MAKING SENSE OF AI LIMITATIONS: HOW INDIVIDUAL PERCEPTIONS SHAPE ORGANIZATIONAL READINESS FOR AI ADOPTION

Thomas Übellacker*

ABSTRACT

This study investigates how individuals' perceptions of artificial intelligence (AI) limitations influence organizational readiness for AI adoption. Through semi-structured interviews with seven AI implementation experts, analyzed using the Gioia methodology, the research reveals that organizational readiness emerges through dynamic interactions between individual sensemaking, social learning, and formal integration processes. The findings demonstrate that hands-on experience with AI limitations leads to more realistic expectations and increased trust. mainly when supported by peer networks and champion systems. Organizations that successfully translate these individual and collective insights into formal governance structures achieve more sustainable AI adoption. The study advances theory by showing how organizational readiness for AI adoption evolves through continuous cycles of individual understanding, social learning, and organizational adaptation. These insights suggest that organizations should approach AI adoption not as a one-time implementation but as an ongoing strategic learning process that balances innovation with practical constraints. The research contributes to organizational readiness theory and practice by illuminating how micro-level perceptions and experiences shape macro-level adoption outcomes.

*Maastricht University; based on original Master thesis.

1 Introduction

Artificial Intelligence (AI) has emerged as a new technology platform, changing how organizations operate and compete. The rapid advancement of AI capabilities, particularly in areas such as Large Language Models (LLMs) and multimodal systems, has created new opportunities for organizations to automate complex tasks, enhance decision-making processes, and drive innovation (Bommasani et al., 2022; Bubeck et al., 2023; Li et al., 2023). Organizations across industries are increasingly seeing AI adoption as a strategic imperative, with 55% of organizations reporting the use of AI in at least one business unit or function as of 2023, up from 50% in 2022 (Maslej et al., 2024) and with global AI spending projected to reach \$631 billion by 2028 (Massey, 2024). However, organizations struggle to implement AI despite investments and evident strategic importance. They encounter challenges beyond technical considerations, encompassing social and organizational dynamics. AI adoption initiatives often fail to deliver their intended benefits, with reasons such as unrealistic expectations, lack of change management, organizational constraints, organizational readiness, and failure to understand users' needs identified as barriers to successful adoption (Cooper, 2024; Westenberger et al., 2022).

Understanding organizational readiness for technological change has become increasingly critical as organizations face the challenges of AI adoption. While traditional models of organizational readiness have focused on structural and technical preparedness (e.g., Weiner (2009)), the unique characteristics of AI technologies their complexity, opacity, and transformative potential demand a more nuanced understanding of how organizations become ready for AI adoption. The role of individual perceptions in forming this readiness is noteworthy, as individuals' understanding and interpretation of AI's limitations can influence an organization's capacity to implement AI systems successfully. These perceptions are not formed in isolation but are shaped through complex social and organizational processes as individuals attempt to make sense of AI's capabilities, limitations, and implications for their work.

Sensemaking theory (Weick et al., 2005) provides a valuable theoretical lens for understanding how individuals interpret and make meaning of AI technologies and their limitations. Through sensemaking processes, individuals construct their understanding of what AI technologies are, how they function, and what implications they have for their work and organizational practices. These interpretations, in turn, shape organizational readiness for AI adoption. However, while existing research has broadly examined organizational readiness for technological change (Armenakis and Harris, 2002; Holt et al., 2007), a theoretical gap exists in understanding how individuals' perceptions of AI-specific limitations influence organizational readiness for AI adoption. Despite the growing body of research on AI implementation and its challenges, we lack a theoretical framework that explains how individuals' sensemaking of AI limitations shapes organizational readiness for AI adoption.

This study seeks to address this gap by examining the following research question: *How do individuals' perceptions of AI limitations influence organizational readiness for adopting AI technologies*? By exploring the interpretive processes through which individuals construct their perceptions of AI limitations and how these perceptions influence organizational readiness, this study seeks to develop a more comprehensive understanding of the social and psychological factors that shape AI adoption success.

This study contributes to organizational readiness theory by showing how employees' firsthand experiences of AI limitations - from biases to technical constraints eventually shape an organization's preparedness for AI adoption. By showing that individual perceptions are enablers or impediments to broader organizational adoption, the research highlights the role of social and experiential processes in driving adoption outcomes. Further, it enriches sensemaking theory by revealing how encounters with AI limitations trigger collective interpretation and trust-building processes, which influence organizational readiness. These insights result in a novel theoretical framework connecting individual-level sensemaking with macro-level readiness dynamics, offering a more holistic view of AI adoption.

In practical terms, the findings give managers actionable strategies to guide AI initiatives effectively. First, they demonstrate how organizations can exploit hands-on experimentation and peer learning to interpret AI limitations to allow user expectations to remain realistic. Second, they show how systematic governance, clear policies, and purposeful integration into existing workflows help solidify organizational readiness. Finally, the research encourages developing an environment that supports iterative learning and trust development, enabling a climate where employees openly engage with AI's evolving capabilities and limitations. These recommendations would allow managers to address individual concerns, refine change management processes, and build an organizational culture that positions AI as a sustainable and value-increasing resource.

2 Literature Review

The relationship between individual perceptions of AI limitations and organizational readiness is a multi-level phenomenon that cannot be fully understood through traditional technology adoption frameworks alone. An integrated theoretical approach incorporating sensemaking processes trust development mechanisms and organizational readiness dynamics is needed.

This literature review approaches AI adoption and readiness as a multi-level phenomenon. It addresses external pressures (such as competitive forces, policy frameworks, and societal discourse), organizational-level readiness (in terms of capabilities, culture, and infrastructure), and finally, individual-level factors (such as perceptions of AI limitations and sensemaking processes). The interplay across these levels highlights how organizations successfully adopt AI.

2.1 AI Adoption in Organizations

AI adoption has several unique characteristics that differentiate it from traditional technology adoption. Weber et al. (2023) identify two characteristics: inscrutability and data dependency. Inscrutability manifests in the difficulty of predicting system behavior and explaining decision processes, while data dependency requires continuous system adjustments as organizational data evolves. These characteristics create increased variability in organizational decision-making processes that require new coordination mechanisms (Agrawal et al., 2024). The inscrutability concept is particularly interesting for understanding individual interactions with AI systems, as it directly influences how organizational members interpret and respond to AI-driven changes.

Agrawal et al. (2024) argue that AI adoption increases decision variation across interconnected organizational tasks, asking organizations to either reduce task interdependencies or implement strong coordination mechanisms. This finding challenges the typical focus on individual task-level AI adoption by highlighting the systemic nature of organizational AI adoption. Yang et al. (2024) extend this understanding by showing how AI adoption introduces both technological affordances and constraints that vary significantly based on organizational size. Their study reveals that while larger firms perceive primarily operational affordances focused on efficiency and quality improvements, smaller firms see marketing affordances as more important, leading to different adoption patterns and outcomes.

With his Technology-Organization-Environment (TOE) framework, Baker (2012) emphasizes that innovation adoption depends on the interplay between technological features, organizational characteristics, and environmen-

tal conditions. Applied to AI adoption, Yang et al. (2024) show how these elements are expressed through innovation management approaches, organizational AI readiness, and environmental pressures. This can also serve as a framework for looking at adoption barriers. Cubric (2020) categorizes them across technical aspects (data availability, model reusability), organizational considerations (resource allocation, support infrastructure), and social dimensions (human-AI interaction, job security concerns, trust issues).

The organizational context shapes adoption patterns through what Weber et al. (2023) identify as implementation capabilities. These capabilities encompass AI project planning, co-development, data management systems, and model lifecycle management processes. Alekseeva et al. (2020) demonstrate that AI adoption among management ranks, rather than just IT specialists, drives positive organizational outcomes. This finding highlights the importance of broad organizational involvement in the adoption process and suggests that successful AI implementation requires capabilities across different organizational levels.

Adopting AI technologies follows patterns that reflect unique characteristics and organizational implications. Henry et al. (2022) emphasize the importance of humanmachine teaming in successful AI adoption, noting that individuals build trust with AI systems through experience, expert endorsement, and systems designed to accommodate professional autonomy. This observation aligns with Kelley (2022) identification of success factors, including effective communication channels, management support, training, and established reporting mechanisms for addressing AI-related concerns.

These implementation patterns reveal several sensitizing concepts important for understanding AI adoption. First, AI inscrutability is fundamental in shaping how organizational members interact with and interpret AI systems. Second, the system-wide impact concept captures the extensive organizational changes that AI adoption necessitates. Third, adoption barriers appear across technical, organizational, and social dimensions, providing observable indicators of adoption challenges. Fourth, capability distribution reflects the spread of AI-related competencies across organizational levels. Finally, implementation patterns capture organizations' observable approaches to managing AI adoption.

The complexity and uniqueness of AI adoption create distinct challenges requiring careful consideration of technical and organizational dimensions. These challenges are particularly evident in what Cubric (2020) identifies as the social considerations of AI adoption, including increased dependence on non-human agents, job security concerns, and trust issues. Understanding these dynamics provides context for examining how organizations develop readiness for AI adoption, particularly considering the role of individual perceptions in shaping adoption outcomes. Beyond these internal adoption challenges, external pressures - such as industry competition, global technology trends, and regulatory policy - further shape the path to AI adoption (Yang et al., 2024). Felemban et al. (2024) highlight the role of government support in the Saudi context, showing how initiatives like Vision 2030 influence adoption through multiple channels: directly through regulatory frameworks and policies and indirectly by shaping senior management support and competitive dynamics between organizations. Their study reveals that government support affects all aspects of the technologyorganization-environment framework, creating opportunities and pressures for adopting organizational AI.

2.2 Organizational Readiness for AI Adoption

Organizational readiness is not only about having the right resources or leadership in place; it also mediates between broad external pressures (e.g., policy mandates and competitive landscapes) and how employees on the ground perceive and engage with AI. Organizational readiness serves as a bridge between broader external forces (such as policy requirements and market competition) and how individual employees actually engage with and implement AI in their daily work. It determines how well an organization can translate high-level strategic demands into successful adoption by its workforce. Jöhnk et al. (2021) emphasize that readiness involves aligning organizational assets, individual capabilities, and leadership commitment to support AI initiatives. They identify five core domains - strategic alignment, resources, knowledge, culture, and data - that collectively determine readiness.

AI readiness demands more than just technical infrastructure. Heimberger et al. (2024) highlight that success depends on how well organizational processes can integrate AI. That includes adapting workflows, ensuring data compatibility, and developing continuous learning and refinement systems. Readiness is, therefore, an evolving state influenced by the organization's ability to adjust and respond to AI's changing demands—a classical organizational learning problem.

Organizations need to develop specific capabilities for successful AI adoption. Weber et al. (2023) identified four concrete organizational capabilities: AI project planning, co-development of AI systems, data management, and AI model lifecycle management. This is a more process-oriented approach to readiness than the readiness factors Jöhnk et al. (2021) synthesized.

Leadership is vital for AI readiness. Felemban et al. (2024) argue that senior management support significantly affects individual attitudes and readiness to adopt AI. Leaders are important in allocating resources, prioritizing AI in strategic plans, and addressing resistance from change recipients (Mikel-Hong et al., 2024).

Trust in AI systems is another determinant for organizational readiness, influencing adoption and sustained engagement (Tursunbayeva and Chalutz-Ben Gal, 2024). Glikson and Woolley (2020) emphasize that trust involves cognitive elements, like reliability and transparency, and emotional elements, such as the perceived humanlikeness of AI. Thiebes et al. (2021) highlight trustworthiness principles - beneficence, non-maleficence, autonomy, justice, and explicability - as critical to fostering trust. Building trust requires consistent system reliability, ethical alignment, and clear explanations of AI behavior. Siau and Wang (2018) emphasize the importance of expert endorsements, validation, and iterative user interactions in increasing trust. Similarly, Henry et al. (2022) found that integrating AI into workflows while respecting user autonomy strengthens trust by framing AI as a collaborative tool rather than a replacement. Addressing these dimensions ensures individuals view AI as reliable and aligned with their roles, reducing resistance and enabling successful adoption.

Individual employees' cultural values collectively shape another critical dimension of organizational preparedness for AI adoption, as these personal orientations aggregate to influence the organization's overall cultural readiness for technological change. According to Sunny et al. (2019), individual cultural values significantly impact technology acceptance and readiness. Their research found that collectivism and long-term orientation positively influence the perceived usefulness and ease of use of new technologies at the individual level. Additionally, they found that a less masculine organizational culture helps reduce employee discomfort with technological change. Hradecky et al. (2022) find that organizations, particularly in the exhibition industry, struggle with cultural barriers, such as risk aversion and resistance to change, which hinder readiness. Conversely, a culture of openness and collaboration can drive more effective adoption processes.

Organizational readiness is not developed in isolation but interacts with external pressures and opportunities. Yang et al. (2024) highlight how competitive environments drive organizations to develop AI capabilities aggressively. Further, government and regulatory support play a significant role in shaping readiness. Indeed, policylevel initiatives can catalyze AI readiness by providing resources or mandating standards (Felemban et al., 2024).

Although organizational readiness lays the strategic and cultural groundwork for AI adoption, its success ultimately depends on how individual employees perceive and integrate these technologies into their work. Jöhnk et al. (2021) highlight the role of workforce capabilities, particularly in developing skills and trust in AI systems. Individuals who view AI as threatening their autonomy or job security may resist its implementation. Addressing these concerns through communication, training, and involvement in AI projects can increase readiness. Hence, the following section turns to the micro-level factors that can accommodate or undermine readiness.

2.3 Individual Perceptions of Limitations

The successful adoption of AI technologies within organizations is not solely determined by technical capabilities but is significantly influenced by individual perceptions of AI limitations (Glikson and Woolley, 2020; Kelley, 2022). These perceptions can act as barriers or facilitators to adoption, affecting organizational readiness and the overall implementation process (Trenerry et al., 2021).

Individuals' perceptions of AI limitations encompass a range of concerns that can hinder the adoption of AI technologies within organizations. One area of concern is the issue of trust and reliability. Nasarian et al. (2024) and Xiangwei et al. (2022) highlight that individuals find building trust in AI systems difficult due to inconsistent or opaque outputs. This lack of trust is further impeded when AI systems fail to perform reliably in critical applications, leading to skepticism about their usefulness, as Singh et al. (2023) noted. Additionally, Choudhary et al. (2024) observe that fear and resistance to adoption can come from a misalignment between AI technologies and individuals' values and anxiety over dealing with complex IT systems.

Transparency and explainability of AI systems are also significant concerns among individuals. The "black box" nature of AI algorithms, particularly in complex models like large language models (LLMs), poses challenges for those who require clear and interpretable decisionmaking processes. Novak et al. (2022) and Haxvig (2024) discuss how the lack of transparency can hinder individuals' understanding and acceptance of AI outputs. Lai et al. (2023) and Morais et al. (2023) further point out that AI systems often cannot provide meaningful, user-aligned explanations, which can decrease trust and confidence among users.

Furthermore, concerns about human-AI interaction play a role in shaping individuals' perceptions. Qian and Wexler (2024) and Bucinca et al. (2021) note that individuals may be cautious of over-reliance on AI and the potential for automation complacency, leading to skill degradation or reduced caution in their roles. Additionally, cognitive and self-serving biases can influence how individuals interpret AI capabilities. von Schenk et al. (2023) demonstrate that when people lack information about how AI systems operate - specifically about what happens to machines' earnings in economic interactions - they tend to form self-serving beliefs that justify less cooperative behavior with the machines. The lack of emotional intelligence in AI systems, especially in contexts requiring empathy and nuanced human interaction, is another limitation that Singh et al. (2023) cited.

