*

ER2. Given that Ericsson both develops and uses AI, how do those two dimensions, building it and working with it internally, interact in your day-to-day experience? *(Unique to Ericsson. The dual relationship with AI is a key differentiator from IKEA.)*

ER3. In a company that works at the cutting edge of technology, how does the organization keep up with AI changing faster than routines and processes can adapt? *(Especially relevant for technical managers dealing with rapid change.)*

Appendix B: Coding Categories Overview

This appendix presents the coding categories that emerged from the open coding process described in Section 3.5.1, following Corbin and Strauss (1990). Categories were derived from the data and organized into within-case and cross-case groupings.

Table B1 IKEA - within-case categories

Code	Category	Description
I-1	Values and people-first identity as cultural anchor	IKEA's eight core values function as a navigational compass for AI decisions. The people-first identity creates both openness to AI and resistance where it risks displacing human contribution.
I-2	Psychological safety, flat hierarchy and informal connection	Minimal hierarchy and strong informal relationships create conditions for honest AI conversations. Informal channels are where AI knowledge actually spreads.
I-3	Emotional spectrum and within-organization variation around AI	Employee responses span from enthusiasm to fear. Variation is acknowledged openly and managed actively, concentrated around role replaceability and prior AI exposure.

I-4	Exploratory, iterative adoption at a human pace	IKEA's approach is experimental and peer-driven. A central tension exists between organizational efficiency pressure and the human pace of genuine adoption.
I-5	AI-driven routine changes - what has genuinely shifted	Concrete changes in meeting transcription, data analysis, research and documentation. Changes cluster where AI supports rather than replaces human judgment.
I-6	Governance, ethics, sustainability and human-AI complementarity	Active governance through ethics policies and sustainability criteria. AI is consistently positioned as a support tool rather than a replacement for human judgment.

Table B2 Ericsson - within-case categories

Code	Category	Description
E-1	Engineering identity and collective team culture	Engineering self-image: analytical, novelty-seeking and precision-oriented. Layered with warm team culture built on knowledge sharing, fika and empowering leadership.
E-2	Psychological safety under commercial and top-down pressure	Stated norms around voice sit uneasily alongside strong top-down AI mandate. Formal safety culture is strained by ambient adoption pressure.
E-3	organizational size as enabler and constraint	Scale gives financial capacity for rapid AI investment but creates structural inertia. Customer pressure adds urgency while organizational mass resists fast turning.
E-4	Differential trust in AI tools - peripheral adoption, core resistance	Trust is tool-specific and built through experience. Internally designed tools earn trust; externally embedded evaluative tools are bypassed.

E-5	organizational overwhelm and tool proliferation	Simultaneous proliferation of tools and initiatives without a coordinating framework creates sensemaking breakdown. Employees are willing but unable to consolidate.
E-6	AI-driven routine changes and human-AI collaboration redesign	Genuine shifts in meeting summarisation, document retrieval and automation. Advanced participants describe deliberate redesign of workflows around human–AI sequencing.

Table B3 Cross-case convergent patterns

Code	Pattern	Description
X-1	organizational overwhelm as primary adoption barrier	Both organizations show employees willing to engage with AI but overwhelmed by the pace and volume of introduction. Avalanche and waterfall imagery appears independently in both cases.
X-2	AI accepted at periphery, resisted at the core	Both organizations accept AI for low-stakes, peripheral tasks and resist it where it encroaches on the judgement-intensive core of professional practice.
X-3	Meeting summarisation as within-sample universally adopted routine change	The single most consistently adopted change across both cases and all roles. Appears unprompted and within-sample universally across all 14 interviews.
X-4	Leader modeling and peer learning as adoption infrastructure	Both organizations identify leader participation in AI as essential for legitimate adoption. Peer sharing is more effective than formal training in both cases.
X-5	Human–AI complementarity - substitution rejected, collaboration embraced	The most analytically mature participants in both cases reject substitution and embrace collaboration. Routines restructure around human–AI sequencing rather than replacement.

Note: Cross-case categories are not codes that appeared verbatim across interviews but pattern-level convergences identified during the constant-comparison stage of analysis (Corbin & Strauss, 1990; Eisenhardt, 1989).

Appendix C: Theoretical Concept and Coding Category Mapping

This appendix presents the mapping between the theoretical concepts developed in Chapter 2 and the coding categories that emerged from open coding in Chapter 3. Following the two-stage analytical process described in Section 3.5, categories were first derived inductively from the empirical material without imposing a predetermined theoretical framework. Once within-case and cross-case categories had stabilized, they were mapped onto the theoretical framework to establish their analytical grounding. This table presents the result of that mapping. It is intended as a reference tool for readers who wish to trace the theoretical basis of specific coding categories or verify the conceptual grounding of the analysis in Chapter 5.

Theoretical concept	Definition	Corresponding coding category
Ostensive aspect	The shared understanding of how a routine should proceed	I-5, E-6, X-3
Performative aspect	What actually happens when the routine is enacted by specific people at a specific time	I-5, E-6, X-3
Cultural embeddedness	The degree to which a routine is anchored in surrounding cultural assumptions	I-1, E-1
AI placement	Whether AI occupies a peripheral or core position in the routine, and whether it supports or evaluates human judgment	I-5, I-6, E-4, E-6, X-2

Basic assumptions	Unconscious, taken-for-granted beliefs that shape how participants perceive and respond to change	I-1, I-6, E-1, E-4
Sociomateriality	The constitutive entanglement of technology and social practice in routine performance	I-5, E-6
Automation vs. augmentation	Whether AI replaces human input or collaborates with it	X-2, X-5
Cultural orientation (CVF)	Dominant clan, adhocracy, hierarchy, or market orientation shaping how change is received	I-1, I-2, E-1, E-2
Routine embeddedness	The strength of the pull back toward established patterns when performative variation enters	I-5, E-4, X-2
Leader participation	The extent to which leaders visibly engage with AI in their own practice	I-2, E-2, X-4
Tool design	Whether an artifact is positioned to support human judgment or to evaluate and replace it	E-4, X-2
Sensemaking	The collective process through which participants construct shared interpretations of new practices and tools	I-3, I-4, E-5, X-1
Exploration vs. exploitation	The organizational tension between keeping space open for learning and closing it down for efficiency	I-4, E-3, E-5

Trial-and-error learning and schema change	The process through which repeated performative variation accumulates into a revised organizational schema over time	I-4, I-5, E-6, X-3
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Appendix D: AI and Tool Use Statement

Tool	Purpose	Sections affected
Claude (Anthropic)	Language feedback, wording and structural suggestions, table formatting	All chapters
Perplexity AI	Literature search and identification of additional academic sources	Chapter 2 and 5
Canva	Design and production of Figures	Chapter 2 and 5
Sunet Scribe (Lund University)	Transcription of interview recordings	Chapter 3, raw data