Bias and fairness issues embedded in AI systems are significant concerns that affect individuals' willingness to adopt these technologies. Muller et al. (2022) discuss how biases in training data can affect AI outputs, leading to unfair or discriminatory outcomes. Allan et al. (2024) and Zhou et al. (2023) emphasize that amplifying societal stereotypes through AI systems poses ethical and legal risks, prompting individuals to question the fairness and appropriateness of AI-driven decisions within their organizations.

Technical limitations, such as inconsistent performance, contribute to individuals' skepticism about AI technologies. Muller et al. (2022) and Lin et al. (2024) report that perceived inconsistencies in AI performance can undermine individual confidence in these systems. Pinto et al. (2024) and Biswas et al. (2023) highlight that AI systems' difficulties in processing nuanced or context-specific information relevant to specific tasks can further diminish individuals' perceptions of AI effectiveness.

Ethical considerations also shape individuals' perceptions of AI limitations. Whittle and Hussain (2021) and Aliman et al. (2021) note that potential societal harm due to bias, misinformation, or unethical use can lead to resistance among individuals prioritizing ethical standards in their work. Zhang et al. (2024) and Fang et al. (2023) observe that gaps between ethical principles and their implementation in AI technologies can result in individuals questioning the adoption of such systems.

Finally, practical challenges in implementing and integrating AI systems into existing workflows are perceived as significant limitations. Boukhelifa et al. (2020) identify key challenges in interactive AI systems, including difficulties in defining appropriate roles between humans and AI, managing trade-offs between competing objectives like accuracy and interpretability, and dealing with multiple sources of uncertainty. The challenges of integrating AI can also vary by context - for instance, in academic writing, Chemaya and Martin (2024) found disagreement among academics about appropriate AI use and reporting requirements, with differences shaped by role, ethics perceptions, and language background. Zhang and Gosline (2023) found that while there was no broad aversion to AI systems, persistent human favoritism could affect integration efforts.

These perceived limitations align with key sensitizing concepts such as AI inscrutability and the adoption barriers across technical, organizational, and social dimensions discussed by Weber et al. (2023), Cubric (2020), and Agrawal et al. (2024). Understanding these perceptions is important for organizations aiming to improve their readiness for AI adoption, as they influence individuals' willingness to engage with and support the integration of AI technologies.

According to Moore and Benbasat (1991), perceptions of adopting an information technology innovation are shaped by factors such as relative advantage, compatibility, complexity, trialability, and observability. In AI adoption, individuals' prior experiences with technology, individual innovativeness, and organizational communication channels contribute to perception formation (Agarwal and Prasad, 1998; Haenssgen and Ariana, 2018). For instance, individuals with higher personal innovativeness are more likely to develop positive perceptions of AI technologies Agarwal and Prasad (1998).

The domain of uncertainty framework suggests that uncertainties associated with change fit into four domains: conceptual uncertainty (What is the change?), functional value uncertainty (What is the value of the change?), process uncertainty (How will the change come about?), and impact uncertainty (What is the broader impact of the change?) (Yin et al., 2024). Individuals form perceptions based on how AI technologies address these uncertainties. For example, conceptual uncertainty arises from a lack of understanding of AI's functionalities, while impact uncertainty pertains to doubts about AI's long-term effects on job security and organizational practices.

External factors such as media representations, societal discourse, and organizational communication strategies influence perception formation (Agarwal and Prasad, 1998; Trenerry et al., 2021). The perceived risks and uncertainties associated with AI, including job displacement and ethical concerns, are amplified or mitigated through these channels (FakhrHosseini et al., 2024; Sadeck, 2022). Communication channels shape perceptions, as individuals rely on mass media and interpersonal communications to develop their understanding of AI technologies (Agarwal and Prasad, 1998).

Finally, the literature highlights that individuals' perceptions of AI limitations are shaped through interpretation and meaning-making processes. Individuals attempt to understand how AI fits into their professional roles, organizational goals, and broader societal contexts, reconciling uncertainties about transparency, fairness, and ethical alignment (Maitlis and Christianson, 2014; Yin et al., 2024). This interpretive process is both individual and collective, as organizational culture, peer interactions, and shared assumptions influence how individuals construct their understanding of AI technologies. Orlikowski and Gash (1994) introduce the concept of "technological frames," highlighting how shared assumptions and knowledge within organizations shape people's perceptions and interactions with technology. Similarly, Balogun and Johnson (2005) demonstrate how informal networks and lateral employee interactions contribute to evolving interpretations during organizational change. These dynamics suggest that perceptions of AI are formed through ongoing collective processes at both personal and organizational levels. Understanding these shared interpretations offers valuable insights into how readiness and adoption are shaped, which will be examined in greater depth in the following section.

2.4 Sensemaking

Sensemaking theory provides a valuable framework for understanding how individuals, teams, and organizations interpret and respond to AI. This approach is inherently multi-level, encompassing the personal sensemaking of employees, the collective sensemaking of groups or departments, and organizational sensemaking processes (Maitlis and Christianson, 2014; Weick et al., 2005). These nested sensemaking processes also incorporate external cues - such as media stories, industry regulations, and competitive forces - reinforcing that AI adoption is shaped by influences from the macro-level to the micro-level.

Sensemaking is triggered by cues that disrupt individuals' existing understanding, prompting them to seek explanations and restore meaning (Maitlis and Christianson, 2014). With their unique characteristics and potential implications, introducing AI technologies can serve as such a trigger, creating a need for individuals to make sense of these new realities (Yin et al., 2024). Weick (1995) identifies seven properties of sensemaking: identity construction, retrospection, enactment, social interaction, ongoing nature, extraction of cues, and plausibility over accuracy. These properties provide a framework for examining how individuals interpret AI limitations and construct their understanding of the technology's role in their work. Identity construction is central to sensemaking, as individuals interpret events in ways that maintain a consistent self-conception (Weick, 1995). In the context of AI adoption, individuals may perceive AI limitations in ways that align with their professional identities and values (Choudhary et al., 2024).

Sensemaking is inherently retrospective, as individuals make sense of events by drawing on past experiences and existing frameworks (Weick, 1995). Individuals' prior experiences with technology adoption and their exposure to the societal discourse around AI can shape their interpretations of AI limitations (Agarwal and Prasad, 1998; Trenerry et al., 2021). This retrospective nature also suggests that individuals' perceptions may evolve as they accumulate experiences with AI technologies over time.

Enactment is another property of sensemaking, emphasizing that individuals actively construct the environments they face (Weick, 1995). In the context of AI adoption, individuals' actions and responses to the technology can shape the organizational reality surrounding AI. For instance, following what we know about confirmation bias, resistance, or avoidance behaviors based on perceived limitations could create self-fulfilling prophecies, reinforcing the challenges of AI integration (Peters, 2022).

Social interaction is important to sensemaking, as individuals rely on shared narratives and collective interpretations to construct meaning (Weick, 1995). Individuals' perceptions of AI limitations are not formed in isolation but are influenced by interactions with colleagues, organizational communication, and broader societal discourse (Agarwal and Prasad, 1998; Trenerry et al., 2021). The social nature of sensemaking suggests that organizations can actively shape individuals' perceptions through strategic communication and promoting a supportive culture around AI adoption.

Sensemaking is an ongoing process, as individuals continuously update their interpretations based on new in-

formation and experiences (Weick, 1995). This ongoing nature is particularly relevant in the rapidly evolving AI landscape, where individuals' perceptions may shift as they encounter new applications, capabilities, and challenges. Organizations need to recognize the dynamic nature of sensemaking and provide ongoing support and communication to help individuals navigate the evolving realities of AI adoption. The extraction of cues refers to the process by which individuals selectively attend to certain aspects of their environment to support their interpretations (Peters, 2022; Weick, 1995). In the context of AI adoption, individuals may focus on cues that reinforce their existing perceptions of AI limitations, such as instances of biased outputs or technical failures. Change agents could actively manage the cues available to individuals by highlighting successful AI implementations and providing transparent information about the technology's capabilities and limitations.

Finally, sensemaking prioritizes plausibility over accuracy, as individuals seek interpretations that are sufficiently coherent and credible to guide action (Weick, 1995). Individuals' perceptions of AI limitations may not always align with the technology's objective realities but are constructed in ways that make sense given their experiences, beliefs, and organizational context. This suggests that organizations must create narratives and experiences that promote positive and plausible interpretations of AI's role in the workplace.

Sensemaking perspective aligns with key insights from the previously discussed literature, such as the importance of addressing conceptual and impact uncertainties (Yin et al., 2024), the role of communication channels in shaping perceptions Agarwal and Prasad (1998), and the influence of organizational culture on adoption readiness Jöhnk et al. (2021). Sensemaking theory extends these insights by providing a framework for understanding the cognitive and social processes through which individuals actively construct their perceptions of AI limitations.

Moreover, a multi-level sensemaking theory offers a dynamic and process-oriented view of perception formation, complementing the more static factors emphasized in technology acceptance models like TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003). By recognizing the ongoing and retrospective nature of sensemaking across different levels (macro to micro), organizations can develop more responsive and adaptive strategies for managing individuals' perceptions throughout the AI adoption process.

However, sensemaking theory also highlights the challenges of managing perceptions in the face of technological complexity and uncertainty. AI technologies' inscrutability and data dependency (Weber et al., 2023) can make it difficult for individuals to extract clear cues and construct plausible interpretations. The rapidly evolving capabilities of AI may also require continuous updating of sensemaking frameworks, placing demands on individuals and organizations to remain adaptable. Bridging the gap between individual-level sensemaking and organizational-level readiness can be understood through organizational learning frameworks, such as the "4I" framework by Crossan et al. (1999). This framework conceptualizes learning as a multi-level process composed of four stages: intuiting, interpreting, integrating, and institutionalizing. At the individual level, individuals' intuit' and 'interpret' cues derived from their encounters with AI technologies and their perceived limitations. For example, employees may intuitively feel uncertainty or distrust when encountering opaque AI-driven decisions. Through personal interpretation, they construct a narrative that explains why the system behaves unpredictably. These individually held narratives converge as individuals engage in conversations and share experiences, moving from isolated interpretations to more collectively shared meanings.

Once collective interpretations solidify, the process shifts into 'integrating' at the group level. Teams develop a shared understanding of AI's limitations - its inscrutability, data dependencies, or fairness issues - and collectively decide how to respond. Over time, these grouplevel interpretations become 'institutionalized' into organizational practices, policies, and routines, shaping how the organization prepares for, manages, and leverages AI. Thus, individual sensemaking about AI limitations diffuses upward through group interactions and ultimately informs the organization's formal systems and culture, influencing organizational readiness for AI adoption. In this way, the alignment (or misalignment) between individual interpretations and organizational-level structures and strategies determines how effectively the organization can integrate AI technologies into its core operations.

While the sensemaking perspective provides valuable insights into how individuals interpret and make meaning of AI technologies, the next step is to distill key concepts that can guide the empirical investigation. Drawing from the literature reviewed above, several sensitizing concepts are particularly relevant for understanding how individuals' perceptions of AI limitations influence organizational readiness. These concepts serve not as rigid theoretical constructs but as flexible guides that orient the investigation while remaining open to emergent themes and patterns.

2.5 Sensitizing Concepts

The literature suggests several interconnected sensitizing concepts that operate across multiple levels - from individual cognition to organizational processes to external influences. These concepts guide the empirical investigation and anticipate the dynamic relationships that emerge in the findings. The concepts are organized to reflect how perceptions of AI limitations flow from individual interpretation through collective sensemaking to organizational adaptation. These concepts also guide the empirical inquiry into how organizations navigate AI adoption, from external demands and industry-wide influences to individual employees' daily interpretations and actions. The literature on AI adoption, organizational readiness, individual perceptions, and sensemaking suggests several interconnected concepts that inform exploration in further empirical investigation. These sensitizing concepts provide a basis for understanding how individuals' perceptions of AI limitations influence organizational readiness for adoption.

The literature suggests that how individuals form and develop their perceptions of AI limitations is a complex process influenced by individual and contextual factors. Understanding how people identify and categorize different types of limitations is crucial at the individual level (Muller et al., 2022; Zhang and Gosline, 2023). Professional background and expertise shape these interpretations, with individuals from different functional areas potentially perceiving limitations differently (Henry et al., 2022).

Contextual influences emerge as equally important in perception formation. The organizational environment, including existing technological infrastructure and support systems, shapes individuals' perceptions of limitations (Weber et al., 2023). Industry-specific challenges and opportunities create unique contexts influencing perception formation (Yang et al., 2024). External discourse, including media representation and professional networks, also contributes to how individuals understand and interpret AI limitations (Trenerry et al., 2021).

The literature highlights sensemaking at both individual and collective levels in how people interpret and respond to AI limitations. At the individual level, sensemaking involves personal interpretation and meaning-making processes Weick (1995). Individuals engage in retrospective reflection on their experiences with AI, drawing on their professional identity and past experiences to make sense of the limitations they encounter (Maitlis and Christianson, 2014). This individual sensemaking process is ongoing, as people continuously update their interpretations based on new experiences and information.

The collective dimension of sensemaking emerges through social interactions and shared meaning construction. Knowledge sharing is an important mechanism, with groups developing shared understandings through formal and informal discussions Weick (1995). Informal networks are particularly important in sharing experiences and interpretations across organizational boundaries. These collective processes do not replace individual sensemaking but interact with it, as individuals draw on collective interpretations while contributing their understanding to the group's sensemaking process. Social dynamics within organizations influence both individual and collective sensemaking. Peer experiences and opinions shape interpretations, while leadership is essential in framing how limitations are understood and addressed (Felemban et al., 2024).

The literature suggests that organizational readiness develops through distinct patterns influenced by organizational responses and cultural evolution. Organizations adapt to perceived limitations through various mechanisms, including resource allocation decisions and capability development (Jöhnk et al., 2021). These responses shape the organization's overall readiness for AI adoption.

Cultural evolution appears to be an important aspect of readiness development. Organizations change work practices and routines as they adapt to AI technologies. Shifts in organizational attitudes and the development of learning processes emerge as important elements of this evolution. Patterns of resistance and acceptance also play a significant role in how readiness develops over time. These sensitizing concepts suggest several key areas for exploration in this empirical investigation. They emphasize the importance of examining individual experiences and collective processes to understand how perceptions influence readiness. They also highlight the need to consider formal organizational responses and informal social dynamics. The concepts serve as a base for the interview guide (see Appendix 12.1), suggesting areas of inquiry while remaining open to emergent themes. These concepts remain deliberately broad to allow for unexpected findings and emerging patterns during data collection. They orient the investigation while maintaining flexibility to explore new directions as they emerge from the interviews.



Figure 1: Sensitizing Concepts

3 Methodology

3.1 Research Design

The study employs a qualitative research design grounded in the principles of grounded theory development. Grounded theory allows for developing a theoretical framework that emerges directly from empirical data (Charmaz, 2012), making it suitable for investigating how perceptions of AI limitations influence organizational readiness.

3.2 Epistemological Considerations

This study is grounded in a constructivist epistemology, which posits that reality is socially constructed through individual and collective interpretations and interactions (Young and Collin, 2004). Constructivism is appropriate

for this research as it emphasizes understanding the subjective meanings that individuals assign to their experiences with AI technologies and how these meanings influence organizational readiness for adoption. By adopting a constructivist lens, the research seeks to co-construct knowledge with participants through in-depth interviews, allowing for a rich exploration of how perceptions of AI limitations emerge and impact organizational readiness. This approach is consistent with qualitative methodologies such as grounded theory and the Gioia method, prioritizing participants' perspectives and the meanings they ascribe to phenomena Gioia et al. (2013). The constructivist epistemology supports grounded theory in allowing theories to emerge from the data rather than imposing preconceived hypotheses (Mills et al., 2006). This is particularly relevant for exploring new and complex phenomena like AI adoption in organizations, where existing

theories may not fully capture the intricacies of human perceptions and social processes.

3.3 Data Collection

To comprehensively address the research question, this study employed a qualitative data collection method using semi-structured expert interviews (see interview guide in Appendix 12.1). This methodological choice aligns with the exploratory nature of the research question and its focus on understanding complex organizational phenomena (Eisenhardt, 1989). Semi-structured interviews are particularly suited for capturing rich insights about technology adoption processes while maintaining systematic data collection (Gioia et al., 2013).

The participant selection uses a purposive convenience sampling strategy, which proves valuable for accessing experts with rich insights on the studied topic (Etikan, 2016). Participants were recruited through two primary channels: personal professional networks (n=3) and the AI Impact Mission community, an active online community of approximately 330 LLM enthusiasts (n=4). This dual-channel approach helped ensure access to participants with deep expertise in AI implementation while maintaining the diversity of perspectives. Informants were selected based on the following criteria: (1) current or recent (within the last two years) involvement in strategic or technical leadership roles; (2) experience with multiple AI adoption projects across organizational contexts; and (3) understanding of both technical and organizational aspects of AI implementation. Selected participants had strategic or technical roles such as "AI Consultant," "Head of AI," and "AI Systems Engineer."

The sampling strategy prioritized information richness over representativeness, focusing on participants who could provide deep insights into AI adoption processes based on their direct involvement in implementation projects across various organizational contexts. This approach aligns with qualitative research best practices, emphasizing depth and quality of insights rather than statistical generalizability (Patton, 2002).

The final sample consisted of seven participants, though additional potential participants had expressed interest in participating. The decision to conclude data collection at seven interviews was guided by data saturation (Guest et al., 2006), which was systematically assessed through quantitative analysis of new code generation (see Appendix 12.2). The analysis revealed a clear pattern of diminishing returns in terms of new insights generated from each subsequent interview. The first interview yielded 105 unique codes, establishing the initial conceptual framework. The second interview contributed 83 new codes, expanding the theoretical understanding significantly while validating many concepts from the first interview. A drop in new code generation was observed with the third interview, which added 52 new codes, suggesting the beginning of saturation.

The pattern of diminishing returns became more pronounced in subsequent interviews, with interviews four through seven, each contributing between 11-25 new codes (see Figure 1). While these later interviews provided valuable validation and a nuanced understanding of existing concepts, the limited number of new codes suggested that the core theoretical categories had been wellestablished. The cumulative number of unique codes reached approximately 320, with the curve showing clear signs of plateauing. This plateauing effect and consistent validation of themes in later interviews provided strong evidence that theoretical saturation had been achieved.

Interviews were conducted remotely via Microsoft Teams over seven days, lasting between 40 and 60 minutes. All interviews were recorded with participant consent, and Microsoft Teams provided automatic transcription. In one case where the automatic transcription with Teams failed, a third-party transcription tool from the recording was utilized to maintain consistency in data capture.

Before each interview, participants were explicitly asked for consent regarding recording and transcription. They were assured that any sensitive information would be handled confidentially and that their insights would only be reported in an aggregated form to maintain anonymity. All participants provided verbal consent to these conditions.

The final sample represented a diverse cross-section of industries and geographical locations. Participants were based in Germany, Austria, and the Netherlands, providing a Central European perspective on AI adoption. The industry distribution included consulting firms, the medical industry, the sustainability sector, and technology companies, offering insights into AI implementation across various organizational contexts. The participants, all male and aged between 23 and 39, held diverse educational qualifications ranging from Bachelor's to Master's degrees and PhDs. They worked in organizations of varying sizes, from small consultancies with approximately 10 employees to global technology and consulting companies with a 6-digit employee headcount.

Initial contact with potential participants was made 1-2 weeks before the interviews. Interview questions were not shared beforehand to maintain spontaneity and avoid prepared responses. While no monetary compensation was offered for participation, participants were promised access to the final research report. All interviews were conducted in English to ensure data collection and analysis consistency.



Figure 2: Data Saturation Analysis

3.4 Data Analysis

Guided by a constructivist epistemology and employing the Gioia method (Gioia et al., 2013) within a grounded theory framework (Charmaz, 2012), the analysis aimed to develop an empirically grounded theoretical understanding of how individual perceptions of AI limitations shape organizational readiness for AI adoption. The data analysis involved iterative coding, constant comparison, and progressive abstraction from initial participant statements to higher-level theoretical constructs. This structured approach ensured that emerging insights remained closely tied to the data while allowing for generating a novel theoretical framework.

The Gioia methodology provides a systematic, inductive process for qualitative data analysis that integrates participants' views with more abstract theoretical concepts. The analysis progressed through three main stages: (1) First-Order (Open) Coding, (2) Second-Order (Axial) Coding, and (3) Aggregate Dimensions (Gioia et al., 2013).

This process was iterative and reflective. Throughout the analysis, I constantly compared new codes and themes against previously coded data, refining concepts and ensuring consistency. Large language models assisted in the data analysis process in a human-supervised way through their text understanding affordance.

3.4.1 First-Order Coding

All seven interviews were transcribed and reviewed in their entirety. The initial coding began by closely reading each transcript line-by-line and assigning codes that captured the meaning of participant statements. At this stage, the codes remained descriptive and "participant-centric," avoiding premature interpretation. For example, statements about employees experimenting with AI tools were coded with phrases like "direct experience is crucial" or "hands-on learning approach." Similarly, when participants discussed informal knowledge-sharing networks among peers, codes such as "peer-based experience sharing" and "informal networks" emerged.

This first iteration of coding yielded a broad set of approximately 320 unique first-order codes (see Appendix 12.3 for the Initial Code Catalogue). These codes reflected a wide range of experiences, including the formation of AI limitations awareness, how trust and skepticism arose from direct experiences, the role of champions within organizations, and the influence of external pressures such as competition or regulation. Example quotes from the interviews were included in the Initial Code Catalogue.

During this phase, data saturation was actively monitored. As detailed in Section 3.3 and Appendix 12.2, the count of new codes diminished sharply after the third interview, indicating that the core concepts were stabilizing. Subsequent interviews mainly confirmed and refined existing codes rather than introducing entirely new concepts. This data saturation suggested a solid empirical foundation for moving toward higher-level conceptualization.

3.4.2 Second-Order Themes

In the second analysis stage, the initial codes were examined for similarities, differences, and conceptual relationships. This step involved moving from the raw "informant terms" toward more abstract, theoretical "researcher terms." Codes that shared conceptual relatedness or addressed related phenomena were clustered to form second-order themes.

For instance, numerous first-order codes related to how employees learned about AI limitations - through trialand-error, observing peers, hands-on prototyping, and receiving training - were synthesized into themes like "Hands-on, Experiential Learning and Prototyping" and "Understanding and Communicating AI Limitations." Similarly, multiple codes describing how trust emerged incrementally through small successes and peer endorsements coalesced into the theme "Trust Building Through Incremental Successes."

Another example involved integrating discussions around internal advocates, knowledge-sharing communities, and informal networks, resulting in themes such as "Social Influence, Peer Learning, and Informal Networks" and "Champion and Ambassador Models." As the analysis progressed, it became clear that these themes were not isolated but were interrelated, often bridging technical understanding, social dynamics, and organizational structures.

A total of 25 second-order themes were distilled (see Appendix 12.4). These themes encompassed key factors such as governance structures, top-down vs. bottom-up adoption tensions, the shift from initial hype to realistic implementation understanding, the importance of crossfunctional collaboration, and the balancing act between innovation and practical utility.

3.4.3 Aggregate Dimensions

In the final step, the second-order themes were clustered into higher-order, aggregate dimensions that captured the holistic patterns and processes emerging from the data. The goal was to develop a coherent theoretical framework showing how individual interpretations of AI limitations collectively influence organizational readiness. This integrative step led to the identification of five aggregate dimensions (see Appendix 12.5): (1) "Individual Sensemaking Foundations," (2) "Social and Organizational Learning Mechanisms," (3) "Organizational Integration and Governance," (4) "Expectation Management and Trust Development" and (5) "Long-Term Adaptation and Value Realization."

4 Results

Figure 3 presents a data structure visualizing how firstorder codes aggregate into second-order themes and finally coalesce into the five aggregate dimensions. This structured representation helps illustrate the "funnel" of abstraction, starting from the richness of participant experience and ending with a theoretical framework that explains how individual-level interpretations of AI limitations shape organizational readiness.





Figure 3: Data Structure

5 Discussion

The empirical findings reveal complex interconnections between individual sensemaking processes and organizational AI readiness. Through analysis of the interview data, several key propositions emerged that help explain how organizations develop readiness for AI adoption. These propositions outline the pathways through which individual perceptions of AI limitations influence organizational readiness, mediated by processes of trust development, social learning, and organizational integration.



Figure 4: Theoretical Model

5.1 AI Limitations and Individual Sensemaking

The analysis reveals how encounters with AI limitations trigger specific sensemaking processes that shape individual understanding and organizational readiness. This relationship manifests distinctly from the trust development and social learning mechanisms discussed earlier, focusing instead on the cognitive processes through which individuals interpret and internalize AI limitations. The data reveals how sensemaking evolves from reactive to proactive as individuals gain experience. Rather than just responding to interruptions, more experienced users actively extract and interpret cues about AI boundaries. As one participant explained, "If you have an idea of the limitation, you can [...] inform them about what you can do and what you can't do" (i_238), indicating a shift from passive discovery to active extraction of cues about limitations. This transition resonates with Weick et al. (2005) observation that sensemaking often emerges from noticing and bracketing of ambiguous cues. In this context, AI limitations act as those cues; by recognizing and labelling them, individuals transform disruptions into actionable insights that reshape how they engage with AI.

This evolution aligns with Weick et al. (2005) description of sensemaking as an ongoing, retrospective process while extending it to show how limitation awareness enables more strategic technology engagement. The data suggests that individuals become better equipped to identify appropriate use cases as their interpretive frameworks become more sophisticated. One participant emphasized how "understanding how your company works [...] dayto-day operations [...] try to improve those" (i_288), highlighting how refined interpretive frameworks enable more targeted implementation.

The data shows that specific technical constraints often serve as interruptions that trigger sensemaking processes. One participant described how "once I ran into an error in developing something, and I am like, OK, this is not possible" (i_142), highlighting how technical barriers interrupt ongoing flows and prompt what (Weick et al., 2005) describe as the noticing and bracketing of cues for interpretation. These confronting limitations represent clear instances where individuals must actively construct meaning from unexpected experiences.

This sensemaking process appears particularly potent when limitations interrupt existing assumptions. As one participant noted, "Someone showed me a prototype and was like, no, I made this. This is exactly what I couldn't do before" (i_143), illustrating how limitation discoveries prompt active revision of understanding. This pattern of limitation discovery triggering interpretive processes suggests the first proposition:

P1: As individuals encounter and discover AI's limitations (e.g., hallucinations, token length constraints, biases), they are triggered to make sense of AI's capabilities and boundaries, refining their interpretations of how AI fits into their work.

These insights advance theory by revealing how sensemaking about AI limitations differs from traditional technology sensemaking processes. Unlike conventional technologies, where limitations might be seen as constraints, AI limitations serve as interruptions that prompt ongoing cycles of noticing, interpretation, and action. This extends Weber et al. (2023) work on AI implementation capabilities by highlighting how individual sensemaking processes around limitations contribute to organizational capability development.

5.2 Individual Perceptions and Trust Development

The data reveals a relationship between how individuals make sense of AI limitations and their development of trust in AI systems. This relationship presents itself through two interrelated processes: the gradual development of trust through direct experience with AI limitations and the subsequent deepening of understanding through increased experimentation that this trust enables.

The findings show that individuals initially approach AI with varying skepticism and uncertainty, often influenced by media narratives and superficial coverage (c_19). However, direct engagement with AI tools, mainly through experimentation and small-scale trials, reshapes these perceptions. One participant emphasized that "direct experience is crucial" (i_38), highlighting how practical interaction helps individuals develop a better understanding of AI's capabilities and constraints. As Weick et al. (2005) argue, sensemaking is an ongoing process that is socially grounded and retrospective. In this case, experimentation with AI "talks" new experiences into being, which then become the basis for revising trust judgments. By looking back on both minor successes and failures, individuals develop more plausible and realistic expectations about AI's utility and constraints.

The data highlights how understanding AI's limitations paradoxically builds rather than reduces trust. When individuals discover specific constraints - such as token length limits or potential for hallucinations - through controlled experimentation, they develop more realistic expectations about AI's role and capabilities. As noted by multiple participants, this understanding prevents the frustration and disappointment often resulting from inflated expectations (i_42). This process resonates with Glikson and Woolley (2020) findings about how transparency about AI limitations can increase rather than undermine trust. This pattern leads to the next proposition:

P2a: When people spend more time working with AI and understanding its limits (through training and experimenting), they trust it more, not less. This happens because they develop realistic expectations and see small successes.

Furthermore, the findings indicate that once initial trust is established, it catalyzes a deeper phase of sensemaking and exploration. Participants described how successful experiences with AI encouraged them to push boundaries and explore new use cases. "Once you start using it [...] you're like, wow, it's actually way better" (i_220), reflecting how positive experiences drive increased engagement. This created what interviewees observed as a recursive learning pattern: initial trust led to more experimentation, which generated a better understanding of capabilities and limitations.

The data shows that this deepened engagement manifests in more sophisticated testing of AI's boundaries. Participants described how growing trust made them "more open to explore or test new technologies" (i_25) and enabled them to "check its credibilities, try and check where it works, where it doesn't work" (i_28). This systematic probing of limitations represents a qualitative shift from initial cautious experimentation to more deliberate boundary testing. As noted by multiple participants, this deeper exploration often revealed nuanced limitations not apparent in initial use, such as specific contexts where AI might produce inconsistent results or require additional verification. These observations lead to another connected proposition:

P2b: Once people trust AI (e.g., after successful projects or recommendations from colleagues), they become more willing to experiment with it in new ways. This exploration helps them better understand what AI can and cannot do. Together, these propositions suggest a mutually reinforcing relationship between sensemaking about AI limitations and trust development at the individual level. Initial sensemaking builds trust through realistic expectation setting and small wins, while established trust enables deeper personal exploration that allows a better understanding of limitations. This integrated understanding of trust development and AI limitation discovery appears promotional for organizational readiness, as it enables a realistic assessment of AI's potential while providing the psychological safety needed for meaningful individual experimentation.

The findings extend research on AI adoption by illuminating how individuals develop trust in AI systems despite, or perhaps because of, their recognition of AI's limitations. Rather than limitations acting as barriers, the findings suggest that understanding limitations through hands-on experience and small successes helps users develop realistic mental models that enable effective use. The key appears to be approaching AI adoption not as a one-time acceptance decision but as an ongoing process where individuals gradually refine their understanding through direct engagement, balancing appreciation of AI's capabilities with a clear awareness of its constraints.

5.3 Individual Sensemaking and Social Learning

The data reveals how individual sensemaking processes interact dynamically with social learning mechanisms to shape organizational readiness for AI adoption. This relationship manifests through two key propositions highlighting how personal insights catalyze collective learning, reshaping individual understanding.

The data shows that as individuals develop more precise insights into AI through direct experience, they naturally share these discoveries with colleagues. Multiple participants described how employees who gained hands-on experience with AI became eager to share what they had learned. For instance, one participant noted that "colleague will start to see you that you are using chat [...] then you start to feel that I need that too" (i_29), highlighting how individual discoveries spark interest in others. This sharing occurred through various channels - informal conversations, champion networks, and innovation labs (i 151, i 22, i 229) - creating multiple pathways for knowledge dissemination. Weick et al. (2005) remind that sensemaking is inherently social; it builds on communication that talks events into existence and promotes shared understanding. In this study, employees' peer-to-peer exchanges mirror that dynamic: individual discoveries become group insights through the ongoing construction and negotiation of meaning within these networks.

This pattern was particularly evident in how organizations leveraged "black belts"/ champions (i_146, i_24) or department representatives who "volunteer to be representative of using AI tools and to share knowledge" (i_147). Having developed personal understanding through experience, these individuals became missionaries for spreading practical insights about AI limitations and capabilities throughout their departments. Participants emphasized how this peer-to-peer knowledge sharing proved "much better than we like as technical people to communicate that to them" (i_29), suggesting that social learning benefits from the authenticity of peer experiences.

The data also revealed that organizations actively cultivated these knowledge-sharing dynamics by creating "voluntary venture labs" (i_151) and establishing regular sharing sessions where employees could "tell us how are you using it and send us a picture" (i_152). These structured opportunities for sharing personal insights amplified the natural tendency for individual learning to spark collective understanding. This leads to the next proposition:

P3a: When employees figure out what AI is good and bad at through direct experience, they share these insights with their coworkers through formal and informal ways.

The relationship between individual sensemaking and social learning appears to be bidirectional. The data showed that as social networks and communities exchanged AI experiences, individuals began reinterpreting their views based on others' experiences. Participants described how "understanding improves through peer interaction and experimentation" (i_29), suggesting that exposure to others' experiences helps refine personal interpretations of AI.

This collective influence on individual sensemaking was particularly evident in how organizations leveraged "echo chambers" (i_162) and interconnected groups where it is "easy to bring this message" (i_164). While the term "echo chambers" might carry negative connotations, in this context, it describes how shared experiences within departments or teams helped reinforce and refine individual understanding. The data showed that these social dynamics were successful when they included concrete examples, with participants noting how "trust builds through peer experience sharing" (i_29).

The influence of collective experience on individual sensemaking aligns with Weick's (1995) emphasis on the social nature of sensemaking processes. The data revealed how "informal network narratives shape organizational readiness" (i_29), suggesting that individual interpretations of AI are continuously refined through exposure to colleagues' experiences, successes, and failures. This recursive relationship between individual and collective understanding leads to proposition P3b:

P3b: As people share their AI experiences in teams and networks, individuals update their understanding of AI based on their colleagues' successes, failures, and best practices. This creates a cycle where personal and group learning reinforce each other.

These propositions advance theory by revealing how AI adoption catalyzes unique dynamics between individual

sensemaking and collective learning processes. While sensemaking theory has traditionally focused on how individuals interpret novel technologies Weick (1995), and organizational learning frameworks examine knowledge transfer across levels (Crossan et al., 1999), the findings show that AI's distinctive characteristics - its opacity, evolving capabilities, and context-dependent performance - require continuous interplay between personal discovery and social validation. The reciprocal relationship between individual exploration and collective sensemaking appears especially critical for AI adoption, as the technology's complexities mean that no single person's understanding is sufficient; instead, organizational readiness emerges through the ongoing synthesis of diverse individual experiences shared through social networks.

5.4 Social Learning and Integration

Building on the previous findings about trust development and social learning, the data reveals distinct patterns in how formalized structures and social learning mechanisms interact to shape organizational AI readiness. This relationship emerges through two key processes: how mature integration frameworks enable systematic knowledge sharing and how collective learning drives organizational adaptation.

The data shows successful organizations develop specific structural mechanisms to facilitate knowledge exchange. Participants described the creation of "voluntary venture labs" (i_151) and regular sharing sessions where employees would "tell us how are you using it and send us a picture" (i_152). These structured opportunities moved beyond informal conversations to create dedicated spaces for knowledge exchange. From Weick et al. (2005) viewpoint, these formalized routines exemplify how organizations can actively shape the environment in which sensemaking unfolds. By creating explicit forums-such as "voluntary venture labs" or cross-functional teams-organizations enact structures that channel how cues are noticed, interpreted, and retained over time. One participant emphasized how organizations established "domain-specific AI communities" (i_65) focused on particular business functions like "AI for tax, AI for others, AI for assurance, AI for knowledge management" (i 65), indicating how formal structures enabled targeted knowledge sharing.

Multiple participants highlighted how these formal mechanisms helped bridge departmental boundaries. One noted that "capabilities and capacity spread across departments that somehow have to communicate" (i_64), while another described "cross-departmental knowledge sharing emerges" as a key outcome of structured integration efforts. The importance of formal support was particularly evident in observations about "creating presentation opportunities" (i_64) and "encouraging external knowledge sharing" (i_64). This alignment of structure and learning leads to the next proposition: P4a: As formal AI integration efforts (e.g., governance committees, embedded AI workflows, robust data infrastructure) mature, they enable more structured environments - like cross-functional teams - that improve social learning and knowledge exchange among employees.

Furthermore, the findings indicate that collective learning drives specific organizational changes. Participants described how shared experiences led organizations to formalize "innovation process[es] from idea" (i_95) and establish systematic approaches to pilot projects. One participant noted how "collective learning through reporting" (i_29) helped organizations identify patterns and standardize successful approaches. This pattern was particularly evident in how "organizations build internal capabilities through testing" (i_27), suggesting that shared learning experiences inform formal capability development.

The data reveals that this process involves creating new organizational roles and structures. Multiple participants described the emergence of "specialized teams in response to AI hype" (i_177) and efforts at "coordinating across departments" (i_178). One participant emphasized how organizations began creating dedicated AI teams (i_298) based on collective learning about what worked. These observations lead to proposition P3b:

P4b: When teams share their AI success stories and best practices, organizations are more likely to make AI a permanent part of their operations by updating their processes and systems.

These propositions illuminate how social learning and formal integration mechanisms reinforce each other. The findings extend research on organizational learning by showing how AI adoption requires both structured knowledge-sharing environments and the ability to translate collective insights into formal organizational changes. Unlike previous technologies, AI's complexity and evolving nature demand continuous interplay between social learning and structural adaptation. This analysis suggests that organizations can actively facilitate this virtuous cycle by creating formal spaces for knowledge exchange while remaining flexible enough to incorporate emerging insights into their structures and processes. The key appears to balance structured support for learning with the ability to evolve organizational frameworks based on collective experience.

5.5 Trust and Integration Effects on Organizational Readiness

The data reveals two distinct but interlinked pathways through which organizations develop readiness for AI adoption. First, trust development emerges from individual sensemaking processes (Section 5.1, 5.2) and catalyzes broader AI acceptance. Second, organizational integration mechanisms - spawned by social learning (Section 5.3, 5.4) - shape the structural and procedural capabilities that sustain AI adoption. Together, these two

factors (trust and integration) help translate micro-level learning (individual sensemaking and social learning) into macro-level change (organizational readiness).

Trust in AI repeatedly surfaces in the findings as a outcome of individual-level sensemaking. Individuals experimenting with AI and discovering its limitations (e.g., hallucinations, token-length constraints) refine their mental models of what AI can and cannot do (i_14, i_238). This process of hands-on sensemaking (i_38, i_142) corrects inflated expectations (i_42), develops realistic understanding, and builds confidence in AI (i_56). In turn:

P5a: Trust translates individuals' refined sensemaking of AI into broader organizational readiness. As trust in AI becomes widespread, the organization becomes more willing to undertake new AI initiatives.

The role of trust is evident in how individuals who "spend more time working with AI and understanding its limits" (P1a) develop not only accurate expectations but also a psychological readiness to champion AI within their teams (i_29). Positive experiences - "wow, it's actually way better" (i_220) - fuel further exploration, demonstrating how trust channels individual insight into deeper organizational buy-in. Even imperfect outcomes can "still increase trust" (i_265) if users come away with a clearer sense of AI's potential and boundaries. Consequently, trust development - anchored in realistic appraisals of AI - reduces perceived risk, mitigates resistance, and paves the way for more extensive AI adoption across the organization (i_175, i_199).

Parallel to trust, organizational integration emerges from collective social learning processes. As people share experiences and best practices (Sections 7.2, 7.3), organizations gradually create formal mechanisms - for example, "domain-specific AI communities" (i_65), "voluntary venture labs" (i_151), or "specialized teams in response to AI hype" (i_177). These structures allow governance, cross-departmental communication channels, and shared technical infrastructure, ensuring that early lessons do not remain isolated within pockets of the organization (i_64, i_72).

P5b: Organizational integration describes the relationship between social learning and organizational readiness. As AI becomes embedded in formal structures and processes, the organization develops more substantial capabilities and frameworks for future AI adoption.

This is reflected in how shared successes and "domainspecific" case studies (i_29, i_96) get systematized into policies and workflows (i_31), establishing consistent practices for AI governance, risk assessment, and capability building. Organizational integration thus institutionalizes the collective insights gained via peer-topeer knowledge exchange and champion networks (i_29, i_146-i_149). Such integration ensures that insights from social learning get translated into formal support structures, ultimately accelerating AI adoption speed, scale, and sustainability.

5.6 Long-term Adaptation

Finally, a temporal dimension of AI adoption emerged in the data, revealing how organizations' approach to AI implementation and value realization evolves over extended periods. This longitudinal perspective provides insights into how initial experiences shape long-term adaptation strategies and eventually influence organizational readiness for AI.

The data shows that organizations' relationship with AI technologies undergoes maturation phases. Initially, as one participant described, organizations often move "from overconfidence to disappointment" (i_16) before developing more nuanced approaches. This evolution was not linear but involved iterative cycles of learning and adaptation. Another participant emphasized how continuous experimentation led to deeper understanding: "Once you start using it [...] you're like, wow, it's actually way better" (i_220), highlighting how direct experience shapes organizational approaches over time.

The findings reveal that successful organizations demonstrated an ability to learn from both positive and negative experiences, using these insights to refine their implementation strategies. One participant noted that "even if the model becomes worse than the expectations, it still increases trust" (i_265), suggesting that even unsuccessful implementations contributed to organizational learning. This pattern was particularly evident in how organizations adjusted their resource allocation and structural arrangements over time. For instance, one participant described how their organization "sourced the three people that were the most affiliated with AI developments into a special task force" (i_177) as a response to accumulated implementation experience.

This approach was not merely reactive but became increasingly strategic as organizations gained experience. One participant emphasized how "understanding how your company works [...] day-to-day operations [...] try to improve those" (i_288) became central to their approach over time. The data shows that organizations that successfully sustained AI adoption developed systematic approaches to capturing and applying lessons learned. Another participant noted that the "continuous mixing of experts in [...] different projects" (i_72) enabled ongoing knowledge transfer and capability development. These observations about organizational learning and adaptation over time lead to the first proposition:

P6a: As organizations gain more experience with AI successes and failures - they adjust their strategies, resources, and structures to keep AI aligned with their long-term goals.

The data further reveals how sustained engagement with AI leads to evolving patterns of value realization. Initially, organizations often focused on immediate efficiency gains but developed more sophisticated approaches to value creation over time. One participant observed that "organizations build internal capabilities through testing" (i_27), suggesting a gradual capability development process. This evolution was particularly evident in how organizations moved from isolated AI experiments to more integrated approaches.

The temporal aspect of value realization emerged strongly in how organizations learned to leverage AI effectively. One participant described how "experience leads to belief updating" (i_144), indicating an iterative learning and value discovery process. Another noted that their organization needed to "make a real process out of it and tell others [...] use this process as it's time efficient" (i_183), showing how initial successes were systematized into repeatable approaches.

This pattern of evolving value realization aligns with Weber et al. (2023) findings about organizations developing specific implementation capabilities over time, including AI project planning, co-development, data management, and model lifecycle management. However, the data extends this understanding by showing how value realization becomes increasingly sophisticated as organizations gain experience. As one participant explained, "If you have an idea of the limitation, you can [...] inform them about what you can do and what you can't do" (i_238), suggesting that accumulated experience enables more strategic deployment of AI capabilities. The long-term pattern of value realization and its impact on organizational embedding leads to the second proposition:

P6b: Over time, continuous learning and integration of AI leads to real organizational benefits, which encourages organizations to embed AI more deeply into their culture and operations.

These propositions advance our understanding of organizational readiness by highlighting its temporal dimension. While previous research has often treated readiness as a static state, the findings suggest it is better understood as an evolving capability that develops through cycles of learning and adaptation. This builds on Jöhnk et al. (2021) framework but adds specific insights about how organizations' ability to realize value from AI improves over time.

The findings reveal that successful long-term adaptation requires organizations to maintain flexible structures while building systematic approaches to learning. One participant noted that they needed to "create groups to exchange knowledge" (i_29) while establishing formal processes for capturing and applying lessons learned. This balance between flexibility and systematization emerged as crucial for sustained AI adoption.

This temporal perspective illuminates how organizations move beyond viewing AI adoption as a discrete change initiative to see it as an ongoing process of organizational evolution. While this aligns with Crossan et al. (1999) organizational learning framework, it adds specific insights into how organizations learn to work with AI technologies over time. The data suggests that successful organizations develop the ability to continuously evolve their approach to AI based on accumulated experience while maintaining alignment with strategic goals.

The findings extend previous research by showing how initial experiences with AI shape longer-term organizational responses. Organizations that successfully sustained AI adoption demonstrated an ability to learn from successes and failures, using these insights to develop more sophisticated approaches to implementation over time. This temporal dimension suggests that organizational readiness for AI is not achieved at a single point but continues to evolve as organizations gain experience and develop a more nuanced understanding of creating value through AI technologies. Consistent with Weick et al. (2005), this readiness emerges through ongoing sensemaking processes, where individuals interpret AI experiences retrospectively, construct trust through realistic expectations, and share knowledge socially. Over time, iterative learning cycles refine practices, align trust with integration, and enable organizations to adapt to the unique challenges of AI, demonstrating that readiness is a dynamic, evolving capability rather than a static state.

6 Practical Implications

The findings of this study indicate that organizational readiness for AI adoption depends not merely on technical infrastructure and leadership directives but also on how employees form and diffuse their understanding of AI's limitations. A first managerial implication is that organizations should prioritize building foundational AI literacy through hands-on experimentation. This aligns with Henry et al. (2022) findings on the importance of human-machine teaming and experiential learning. Conceptual overviews, though important, are insufficient for helping individuals understand AI's actual boundaries, such as hallucination tendencies or token-length constraints. When employees are encouraged to test AI tools in sandbox environments or pilot projects, they develop more realistic expectations and cultivate a measured confidence in the technology's potential, consistent with Weber et al. (2023) emphasis on implementation capabilities. These incremental "wins" help mitigate the disillusionment that often arises when inflated expectations clash with technical realities. Organizations can actively facilitate this sensemaking by creating formal and informal knowledge-sharing spaces, cultivating champion networks, and encouraging cross-functional exchange, as supported by Kelley (2022) identification of success factors. However, the data emphasizes that these social learning mechanisms work best when they emerge organically from genuine individual insights rather than top-down initiatives.

A second implication underscores the significance of cultivating trust gradually through tangible success stories and demonstrable improvements in workplace tasks, aligning with Glikson and Woolley (2020) findings on trust development in AI systems. Even if AI systems produce imperfect outcomes, employees who see clear efficiency gains become more open to more advanced experimentation. This trust-building process benefits significantly from the support of champions and peer-to-peer advocacy, reflecting Siau and Wang (2018) emphasis on the importance of expert endorsements and iterative user interactions in increasing trust. Formal directives from senior management can initiate AI adoption. However, as Felemban et al. (2024) demonstrate, genuine, sustained acceptance often flows from informal networks where colleagues coach one another and share pragmatic guidance.

Beyond these points, the study highlights that structured governance and clear policies are necessary to manage potential risks without stifling innovation, consistent with Jöhnk et al. (2021) framework of core readiness domains. Particularly in regulated sectors, compliance, and liability concerns demand a thoughtful approach that offers employees enough flexibility to discover practical uses for AI while maintaining safeguards around data privacy and ethical standards. However, such oversight remains most effective when paired with a robust internal communication strategy that reconciles the enthusiasm of senior leaders with the daily realities and valid concerns of end-users, as emphasized by Mikel-Hong et al. (2024) regarding the role of leadership in addressing resistance.

A further implication pertains to the need for continuous alignment between AI initiatives and broader organizational processes and culture. Rather than treating AI as a standalone innovation, managers can embed it into existing operations and strategic roadmaps, as suggested by Heimberger et al. (2024) findings on process integration. Sustained readiness similarly relies on adapting as technology evolves, so policies, pilot projects, and success metrics must be reviewed continuously to capture new opportunities or address emerging limitations. Over time, demonstrating tangible outcomes strengthens organizational buy-in. It justifies further investment in AI's technical and human dimensions, aligning with Yang et al. (2024) observations about how organizations perceive and realize AI's affordances.

7 Limitations and Future Directions

While this research draws strength from its qualitative, expert-interview approach and provides in-depth perspectives on individual sensemaking, three main limitations warrant attention and suggest avenues for future inquiry.

First, the study focuses on individual-level interpretations, offering limited insight into how these perceptions coalesce into collective readiness across organizational tiers (Crossan et al., 1999). Given the intermediate state of theory connecting individual perceptions to organizational readiness, future research could employ hybrid methods combining qualitative and quantitative approaches (Edmondson and McManus, 2007) through longitudinal or multi-level case studies. Such nested designs involving frontline employees and middle managers could investigate how individual sensemaking about AI's constraints ultimately drives or hinders systemic transformation (Maitlis and Christianson, 2014; Orlikowski and Gash, 1994; Weiner, 2009).

Second, the purely qualitative design, while appropriate for exploring novel phenomena Edmondson and Mc-Manus (2007), foregrounds subjective narratives, which raises concerns about potential bias and the risk of overemphasizing anecdotal success stories or attributing failures to external factors. As theory in this domain matures, scholars could integrate mixed methods approaches, coupling in-depth interviews with large-scale quantitative surveys or archival data to validate and expand upon the themes identified here. For instance, measuring constructs such as trust, readiness, or perceived limitations at scale would help verify whether the patterns observed in interviews generalize to broader organizational contexts.

Third, the small sample of AI-focused experts, while rich in detail and appropriate for nascent theory development (Edmondson and McManus, 2007), may tilt findings toward those who are technologically forward-thinking or predisposed toward AI experimentation. Future work could involve a more diverse cohort of informants—such as frontline staff, middle managers, or external partners—and broaden the industry scope to gauge whether these insights remain consistent across different sectors. This expanded approach can reveal the extent to which varying organizational cultures, regulatory environments, or leadership styles shape readiness and adoption trajectories.

Finally, given the dynamic AI landscape, ongoing advances in model architectures, data processing, and training methods may mitigate or eliminate some limitations identified here (Bommasani et al., 2022; Bubeck et al., 2023). As theory development progresses from nascent to intermediate stages, longitudinal research that examines AI adoption over extended periods could illustrate how early, significant barriers diminish once organizations refine data pipelines, cultivate new skill sets, or implement governance structures. Such designs would clarify how shifting technical and organizational landscapes influence the evolution of trust, readiness, and overall AI strategy (Henry et al., 2022; Weick et al., 2005; Crossan et al., 1999).

8 Conclusion

This work examines how individual perceptions of AI limitations influence organizational readiness for AI adoption. The findings reveal a dynamic interplay between individual sensemaking processes, social learning mechanisms, and formal organizational structures. When employees encounter AI limitations through hands-on experience, they develop more realistic expectations and greater trust in the technology, mainly when supported

by peer networks and champion systems. Organizations that successfully translate these individual and collective insights into formal governance structures and processes are better positioned for sustainable AI adoption. The research demonstrates that organizational AI readiness is not a static state but an evolving capability that emerges through the continuous interaction between individual understanding, social learning, and organizational adaptation. This suggests that organizations should approach AI adoption not as a one-time implementation but as an ongoing strategic learning process that balances innovation with practical constraints.

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9 Appendix

Appendix 1: Interview Guide

Introduction

- Welcome and Introduction
- Purpose of the Study
 - The purpose of this study is to gain insights from experts like you on the factors that impact AI adoption in organizations, specifically focusing on perceptions of AI limitations.
- Confidentiality
- Consent to recording

Context

• Could you briefly describe your experience with AI implementation projects in organizations?

Theme 1: Perception Formation of AI Limitation

- Based on your observations, how do individuals in organizations typically develop their understanding of AI limitations?
 - Probe: Role of professional background (technical vs non-technical?)
 - Probe: Impact of direct experiences vs. indirect knowledge
 - Probe: Through formal training, peer discussions, hands-on experience, or other means?
 - Probe: Industry context influence
 - Probe: External discourse influence (E.g. media coverage? Failed projects? Successful projects in other organizations?)

Theme 2: Individual and Collective Sensemaking

- How have you seen individuals interpret and make sense of their experiences with AI limitations?
 - Probe: Trust-building
 - Probe: Contradictions between their expectations and actual AI performance
 - Probe: Role of professional identity
 - Probe: Impact of past experiences
 - Probe: Experimentation
 - Probe: Process of updating interpretations (What triggers change over time?)
- In your experience, how do collective interpretations of AI limitations develop within organizations?
 - Probe: Knowledge sharing mechanisms (How do organizational stories or narratives about AI successes/failures spread?)
 - Probe: Informal networks' role
 - Probe: Leadership influences
 - Probe: Resolution of conflicting perspectives

Theme 3: Impact on Organizational Readiness

- How do individual understandings of AI limitations shape an organization's readiness for adoption?
 - Probe: Change management
 - Probe: Communication
 - Probe: Change in culture
 - Probe: Risk assessment
 - Probe Cross-functional coordination
 - Probe: Changes in strategic planning

- Probe: Adjustments to implementation timelines
- Probe: Development of support structures
- How does an organization adapt its practices when confronted with AI limitations identified by employees?
 - Probe: Resource reallocation (Hiring? Skill development?)
 - Probe: Training program modifications
 - Probe: Process redesign efforts
- What role do collective experiences with AI limitations play in shaping organizational capabilities?
 - Probe: Changes in collaboration patterns
 - Probe: Changes in decision-making processes

Closing

- Based on your observations, what do you see as the most critical connection between individual perceptions of AI limitations and organizational readiness?
- Is there anything else you'd like to add about how perceptions of AI limitations influence organizational readiness for AI adoption?

Thanking the participant

Appendix 2: Data Saturation

```
import pandas as pd
# Load the uploaded CSV file
file_path = "/mnt/data/Initial Codes - Sheet4.csv"
data = pd.read_csv(file_path)
# Display the first few rows of the dataset to understand its structure
data.head(), data.columns
# List of interviewees in the order they were conducted
interviewees = [
    "Interviewee 1",
    "Interviewee 2",
    "Interviewee 3",
    "Interviewee 4",
    "Interviewee 5",
    "Interviewee 6",
    "Interviewee 7",
]
# Extract the interviewee's name from each quote and create a new column for
   clarity
data['Interviewee'] = data['Quotes'].apply(
    lambda quote: next((name for name in interviewees if name in quote), None)
)
# Count occurrences of interviewees
interview_counts = data['Interviewee'].value_counts()
# Identify new codes introduced by each interviewee
codes_per_interviewee = data.groupby('Interviewee')['Code'].apply(lambda codes:
   codes.unique())
# Check cumulative data saturation (unique codes found per interviewee as they
   appear in order)
saturation_data = {}
unique_codes = set()
```

```
for interviewee in interviewees:
    if interviewee in codes_per_interviewee:
        new_codes = set(codes_per_interviewee[interviewee]) - unique_codes
        unique_codes.update(new_codes)
        saturation_data[interviewee] = {"New Codes": len(new_codes), "Total Codes
           ": len(unique_codes)}
# Convert saturation data to a DataFrame for better visualization
saturation_df = pd.DataFrame.from_dict(saturation_data, orient='index')
import ace_tools as tools; tools.display_dataframe_to_user(name="Interview Data
   Saturation Analysis", dataframe=saturation_df)
import matplotlib.pyplot as plt
# Create a graph for data saturation
plt.figure(figsize=(10, 6))
# Plot total codes and new codes
plt.plot(
    saturation_df.index, saturation_df["Total Codes"], marker="o", label="Total
       Codes"
plt.bar(saturation_df.index, saturation_df["New Codes"], alpha=0.7, label="New
   Codes")
# Add titles and labels
plt.title("Data Saturation Analysis by Interview", fontsize=16)
plt.xlabel("Interviewee", fontsize=12)
plt.ylabel("Number of Codes", fontsize=12)
plt.legend()
plt.grid(axis="y", linestyle="--", alpha=0.7)
# Show the graph
plt.tight_layout()
plt.show()
```

Appendix 3	Initial	Code	Catalogue
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Identifier	Code	Representative Quotes
i_1	dual role as internal solution provider and employee support	"[] we developed AI solutions for [pseudonymized entity] itself [] we support [pseudonymized entity] employees"
i_2	informal nature of AI adoption initiatives	"[] more like breakfast. When when [pseudonymized entity]", "we talked about this not like in a serious context, but, like, in, like, a marching environment with, like, a coffee in our hand"
i_3	structuring as both support team and production factory	"[] as our team is like AI team and AI factory team"
i_4	prioritizing upskilling before tool deployment	"[] first, by upscaling them about what AI tools do we have"
i_5	mix of vendor and internally developed AI tools	"[] we have copilot Microsoft Co pilot we have another tool that developed by [pseudonymized entity] Global", "What they have created so far is just an internal instance of chat of Azure open AI []"
i_6	adapting public AI tools for compliance requirements	"[] it's called Chat [pseudonymized entity], which is actually ChatGPT, but more like compliance outside"

i_7	establishing private cloud partnerships for security	"[] we have kind of agreement with with Azure to have kind of private clouds solution"
i_8	domain-specific AI tools for specialized functions	"[] another part on which called Harvey which is a large language model for legal", "Lack of domain-specific AI adaptation leads to failure", "Environmental matching guides AI adoption", "Specialization multiplies AI productivity gains"
i_9	formalizing AI education through academy structure	"[] we run this, what we call AI Academy", "Education adapting to AI usage patterns"
i_10	creating internal data science capabilities	"[] upscaling programme for citizen data scientist"
i_11	progressive learning path from basics to advanced	"[] starting from basics to machine learning, then to our large language model, then to prompting techniques", "Self-learning prompt engineering techniques"
i_12	keeping technical training accessible	"[] course is not that technical"
i_13	focusing on conceptual understanding	"[] the content is more like an abstract", "You also have to learn not just how to use them but also why are they []"
i_14	understanding AI capabilities and limitations	"[] help our colleagues first understand limitation of AI use cases", "[] what is hallucination when it comes to LM?", "to really grasp the limitations is is a whole other step", "Requiring hands-on experience for limitation understanding", "Learning limitations through prototyping", "Discovering limitations through actual testing", "Needing direct interaction beyond theoretical knowledge", "Understanding limitations as separate learning phase", "Learning limitations through direct experimentation", "Trial and error reveals underlying AI biases", "Direct failure experiences breed AI skepticism", "Domain-specific trust through experimentation", "Negative experiences lead to sweeping dismissals", "Limitation knowledge improves efficiency", "Limitations guide specific applications", "Learning from industry failures", "Short-term memory of AI limitations", "[] getting a bit of a feeling of how it works and what it can do and what it can't do", "[] familiarity builds predictability expectations", "[] repeated use creates output expectations", "[] failed attempts improve mental models", "[] experience leads to belief updating", "Being blind to potential limitations", "Learning limitations through hallucination experiences", "Developing deep limitation awareness through technical knowledge", "Using limitation knowledge to filter use cases", "Improving risk assessment through limitation knowledge"
i_15	breaking down AI capabilities into specific use cases	"[] what is in OCR? What is the data extraction? What is the translation? What is summarization?", "[] which use cases are relevant to them and what they should try out", "[] I think actually the most useful support structure companies are providing are direct specific business use cases"
i_16	managing expectations during introduction	"[] not because we want to build them an experts", "[] help our colleagues first understand limitation of AI use cases", "[] expectation management part of it [] when we introducing the tool to them", "[] realistic expectations for skill development", "Unrealistic expectations waste resources", "Developing unrealistic expectations after ChatGPT", "Moving from overconfidence to disappointment", "Building applications while managing stakeholder expectations simultaneously", "Stakeholder misunderstanding project completion status"

i_17	establishing shared vocabulary for AI discussions	"[] when we are trying to communicate in you tool then we have kind of common language", "Translating technical knowledge"
i_18	building technical literacy without technical expertise	"[] they can understand what we say right solution when we say fine tuning"
i_19	leveraging business-side perspective	"[] they are more like attached to business services"
i_20	enabling business-driven AI ideation	"[] they cannot come to us with ideas like, yeah, I have this idea to to be solved with AI", "[] start from business needs not AI capabilities"
i_21	factory model for converting ideas to products	"[] we can as a factory here we can take it and build product out of it, of course, if it's feasible"
i_22	tool-specific champion approach	"[] Champions for each tool"
i_23	identifying AI-knowledgeable employees	"[] individuals within the firm that first has some understanding of AI"
i_24	selecting champions from business units	"[] they are coming from from the business"
i_25	valuing technological openness	"[] open to explore or test new technologies"
i_26	avoiding change-resistant individuals as champions	"[] not really that manual or don't like to test any technology or don't like to change"
i_27	tool-specific experimentation process	"[] for example, for a specific tool like copilot start experiment with copilot", "Organizations build internal capabilities through testing"
i_28	systematic capability assessment	"[] check its credilities try and check where where it works, where it doesn't work", "Technical backgrounds drive quantitative capability assessment", "Technical orientation creates demand for quantitative analysis"
i_29	peer-based experience sharing	"[] these champions start to communicate that experience to their peers" , "[] much better than we like as a tech technical people to to communicate that to them", "[] colleague will start to see you that you are using chat [] then you start to to feel that I need that too", "[] join groups to exchange themselves and try to prototype", "[] create groups to exchange knowledge", "[] the best way of expanding your tool or having more people to use. This is really the mouth to mouth", "Non-technical knowledge spreads through informal channels", "Social pressure drives adoption", "FOMO influences adoption", "Peer pressure against automation", "Collective learning through reporting", "Sharing AI best practices", "[] understanding improves through peer interaction and experimentation", "[] trust builds through peer experience sharing" , "[] informal network narratives shape organizational readiness", "Encouraging solution discussions", "Enabling informal knowledge sharing through office presence", "Struggling with remote knowledge sharing", "Motivating learning through sharing requirements", "Trust-based solution propagation through colleagues", "Colleague recommendations driving solution adoption"
i_30	client-specific champion identification	"[] for each customer client we have people who are actually interested to test it or try it"

i_31	operating under regulatory constraints	"[] [pseudonymized entity] is very highly regulated company", "[] works with topics like tax, legal audit and financial services", "Institutional AI use policies emerging", "Privacy concerns in sensitive industries", "[] European organizations prioritize policy documentation", "[] Organizations implement restrictive policies and controlled testing", "[] Organizations begin with comprehensive policy creation", "[] Early policies reflect superficial understanding", "[] Restrictive policies impede adoption", "Implementing blanket AI prohibitions", "Preventing learning through usage restrictions", "Choosing prohibition over training investment", "Defaulting to bans before evaluation", "Implementing and reinforcing AI policies", "Installing technical blocks", "Enforcing usage restrictions with penalties", "Monitoring frequently changing regulatory landscape", "Prioritizing between regulation types and timeframes", "Data safety through usage and transmission transparency", "Prioritizing data and prompt security", "Ethics approval accelerating implementation"
i_32	handling sensitive business domains	"[] works with topics like tax, legal audit and financial services"
i_33	maintaining human oversight requirements	"[] having human uncontrolled human in the loop is is very important", "Fearing unchecked AI output usage", "Maintaining human-centered decision making", "Maintaining human oversight for critical decisions"
i_34	systematic feedback collection	"[] we try to have mechanism where we can collect user's feedback", "[] if we have to go about like models that we train or fine tune, we use this feedback to further train the model", "[] if it is like a chat [pseudonymized entity] or rack solution then we just collect this feedback as a ticket"
i_35	preserving user autonomy	"[] have them kind of to feel that they are not losing their agency"
i_36	involving users in development decisions	"[] they are involved into development of the tool and also involved into the the decision"
i_37	starting with tool background education	"[] they developed first but I think a bit of background first about yeah the tool"
i_38	hands-on learning approach	"[] by experimenting with the tool or the product or the service itself", "direct experience is crucial", "formal training with practical component", "you have to experience it hands-on", "user testing and prototyping to learn limitations", "once you start using it and do one prompt, you learn by doing", "Hands-on experience demonstrates value generation", "Initial experimentation reveals deeper potential", "Hands-on validation reduces adoption risk", "New models reset experimentation cycle", "Experimentation reveals belief systems", "[] direct interaction leads to more nuanced understanding", "[] experimentation leads to realistic understanding"
i_39	maintaining ongoing communication channels	"[] they need to be always kind of communication channel or communication looks between us"
i_40	avoiding large-scale immediate deployment	"[] we don't recommend to [pseudonymized entity] or to clients to buy all of a sudden 100 or 1000 licences at once"
i_41	risk of widespread tool abandonment	"[] burn the whole product because you might find one two person using it"
i_42	understanding prevents user frustration	"[] they don't understand it, they don't understand how to use it. Maybe they will get frustrated"

i_43	considering cost-utilization ratio	"[] high cost for companies to buy all of that and not utilise it"
i_44	partnership for value assessment	"[] we did this together with Microsoft, like value discovery"
i_45	multi-tool usage assessment	"[] we have asked users like following different copilot applications"
i_46	focusing on time savings metrics	"[] how much time they are saving", "quantifying productivity gains", "Time savings offset by debugging needs", "Natural tendency toward efficiency"
i_47	quantifying productivity gains	"[] one client we found that they are saving around like one working a day"
i_48	questioning productivity implications	"[] what is next? Because what we would do is is to working days"
i_49	emphasizing direct tool experience	"[] mostly direct experience [] direct experience, my testing, the tools"
i_50	early capability education	"[] helping them person understand the capability of the tool at the start"
i_51	avoiding tool dumping	"[] not just like just you have a tool now. Please use it", "[] if they just have access to it [] very hard for people for the most of people to to make any sense or any use of of just access"
i_52	creating user-tool interfaces	"[] build an interface between users and the toolbar"
i_53	tool functionality education	"[] explain them how the tool works"
i_54	supported testing process	"[] helping users test the tool itself"
i_55	structured prompt guidance	"[] not just like specialised come to LM or Gbts just not to throw any prompts", "[] give them kind of prompt template that they can use to experiment with", "Planning prompt engineering training programs", "Ineffective prompt writing hindering problem solving", "Prompt inconsistency as common problem across companies"
i_56	building initial tool trust	"[] build this first trust with the tool itself", "[] can do some good, good stuff", "Domain success builds specific trust", "Historical improvements build future trust", "Successful experiences drive increased AI adoption", "[] trust builds through peer experience sharing", "[] Both positive and negative experiences can build trust", "Building trust through knowledge development", "Experience-based development of consistency trust"
i_57	encouraging user feedback	"[] letting them give a feedback"
i_58	differentiating AI from conventional tools	"[] when we are communicating a new AI solution [] mention that now it's something different from other tools", "Explaining AI differences to justify usefulness"
i_59	explaining AI unpredictability	"[] not like conventional software system that whenever you click the same button you get all of the same answer", "[] there's also uncertainty, there's also like [] deterministic outputs", "[] at the beginning it was a bit difficult and challenging for users", "Dealing with AI unpredictability"

i_60	shift in user understanding	"[] this is now changing. So they started to understand that AI is not [] automation tool"
i_61	conceptualizing AI as intern not automation	"[] it's like an intern in the company [] not that's not the automation tool", "[] had a thinking process outside and it might fail", "[] you need to be in control", "[] you need to know how can I get benefit out of this tool", "[] like again like an internal person in the company. You need to know how to build this person", "Teaching AI requires treating it like an intern", "AI needs human experience transfer", "Anthropomorphic AI assessment", "Increasing anthropomorphization with AI advancement", "Recognition of need for AI augmentation"
i_62	product-specific governance committees	"[] we have kind of operating committee we can we call for each product each tool", "Multiple commission approvals needed before release"
i_63	distinguishing tool vs usage failures	"[] check whether actually it's a failure of the tool itself or actually failure of because they didn't use it properly"
i_64	multiple knowledge sharing networks	"[] many knowledge communities or knowledge sharing communities", "[] domain-specific AI communities", "[] community I would say of experts not AI experts here more like from the core business", "[] multiple knowledge sharing networks", "[] I see a lot of [] informal alliances structures networks whatever forming", "[] spontaneous formation of AI knowledge networks", "[] capabilities and capacity spread across departments that somehow have to communicate", "Cross-departmental knowledge sharing emerges", "Varying by knowledge sharing culture", "Creating presentation opportunities", "Encouraging external knowledge sharing"
i_65	domain-specific AI communities	"[] AI in tax or AI for tax, AI for others, they are for assurance, AI for knowledge management", "[] organizational subcultures develop around AI"
i_66	business expert communities	"[] community I would say of experts not AI experts here more like from from the core business"
i_67	practical AI experience emphasis	"[] has experience in using AI tools"
i_68	network vs hierarchical structure	"[] we see is more like a network of firms. So it's not like hierarchical firm"
i_69	tool duplication challenges	"[] you would see a lot of duplication or replication of the same tool or the same concept across the network"
i_70	solution proliferation	"[] hundreds of right solutions"
i_71	tool consolidation efforts	"[] combining or recommending merging some of the tools"
i_72	ongoing expert mixing	"[] continuous mixing of experts in in like different projects"
i_73	project-based knowledge sharing	"[] project based would be one-on-one of it"
i_74	cross-functional regulatory work	"[] worked with legal on the EU AI Act"
i_75	combining technical and legal expertise	"[] kind of technical expert to use legal basically expertise together"
i_76	bi-directional expertise exchange	"[] gained knowledge from them about the act [] knowledge from us about the mitigation"

i_77	leadership setting AI strategy	"[] leadership actually playing [] in putting we these new strategies", "External expertise guides management", "Management struggles with AI prioritization", "Executive interest driving innovation focus over specific technologies", "Leadership providing innovation infrastructure"
i_78	strategic pivots for emerging tech	"[] pivoting our strategy [] whenever there's an emerging technology" , "Shifting focus in AI technologies", "Technology cycles may repeat", "Changing strategy in AI solution providers", "Shifting product focus to AI agent capabilities", "Team-driven technology pivot based on potential", "Rapid team adaptation to new technology focus"
i_79	recognizing internal disruption	"[] shows first of all that it is disrupting our own line of services"
i_80	multi-faceted strategic response	"[] build a strategy around it, to upskill its people, or building maybe build assets"
i_81	service delivery improvement focus	"[] enable our people to be and deliver better services"
i_82	enabling knowledge sharing	"[] enable knowledge management, positive knowledge sharing"
i_83	cross-product expertise mixing	"[] mixing expertise in different products"
i_84	expanding AI expertise reach	"[] try to bring like AI expert for all the projects, even if not AI really related"
i_85	identifying AI solution opportunities	"[] maybe can be solved in the area", "Stakeholders identifying simple but tedious problems for AI solutions", "Identifying tedious processes as AI opportunities"
i_86	top-down education approach	"[] we always start with actually upscaling our education from from the top management level", "Top-down knowledge distribution preferred", "Companies attempt top-down AI introduction", "Top-down AI introduction through tool provision"
i_87	cascading AI adoption	"[] partners, directors to start using AI and then communicate to to their employees", "Bottom-up adoption pattern", "Individual usage drives organizational adaptation"
i_88	client interest driving adoption	"[] clients are asking about it [] want to know what's what AI can do" , "Industry adoption creates pressure"
i_89	client questions spurring expertise	"[] drive our experts to think about these questions"
i_90	governance preventing pilot proliferation	"[] if you don't have a good proper governance then you might get a lot of pilots or Pocs"
i_91	avoiding skillless implementation	"[] without any skill or without any product"
i_92	identifying signs of failed adoption	"[] failed adoption [] if you ever don't know like 1000 pilots or agents in the company, but none of them is in use or in production"
i_93	distinguishing innovation from adoption	"[] very innovative but they are not actually [] adopting AI", "just like you are playing with AI", "Avoiding AI experimentation without purpose", "Pursuing AI without clear benefits", "Making superficial AI implementations"
i_94	avoiding AI experimentation without purpose	"[] just like you are playing with AI", "Questioning AI necessity when benefits unclear"

i_95	structured innovation governance	"[] governance framework [] which means [] innovation process from idea", "[] having more governance lead actually to more adoption", "[] leading to killing many ideas", "[] failed [] passing [] the business case evaluation or the risk evaluation", "Policies can stifle organic innovation", "Formalization can harm organic collaboration"
i_96	dual evaluation: business case and risk	"[] evaluating the business case of that idea and then evaluating the risk", "Fear of investment failure inhibits adoption", "Case studies improve risk assessment", "Nuanced understanding enables detailed risk assessment", "Subculture influence shapes risk assessment", "Basing AI adoption on profit potential"
i_97	AI skills as job requirement	"[] AI will not replace jobs, but we replace people that are not using AI", "Job security fears", "Need for job security guarantees", "Fear of job automation and skill obsolescence slows adoption", "Worrying about AI job displacement"
i_98	scale of service operations	"[] organisation is running [] thousands and 100 services or task"
i_99	automation vs augmentation expectations	"[] expectation how AI is automating or augmented augmenting this task", "Mixed impact of automation"
i_100	individual expectation management	"[] individually [] expectation management is important"
i_101	connecting expertise to business needs	"[] upscaling is important then connecting expert that or like business need to AI"
i_102	parallel individual- organizational patterns	"[] same from my experience to the whole organisation"
i_103	focusing on daily work upskilling	"[] focus on their their daily tasks, their daily work being upskilled"
i_104	automation potential evaluation	"[] evaluate what does can be automated by AI"
i_105	adaptation strategy development	"[] how can they not cope with that"
i_106	Shifting from internal AI projects to external consulting role	"[] I basically have experiences for multiple companies [] where I was just a consultant and helped to basically try to build up this Gen AI knowledge"
i_107	Moving from knowledge building to practical capability development	"[] try to build up this Gen AI knowledge and also develop small prototypes [] try to build up your internal capabilities"
i_108	Taking possibilities to decision makers	"[] make the the responsible people aware of the possibilities that are out there"
i_109	People's roles and tech optimism shaping information seeking	"[] this comes down to how people inform themselves, and this differs [] between yeah, the role and also the yeah, tech optimism a person has"
i_110	Getting insights even from supposedly innovative teams	"[] spoken to startup founders that could give me insights in in their team [] even in startups"
i_111	Staying passive consumers of AI news	"[] Some people might be just [] might even not use for example Gen AI tools at all and just get news from the web"

i_112	Having no practical understanding of capabilities	"[] they basically don't have a clue how to use it and also what the limitations are"
i_113	Using only publicly available AI tools	"[] middle group [] people that somehow use all the customer facing tools or some customer facing tools"
i_114	Lacking advanced usage knowledge despite regular use	"[] They might know that it exists and are using it, but they don't really know how. All the tricks and hacks"
i_115	Missing efficiency optimization in tool use	"[] don't really know how to efficiently are really make use of it"
i_116	Actively seeking out AI information	"[] power users [] that really actively inform themselves"
i_117	Constantly searching for new developments	"[] try to look into what they can find, what's the newest thing"
i_118	Having few power users even in innovative contexts	"[] small subset of real power users, even in the startup bubble, which is innovative"
i_119	Finding even fewer power users in traditional companies	"[] So you could only guess in rather conservative corporates. This number is even less"
i_120	Tech workers staying uninformed about AI	"[] in a rather conservative bigger corporation [] I tea people, software developers, but still even them did not really inform themselves"
i_121	Missing emerging AI developments	"[] about new movements or new topics coming up in the field of AI Gen AI"
i_122	Not understanding limitations due to capability ignorance	"[] they also didn't have a clue about the limitations because they didn't know what actually was possible"
i_123	Expressing surprise at tech worker ignorance	"[] which was surprising to myself"
i_124	Seeing immediate reaction to direct experience	"[] you could really put us or see a spark in their faces"
i_125	Demonstrating possibilities creates excitement	"[] when you show them what can be done"
i_126	Including executives in hands-on learning	"[] even for the C level executives"
i_127	Facing overwhelming variety of use cases	"[] There's so much going on in different branches and different industries, different use cases"
i_128	Sharing knowledge within industry groups	"[] really important to also exchange themselves among startups in their industry"
i_129	Struggling to track developments despite positive attitude	"[] even though they were really yeah technology positive it's hard to keep up with the developments"
i_130	Connecting AI to daily work activities	"[] experiment and test out use cases that are close to what you are doing in your daily life"

i_131	Moving from novelty to practical utility	"[] see utility in, in what this could mean for their daily life, not just be like a nice thing to play around"
i_132	Feeling pressure from public competitor success	"[] There's strong influence because if you see your competitors having some use cases in place publicly"
i_133	Falling behind in prototyping efforts	"[] means they have played around with it beforehand and you don't even have any prototype"
i_134	Experiencing competitive stress	"[] then it creates stress"
i_135	Getting questioned about AI initiatives	"[] Hey, what are you doing in the regard of AI? Hey, we've seen competitor X doing this"
i_136	Facing pressure to show AI roadmap	"[] How do you plan to utilise it? What are the processes that you can do"
i_137	Receiving pressure from multiple stakeholders	"[] a lot of different stakeholders that bring stress"
i_138	Struggling with efficient and sustainable implementation	"[] issue that they're facing is how to make use of it efficiently for their own organisation, also sustainably"
i_139	Experiencing competition as pressure rather than inspiration	"[] one component of distress is is competition [] rather a push"
i_140	Getting pushed by external stakeholders	"[] if someone is doing something cool, it's pushed to a lot of other people because of advisors or investors"
i_141	Missing internal motivation for AI adoption	"[] rather than companies pulling OK, looking for good use cases"
i_142	Hitting perceived technical limitations	"[] Once I ran into an error in developing something and I'm like, OK, this is not possible"
i_143	Having limitations proven wrong by others	"[] someone showed me a prototype and was like, no, I made this. This is exactly what I couldn't do before"
i_144	Finding development pace surprising even for experts	"[] pace of the development of those tools is surprising even to [] used to this rather fast pace"
i_145	Seeing generational gap in understanding	"[] cannot imagine how it is for like people that are older or yeah stem from times where the digital age was not there"
i_146	Creating department representatives	"[] role of so-called black belts [] pick people that represent best case every department or every team"
i_147	Having voluntary knowledge sharing	"[] volunteer to be representative of using AI tools and to share knowledge"
i_148	Communicating tool limitations	"[] share limitations of it"
i_149	Building internal ambassador network	"[] make them the ambassadors within your company to spread it"
i_150	Creating common knowledge foundation	"[] train let's say 10 or 20 or 30 people at once that you can have a common knowledge base"
i_151	Setting up voluntary innovation labs	"[] voluntary venture labs kind of for Jenny I labs, where people that are just interested can show up"

i_152	Regular sharing of AI usage examples	"[] Please everyone in this two-month circle tell us how are you using it and send us a picture"	
i_153	Recognizing successful AI implementation	"[] person who's using it best is gets an achievement"	
i_154	Getting CEO commitment to AI	"[] CEO would go and we as an organisation we see the potential of of this tools"	
i_155	Building interest from scratch	"[] naturally try to root out this interest for the topic where there was no interest before"	
i_156	Traditional AI experts resisting new tools	"[] tech guy that has worked with all of like decision trees or neural networks [] is reluctant to use geniard tools"	
i_157	Business users adopting faster than tech experts	"[] He's using those tools way more than his technical Co founder"	
i_158	Allowing different adoption speeds	"[] They didn't solve the situation [] everyone can can work in their own ways"	
i_159	Maintaining positive messaging about AI	"[] Try to have a positive note on topics as sea level as Department manager"	
i_160	Demonstrating AI value individually	"[] do it as an individual level to show them basically"	
i_161	Following peer behavior patterns	"[] You are what your peers are [] you reflect what your peers are and do"	
i_162	Creating departmental echo chambers	"[] echo chambers [] in in an organisation"	
i_163	Staying isolated from external influence	"[] nothing external coming inside. They're doing what they're doing"	
i_164	Finding connected groups easier to influence	"[] Easy to bring this message [] to like very interconnected echo chambers"	
i_165	Struggling to reach isolated groups	"[] rather hard to bring it to the ones where there's not much exchange going on"	
i_166	Valuing opinion changes highly	"[] Every employee [] that switches an opinion is maybe more important"	
i_167	Focusing on leadership communication	"[] Leadership is in I would say it's it's really a lot about communication"	
i_168	Preferring inspiration over force	"[] Leadership should be inspiring and not [] punishment or like have deadlines"	
i_169	Leading by example	"[] being a role model as well which is important"	
i_170	Showing not just telling	"[] demonstrate also the things that you preach"	
i_171	Breaking age-related tech stereotypes	"[] known to be rather old and not that tech invested, but then all of a sudden you're really, positively speaking about this technology"	
i_172	Demonstrating personal AI engagement	"[] Showcasing in front of a town hall a demonstration yourself"	
i_173	Moving from knowledge to experimentation	"[] One thing is knowing about what it can do [] Then it's about this spirit of experimenting"	
i_174	Starting with knowledge building	"[] The first stop step is like gaining knowledge and activating people"	
i_175	Growing comfort through experience	"[] assess it as less risky if they have experience with it"	
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i_176	Learning real costs through failure	"[] maybe because they've seen OK, this fails and it's more expensive than we thought"	
i_177	Creating dedicated AI teams	"[] sourced the three people that were the most affiliated with AI developments into a special task force", "Creating specialized teams in response to AI hype"	
i_178	Coordinating across departments	"[] act as yeah, the office that cheques in with all the departments"	
i_179	Valuing practical experience	"[] people that have experience on their own of the daily doing of this line tasks"	
i_180	Leveraging existing networks	"[] known within the company that have a network beforehand"	
i_181	Resisting process changes	"[] not innovative [] not a lot of process change changes"	
i_182	Changing research methodologies	"[] try to develop new processes on how to do like literature [] scientific research"	
i_183	Formalizing efficient processes	"[] make a real process out of it and tell others [] use this process as it's time efficient"	
i_184	Distinguishing personal from organizational use	"[] use cases on a personal level are [] different to the ones in an organisational level"	
i_185	Embracing change mindset	"[] growth mindset of trying new things, of changing the way what you're doing"	
i_186	Setting higher organizational standards	"[] Different requirements in term of what comes out output different requirements on on accuracy levels"	
i_187	Needing technical infrastructure	"[] Requirement of capabilities in terms of tech [] would be super detrimental for this organisational AI readiness"	
i_188	Cross-industry AI implementation experience revealing different adoption patterns	"[] I've done quite a variety of implementation projects in a number of industries"	
i_189	Evolution from basic AI applications to specialized technical solutions	"[] build a search tool [] that involves the part of the vector database and similarity search"	
i_190	Confronting reality of workflow integration challenges after initial excitement	"[] they were like, OK, this is great, but now I want to integrate this in my flow everyday flow of information. How do I do that?"	
i_191	Discovery of hidden data preparation requirements	"[] you need a lot of preprocessing and a lot of data curation before you can actually use these pipelines"	
i_192	Shift from AI-centric thinking to understanding broader implementation challenges	"[] Companies and people think it's way easier and they're just worried about the AI part, but there's a lot behind that"	

i_193	Uncovering cascading changes needed in existing systems	"[] maybe they need anonymized data [] how do you get this anonymized data is a whole new process"	
i_194	Recognition of necessary modifications to existing automation	"[] they already have automated systems, which they have to change to fulfil this"	
i_195	Initial phase of viewing AI as universal solution	"[] Before they start diving deep into AI [] think AI can solve all my problems"	
i_196	Understanding specific technical constraints through practice	"[] AI is not made to just make write a whole book at once, because it doesn't have that length token"	
i_197	Discovery that integration complexity exceeds AI implementation	"[] implementing that into their systems [] is where all a lot of work lies"	
i_198	Realization of AI as minor component in larger system	"[] it's a very small piece in a whole system"	
i_199	Management's initial overenthusiasm about AI potential	"[] managers were very much like very excited. First of all"	
i_200	End-user skepticism contrasting with management enthusiasm	"[] The people that have to work with it [] were a bit more sceptical"	
i_201	Resistance to changing established work practices	"[] we've always done things a certain way. Why do we have to go change that around"	
i_202	Gap in technical understanding even among IT professionals	"[] Most technical persons also don't really know if we'd start talking about vector databases"	
i_203	Media tends to overhype or distort AI	"the general tendency of general media is either you know overhyping or or distorting the view", "Reliance on reputable sources for AI understanding", "Media coverage provides superficial understanding", "Seeing only positive social media examples", "Building false confidence from positive examples"	
i_204	Shift from cautious approach to competitive pressure driving adoption	"[] now their position now is a bit like oh damn [] if we don't start doing something about it, our competitors will"	
i_205	Different stakeholder groups having distinct concerns	"[] if you ask the technical people, they might be sceptical for different reasons such as security"	
i_206	Recognition of need for expert guidance	"[] until you don't have, let's say, an AI expert on boards [] you don't really get guidance"	
i_207	Gap between initial vision and implementation reality	"[] they start with this idea [] and they realise it's not as easy or as good as they thought"	
i_208	Disappointment followed by realistic understanding	"[] they are disappointed, but they also realise it's just really hard to attain"	

i_209	Post-purchase rationalization of AI solutions	"[] even if the app is not performing [] people that buy it tend to basically be extremely happy"	
i_210	Separation of innovation from core operations	"[] they have a different branch that manages innovation [] without influencing the rest of the company"	
i_211	Need for tool access to enable experimentation	"[] if you don't give any of your workers access to [] AI tools [] you can't complain that no one is testing out"	
i_212	Evolution of cross-functional collaboration	"[] when really the managing one of the managers sits with the doctors [] and just develops this idea"	
i_213	Balancing competing stakeholder perspectives	"[] you get the side of the manager [] and the psychologist, which is more realistic", "Non-technical factors as main implementation bottlenecks", "Complex stakeholder management slowing progress", "Power dynamics creating implementation friction"	
i_214	Sustained cross-functional engagement enabling practical adoption	"[] the structure of really having all these different characters in one room can really help"	
i_215	Hype-driven excitement to external prototype development	"[] companies hire a third party company [] to make a prototype"	
i_216	Reality check through prototype results	"[] once they see the results of that, maybe they're not matching their expectation"	
i_217	Prototyping as organizational learning process	"[] it's still a very good learning curve", "Quick prototyping followed by extensive use case validation"	
i_218	Resistance to switching from familiar to new AI tools	"[] I was always using ChatGPT and [] told me hey, try Claude"	
i_219	Need for strong advocacy to overcome tool switching resistance	"[] if was one of the Co founders, that really pushed me"	
i_220	Building trust through direct comparative experience	"[] once you start using it [] you're like, wow, it's actually way better"	
i_221	Natural resistance to leaving comfort zones	"[] Most people are not naturally curious or wanna go outside of their comfort zone"	
i_222	Overcoming initial end-user resistance through management push	"[] you need the manager to really push them to try this"	
i_223	Limited effectiveness of formal promotion	"[] you can put ads everywhere. But I think ads works way worse"	
i_224	Surprise at AI capabilities while maintaining data privacy	"[] and it's gonna have all the knowledge of my data without making it open to the world"	
i_225	Value found in failed experiments through learning	"[] Even in those cases, they're happy that they learn something"	

i_226	Cost-benefit evaluation framework	"[] it's not worth it for a very niche or small task [] if your whole business is based on that, yes, maybe"	
i_227	Self-convincing behavior after investment	"[] they will tell themselves and tell other people it's great"	
i_228	Credibility preservation affecting feedback honesty	"[] they want to seem credible"	
i_229	Informal knowledge sharing through daily interaction	"[] mostly just with conversation and with exchange of ideas"	
i_230	Value of diverse team characteristics	"[] it's good to have a group with different type of specifications"	
i_231	Role of curiosity-driven experimentation	"[] curious ones will see new posts [] and play around with it"	
i_232	Cross-pollination between different personality types	"[] Post it or share it to their friends, which are maybe less curious but more hardworking"	
i_233	Distributed knowledge gathering through community	"[] you keep on getting from everyone the latest knowledge"	
i_234	Collective knowledge accumulation benefit	"[] at the end you receive the full package"	
i_235	Resistance to top-down AI implementation	"[] if leaders would impose this maybe would be seen in a worse light	
i_236	Importance of individual motivation	"[] if they're not interested, or if they're not curious [] nothing's gonna come out of it"	
i_237	Protected space for innovation exploration	"[] they have one or two teams [] goal is to take an innovative idea and develop it [] Without influencing the rest of the company"	
i_238	Limitation documentation enabling realistic expectations	"[] if you have an idea of the limitation, you can [] inform them about what you can do and what you can't do"	
i_239	Need for seamless integration	"[] implement the whole flow for them to really enjoy it and have a good experience"	
i_240	Ease of use and clear benefits driving adoption	"[] once you start using it and you do one prompt [] let me try it twice"	
i_241	AI evangelists expecting AGI and human replacement	"there are the AI evangelists which say, oh, this is gonna be able to do everything very soon. We're gonna have AGI in Singularity", "We're not gonna need people that kind of people", "Romanticization drives innovation"	
i_242	Historical training lacks AI relevance	"Back in the day, they were getting formal training. AI wasn't that much of a thing []"	
i_243	Case studies drive decision-making	"one of the key decision making processes [] is seeing case studies", "they try to match it with their environment []"	
i_244	Actions over words in support	"it's not the supporting with words, it's the supporting with actions within the organisations"	
i_245	Resource allocation for AI learning	"the resources should be allocated and designed in the company for people to test it []"	

i_246	Future uncertainty suggests avoiding generalizations	"people just should avoid making general comments about AI. You don't we don't know what's next"	
i_247	Concerns about AI-dependent slacking	"the thing that they were most concerned about was people slacking and only using AI and not checking the responses"	
i_248	Aggressive layoff trends due to automation	"especially in U.S. companies, there is a very aggressive tendency right now to do the the layoffs"	
i_249	Uncertainty drives emotional responses	"this lack of knowledge, this uncertainty is what's driving a more visceral and emotional response within people"	
i_250	Intrapreneurship drives culture	"supporting Intrapreneurship is going to be a very strong culture driver"	
i_251	People construct beliefs from fragmented information sources	"[] views of most people form by random snippets of information [] it's often very weakly grounded []"	
i_252	People align AI views with political identity	"[] starting to [] connect their political identity to some form of role they take"	
i_253	Integration into daily workflows most effective	"[] most useful support structure companies are providing are direct specific business use cases [] integrated into the procedures of people in their everyday work"	
i_254	Corporate tools both enable and constrain exploration	"[] if management [] integrates it somehow in the workflow [] on the other hand it also limits them"	
i_255	Lack of corporate tools drives external exploration	"[] if you don't have this and you have to you know find your own GP4 access outside"	
i_256	Freedom from regulation enables broader experimentation	"[] breadth of tools [] greater because not subject to popular regulation"	
i_257	Previous technology adoption creates openness to new projects	"[] the very existence of technology adoption projects makes people more open []"	
i_258	Organizational culture shows high resilience	"[] the stiff culture updated [] but overall kept the culture relatively resilient"	
i_259	Diverse understanding levels exist within organizations	"[] in many organisations most people have [] all sorts of the understanding of AI capabilities and limitations"	
i_260	Conservative finance culture creates resistance to AI adoption	"[] finance partners are known to be traditionally quite conservative [] concerns about job security, explainability and reliability"	
i_261	Beliefs spread and evolve through social exchange	"[] evolved by them telling these mostly wrong beliefs to some other people [] exchanging in debate with others"	
i_262	Media and superficial sources shape beliefs	"[] media political magazines just randomly informal talks [] super superficial coverage"	
i_263	Indirect knowledge becomes politicized	"[] indirect information is [] politicised weapon model [] agenda behind"	
i_264	Getting used to AI reduces uncertainty and builds confidence	"[] see how things work and how they don't [] reduces uncertainty and confidence"	

i_265	Even failed experiences improve mental models and trust	"[] even if the model becomes worse than the expectations it still increases trust []"	
i_266	Risk assessment quality depends on understanding depth	"[] whether the outcome of the risk assessment is based on more superficial understandings []"	
i_267	Attempting coordinated top-down policy introduction	"[] I see some companies [] trying to introduce top level via policy []"	
i_268	Overly policy-driven approaches hinder innovation	"[] if the understanding is superficial [] leads to nonsensical policy"	
i_269	Long-standing procedures create resistance	"[] many people are kind of stuck in the fixed procedures they have had for years or even decades"	
i_270	Failed projects influence future attitudes	"[] if these were big failures [] negative intuition [] but people are more open than not having had them at all"	
i_271	Polarization between utopian and pessimistic views	"[] a lot of individuals are either caught in a overwhelmingly positive [] or in a more negative []"	
i_272	Moving from technical education into consulting large companies	"I did my bachelor's in computer science [] Data science [] work as a consultant [] large companies"	
i_273	Paying premium for unstructured data delivery	"A company pays quite a lot of money [] provider does not provide structured format but PDF"	
i_274	Using PDF reports for strategic business decisions	"They use these PDF reports [] to make decisions [] which companies to approach"	
i_275	Expanding LLM use beyond initial project scope	"While I was expecting that we would use llms in the second phase [] we used them for extracting data as well"	
i_276	Starting with traditional solution approach	"When we started the project I had one idea in mind: Azure document intelligence"	
i_277	Struggling with manual data labeling requirements	"We had to label the data ourselves [] highlight parts to extract"	
i_278	Experiencing poor performance despite extensive training data	"We did that for more than 100 documents and accuracy was to like 8%"	
i_279	Struggling to communicate AI value to business stakeholders	"The biggest hurdle [] is to try and understand to business people what the value is"	
i_280	Competing with cheap manual labor alternatives	"Business people say well I can hire juniors and pay them low salaries"	
i_281	Proposing ML for anomaly detection	"We were proposing a machine learning solution that would detect irregularities"	

i_282	Breaking down over liability assignment	"The project failed [] could not agree who was liable if algorithm failed"	
i_283	Drawing parallels to self-driving car liability issues	"Similar to a self driving car [] if it crashes, who is responsible?"	
i_284	Limiting actual usage to simple tasks	"They only use it to write emails but not for important reports"	
i_285	Operating in non-technical awareness bubble	"For non-technical people it's like a bubble [] they don't see that much"	
i_286	Fearing unknown technologies	"People fear things they don't know [] no proper knowledge"	
i_287	Experiencing amazement without prior expectations	"If there aren't any expectations [] sense is positive, like wow how is this possible"	
i_288	Starting from operational understanding	"Understanding how your company works [] day-to-day operations [] try to improve those"	
i_289	Selecting tools based on specific cases	"The tool you choose is based on a case by case basis"	
i_290	Pushing for advanced internal AI solutions	"We encouraged the internal team to create more llm agents"	
i_291	Proposing AI for internal resource matching	"Extract data from CVs [] know the profiles of colleagues [] match to new openings"	
i_292	Building reusable AI infrastructure	"Let's build a tool that deploys internal chat bots in different departments"	
i_293	Adding AI to corporate values	"Companies now want to put the AI keyword in their value system"	
i_294	Avoiding AI for critical decisions	"For really important decisions AI is scarcely used"	
i_295	Combining tool and organizational knowledge	"Having the knowledge of the tool and of the company operations plays a huge role"	
i_296	Failing from lack of operational understanding	"If you do that it shows you do not fully understand the day-to-day operations"	
i_297	Incentivizing knowledge documentation	"Providing bonuses for people that write articles in different mediums"	
i_298	Creating dedicated AI teams	"[] sourced the three people that were the most affiliated with AI developments into a special task force", "[] after yeah. And we'll who also want to, like, like, for the AI hype, want to, like, have, like, for, like, one of their products, have, like, a special, app, AI innovation team"	
i_299	Leveraging AI agents for process automation through software component access	"[] focusing on, on AI agents", "What is nice [] access to other software components in terms of automation"	
i_300	Experimental nature reducing trust expectations	"[] there wasn't really a trust. It was more like we always knew, yo, this is an experiment"	

i_301	Partner agreements as trust building mechanism	"[] What are the partner agreements?"	
i_302	Complex stakeholder management slowing progress	"[] stakeholder management [] who was given who the task", "Power dynamics creating implementation friction", "Non-technical factors as main implementation bottlenecks"	
i_303	Database access requirements causing delays	"[] you had to get access to those regulations [] asking them for database access"	
i_304	Technical architecture limitations requiring workarounds	"[] there is like an actually back end user and there's front end users. And this app was only programmed for front end"	
i_305	Central AI system imposing rate limits	"[] we had, like, some rate limiting by all, like, central [] AI thing"	
i_306	Explaining AI differences to justify usefulness	(Already included above)	
i_307	Limited specialized AI expertise in team	"[] neither of my colleagues are [] super specialized"	
i_308	Solution value extending beyond initial use case	"[] usability guys found it helpful, not only for this use case, but also for others"	
i_309	Limited effectiveness of formal documentation	"[] internal blog posts, but, I'm not only just scan over them"	
i_310	Resource allocation for technical talent acquisition	"[] you have to give money for job postings to have engineers"	
i_311	Monthly calls for sharing innovation updates	"[] once a month, like, a bigger call where interesting news were presented"	
i_312	Technical team alignment on AI capabilities	"[] data scientists and engineers, we mostly had, like, the same ideas about what AI can and can't"	
i_313	Dismissing non-technical perspectives on implementation details	"[] their perspective was not really interesting [] they are not there for giving technical advice"	
i_314	Prioritizing functionality over technical understanding	"[] at the end, it's just important, does it work, or doesn't it work?"	
i_315	Growing acceptance despite technical complexity	"[] you have more and more acceptance [] even if there's complexity"	
i_316	Buzzwords and conceptual confusion	"[] you have a lot of buzz wording [] similar ideas got disconnected", "AI and data science, 2 separate things [] super similar"	
i_317	Avoiding solution suggestions from non-experts	"[] we didn't ask people what is a good solution because they don't know our AI solution"	
i_318	Focusing implementation on low-risk areas	"[] things we tackled were never something super dangerous"	

i_319	Companies collaborating on safe AI interaction standards	"[] bigger tech companies talk about what is a good and safe way agents talk with each other"	
i_320	Technical stack flexibility as critical requirement	"[] technical stack has to be flexible"	
i_321	Hierarchical structures creating team communication barriers	"[] 2 big engineering teams who were not talking to each other becau of some hierarchical stuff", "Hierarchical barriers multiplying implementation time"	
i_322	Open and observable communication as organizational requirement	"[] communication is also open and observable"	

Appendix 4: Second-order Concept Catalogue

Code	Initial Codes	Theme	Description
c_1	i_4, i_9, i_10, i_11, i_12, i_13, i_17, i_18, i_50, i_101, i_174, i_242, i_259, i_288	Developing Foundational AI Literacy	Organizations foster basic understanding of AI capabilities, terminology, and concepts to prepare employees for meaningful tool usage.
c_2	i_14, i_16, i_59, i_61, i_148, i_196, i_238, i_246, i_63, i_142, i_306, i_314, i_318	Understanding and Communicating AI Limitations	Employees must learn where AI falls short—hallucinations, token length limits, biases—to form realistic expectations, avoid frustration, and refine use cases.
c_3	i_38, i_49, i_54, i_130, i_173, i_190, i_217, i_219, i_220, i_264, i_265, i_289	Hands-on, Experiential Learning and Prototyping	Direct experience—from small tests to prototypes—helps individuals understand AI's capabilities, revealing hidden constraints and building accurate mental models.
c_4	i_29, i_56, i_57, i_105, i_173, i_175, i_209, i_220, i_264, i_265, i_240, i_308	Trust Building Through Incremental Successes	Trust grows gradually as users see AI deliver small, reliable benefits. Positive peer experiences, quick wins, and iterative improvements cultivate confidence.
c_5	i_22, i_23, i_29, i_64, i_65, i_147, i_161, i_232, i_233, i_250, i_161, i_164, i_229	Social Influence, Peer Learning, and Informal Networks	Informal peer-to-peer interactions, community groups, and champions spread know-how, drive FOMO, and reinforce adoption. Word-of-mouth outperforms formal communication.
c_6	i_22, i_24, i_25, i_26, i_146, i_149, i_150, i_153, i_180, i_147, i_23, i_298	Champion and Ambassador Models	Designating champions—enthusiastic, knowledgeable employees—accelerates AI diffusion. They translate tech capabilities, demonstrate benefits, and help peers overcome barriers.
c_7	i_31, i_33, i_62, i_90, i_95, i_96, i_301, i_319, i_268, i_294, i_283, i_303	Governance, Policies, and Compliance Structures	Strict governance and compliance frameworks (data security, human-in-the-loop, legal liabilities) shape permissible AI use, sometimes stifling innovation but ensuring safe practices.
c_8	i_77, i_78, i_80, i_86, i_87, i_167, i_168, i_169, i_177, i_154, i_235, i_244	Balancing Top-Down Strategic Direction and Bottom-Up Adoption	Senior leaders provide vision, allocate resources, and set priorities, while grassroots experimentation and user-driven innovation ensure practicality and long-term readiness.

c_9	i_199, i_200, i_201,	Reconciling	Managers often overestimate AI's transformative
	i_207, i_208, i_228, i_313, i_314, i_97, i_141, i_248	Management Enthusiasm with End-User Skepticism	power, while end-users doubt its practicality. Bridging these views—through communication, demonstration, and risk reduction—is crucial.
c_10	i_88, i_132, i_133, i_134, i_135, i_139, i_140, i_204, i_141, i_132, i_255	Competitive and Environmental Pressures	External triggers—rivals' successes, client queries, media hype—push organizations to adopt AI faster, sometimes prematurely. Perceived competitive lag fuels anxiety and rushed action.
c_11	i_192, i_193, i_195, i_198, i_216, i_219, i_226, i_270, i_243, i_203	From Hype to Realistic Implementation Understanding	Initial hype frames AI as a panacea. Experience reveals complexity: data prep, integration challenges, and infrastructure demands. Over time, organizations refine expectations and approaches.
c_12	i_20, i_21, i_39, i_82, i_103, i_185, i_239, i_253, i_296, i_297, i_254	Aligning AI with Existing Workflows and Processes	Seamlessly integrating AI into current routines (rather than forcing radical process changes) encourages adoption. Alignment reduces friction and supports sustained use.
c_13	i_7, i_28, i_187, i_191, i_193, i_197, i_289, i_320, i_310, i_291, i_292	Data Preparedness and Technical Infrastructure	Successful AI adoption hinges on robust data handling, secure environments, flexible architectures, and the right technical skill sets. Poor data readiness undermines trust and results.
c_14	i_16, i_42, i_41, i_208, i_194, i_271, i_246, i_248, i_258, i_223, i_176	Managing Expectations and Mitigating Disappointment	Avoiding inflated expectations prevents frustration and abandonment. Proactive communication about limitations, costs, and realistic benefits curbs disillusionment as reality sets in.
c_15	i_31, i_33, i_97, i_282, i_283, i_294, i_319, i_247, i_269, i_318, i_263	Ethical, Legal, and Human Oversight Concerns	Ensuring human-in-the-loop, addressing biases, and clarifying liability builds confidence that AI aligns with core values, mitigates risks, and respects regulations.
c_16	i_151, i_237, i_177, i_210, i_298, i_250, i_215, i_244, i_211, i_106	Intrapreneurship, Innovation Labs, and Safe Experimentation Spaces	Dedicated spaces (labs, special teams) encourage experimentation, learning, and controlled risk-taking, fostering organizational readiness without threatening core operations.
c_17	i_201, i_97, i_200, i_221, i_222, i_236, i_286, i_269, i_156, i_248, i_294	Overcoming Resistance and Fear of Change	Some employees resist AI due to uncertainty, job threats, or comfort with old methods. Overcoming this requires reassurance, showing incremental value, and respecting existing expertise.
c_18	i_109, i_111, i_113, i_114, i_116, i_118, i_119, i_120, i_231, i_157, i_145	Variation in Individual Engagement Levels	Engagement differs: some are passive, others merely dabble, and a few are "power users" who stay ahead. These differences influence how quickly AI readiness spreads.
c_19	i_203, i_251, i_252, i_262, i_263, i_241, i_271, i_246, i_203, i_115	Influence of Media, Narratives, and External Discourse	Media hype, politicization, and superficial coverage skew perceptions. Employees form beliefs from fragmented info, leading to either unwarranted optimism or undue fear.

c_20	i_74, i_75, i_76, i_212, i_213, i_214, i_230, i_295, i_321, i_313, i_312, i_203	Cross-Functional Collaboration and Knowledge Integration	AI solutions require blending technical, legal, and business expertise. Cross-functional collaboration breaks silos, improves solution design, and aligns AI with organizational realities.
c_21	i_78, i_79, i_106, i_107, i_257, i_259, i_273, i_320, i_174, i_144	Continuous Adaptation and Strategic Realignment	Rapid AI evolution demands ongoing strategy pivots, updating tools, retraining staff, and shifting focus as new capabilities emerge and old assumptions fail.
c_22	i_85, i_93, i_94, i_226, i_243, i_290, i_311, i_316, i_313, i_315	Balancing Innovation and Utility	Effective readiness means not just chasing novelty but ensuring AI delivers concrete improvements. Avoiding "innovation theater" prevents resource waste and mistrust.
c_23	i_61, i_58, i_60, i_99, i_241, i_247, i_116, i_185, i_55, i_1	Anthropomorphizing and Conceptualizing AI as a Colleague	Users often treat AI like a human "intern," recognizing its fallibility and intelligence. This human-like framing helps set appropriate expectations and facilitate adoption.
c_24	i_5, i_7, i_44, i_108, i_110, i_140, i_215, i_206, i_283, i_301, i_244	Leveraging External Expertise and Partnerships	Collaborations with vendors, consultants, and industry peers help organizations navigate complexity, access specialized knowledge, and accelerate readiness.
c_25	i_46, i_47, i_48, i_280, i_281, i_226, i_243, i_314, i_315, i_240, i_226	Measuring and Demonstrating Tangible Value	Quantifying productivity gains, time savings, or improved outcomes convinces skeptics, aligns stakeholders, and solidifies organizational readiness by showing AI's worth in concrete terms.

Appendix 5: Aggregate Dimensions

Aggregate Dimension (a_x)	Second-Order Themes (c_x) Integrated	Description of Aggregate Dimension
a_1: Individual Sense- making Foundations	c_1: Developing Founda- tional AI Literacy c_2: Understanding and Communicating AI Limi- tations c_3: Hands-on, Experien- tial Learning and Proto- typing c_18: Variation in Indi- vidual Engagement Lev- els c_19: Influence of Media, Narratives, and External Discourse	Individuals develop initial perceptions of AI capabilities and limitations through basic education, direct experimentation, and external narratives. Engagement levels differ, and media influences shape early assumptions, forming the groundwork for organizational readiness.

a_2: Social and Or- ganizational Learning Mechanisms	c_5: Social Influence, Peer Learning, and Informal Networks c_6: Champion and Ambassador Models c_20: Cross-Functional Collaboration and Knowledge Integration c_16: Intrapreneurship, Innovation Labs, and Safe Experimentation Spaces	Social processes, such as peer learning, champions, cross- functional teams, and safe innovation spaces, transform indi- vidual knowledge into collective competencies. These mech- anisms encourage shared understanding, alignment, and the scaling of AI adoption throughout the organization.
a_3: Organizational In- tegration and Gover- nance	c_7: Governance, Poli- cies, and Compliance Structures c_8: Balancing Top- Down Strategic Direction and Bottom-Up Adoption c_9: Reconciling Man- agement Enthusiasm with End-User Skepti- cism c_12: Aligning AI with Existing Workflows and Processes c_13: Data Preparedness and Technical Infrastruc- ture c_15: Ethical, Legal, and Human Oversight Concerns	Organizational readiness involves establishing clear gover- nance, policies, and infrastructure that enable AI while re- specting constraints. Integrating AI into workflows, balanc- ing leadership visions with frontline realities, ensuring data readiness, and addressing ethical/legal issues create a stable environment for sustainable adoption.
a_4: Expectation Man- agement and Trust De- velopment	c_4: Trust Building Through Incremental Successes c_14: Managing Expec- tations and Mitigating Disappointment c_11: From Hype to Realistic Implementation Understanding c_10: Competitive and Environmental Pressures	As organizations and individuals learn the constraints of AI, establishing trust and managing expectations become paramount. Over time, the shift from initial hype to informed realism, along with competitive pressures, shapes how stakeholders perceive AI's role and value.

a_5: Long-Term Adap- tation and Value Real- ization	c_17: Overcoming Resis- tance and Fear of Change c_21: Continuous Adap- tation and Strategic Re- alignment c_22: Balancing Innova- tion and Utility	Organizations sustain readiness by continuously adapting strategies, overcoming internal resistance, ensuring AI initia- tives produce real value, and learning from external expertise. Conceptualizing AI as a collaborative agent and demonstrat- ing tangible benefits build a lasting foundation for AI-driven transformation.
	c_22: Balancing Innova-	6 6
	c_23: Anthropomorphiz- ing and Conceptualizing	
	AI as a Colleague c_24: Leveraging Exter-	
	nal Expertise and Partner- ships	
	c_25: Measuring and Demonstrating Tangible Value	