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HOW MANAGERS MAKE SENSE OF AI INTEGRATION: A SENSEMAKING STUDY OF ORGANIZATIONAL TRANSITION

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Abstract

This qualitative study examines how managers construct meaning and navigate organizational transitions during artificial intelligence (AI) integration processes. Drawing on Weick's (1995) sensemaking theory, this research explores the cognitive and social processes through which 24 middle and senior managers from Malaysian manufacturing and service organizations interpret, understand, and respond to AI implementation challenges. Through semi-structured interviews and thematic analysis, this study reveals that managers engage in retrospective interpretation, social construction of meaning, and identity negotiation as they reconcile technological disruption with established organizational practices. Findings indicate that successful AI integration depends not merely on technical capabilities but on managers' ability to create coherent narratives that bridge past experiences with future technological possibilities. The study identifies four critical sensemaking patterns: technological frame alignment, adaptive identity work, collaborative meaning construction, and strategic ambiguity management. These findings contribute to organizational change literature by illuminating the micro-processes through which managers mediate between technological imperatives and human organizational realities, offering practical implications for managing AI-driven transitions.

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Introduction

The integration of artificial intelligence (AI) technologies into organizational operations represents one of the most significant transformations in contemporary business environments, fundamentally altering decision-making processes, operational structures, and managerial roles (Davenport & Ronanki, 2018; Ransbotham et al., 2020). Organizations worldwide are investing substantial resources in AI capabilities, with global spending on AI systems projected to exceed $300 billion by 2026, reflecting the technology's perceived strategic importance (IDC, 2022). However, despite considerable financial investments and technological advancements, empirical evidence suggests that between 60% and 85% of AI implementation initiatives fail to achieve their intended objectives or remain trapped in pilot phases, indicating a substantial gap between technological potential and organizational realization (Fountaine et al., 2019; Kulkov et al., 2021). This persistent implementation challenge has prompted scholars to shift attention from purely technical considerations toward understanding the human and organizational dimensions of AI adoption, particularly the interpretive processes through which organizational members make sense of technological disruption.

Managers occupy a pivotal position in this technological transition, serving as both recipients of strategic directives from senior leadership and architects of implementation at operational levels (Hitt et al., 2016; Raisch & Krakowski, 2021). Their capacity to interpret ambiguous technological signals, construct meaningful narratives about AI's organizational implications, and facilitate collective understanding among diverse stakeholders fundamentally shapes the trajectory and outcomes of AI integration efforts (Maitlis & Christianson, 2014; Weick, 1995). Yet, existing research has predominantly focused on either macro-level organizational strategies for AI adoption or micro-level technical implementation details, with limited attention to the cognitive and social processes through which managers navigate the inherent uncertainties, paradoxes, and identity challenges accompanying AI integration (Lebovitz et al., 2021; Sturm et al., 2021). Understanding how managers make sense of AI technologies—how they interpret their meaning, reconcile conflicting demands, negotiate changing roles, and construct actionable frameworks—remains critically underexplored despite its fundamental importance to successful organizational transitions.

Introduction to Sensemaking in Technological Transitions

Sensemaking, as conceptualized by Weick (1995), refers to the ongoing retrospective process through which individuals construct plausible interpretations of ambiguous situations, enabling them to understand "what is going on" and determine appropriate courses of action. This theoretical framework proves particularly salient in contexts of technological disruption, where established assumptions, routines, and identity constructions face significant challenges (Maitlis & Sonenshein, 2010; Sandberg & Tsoukas, 2015). AI integration introduces profound ambiguities into organizational life: the technology itself operates through opaque algorithmic processes that challenge human comprehension; its implications for work roles, decision-making authority, and organizational structures remain uncertain; and its introduction often triggers fundamental questions about organizational identity, purpose, and values (Lebovitz et al., 2022; Möhlmann et al., 2021). Managers confronting AI integration thus engage in intensive sensemaking activities, drawing upon cognitive schemas, social interactions, and organizational narratives to transform confusion into comprehension and uncertainty into actionable understanding.

The sensemaking perspective offers distinct advantages for examining AI integration because it directs analytical attention toward the interpretive processes that mediate between technological artifacts and organizational outcomes (Gioia & Chittipeddi, 1991; Weick et al., 2005). Rather than treating AI adoption as a rational, linear implementation process, sensemaking theory recognizes that managers actively construct the meaning of AI technologies through social interactions, retrospective interpretations of experience, and ongoing negotiations between competing frames of reference (Barley, 2020; Orlikowski & Gash, 1994). This theoretical lens illuminates how managers reconcile the promises articulated by technology vendors and senior executives with the practical realities encountered during implementation, how they negotiate threats to professional identity and autonomy posed by intelligent systems, and how they facilitate collective understanding among stakeholders with divergent interests and expertise (Beane, 2019; Kellogg et al., 2020). By foregrounding these interpretive dynamics, sensemaking theory enables researchers to understand why technologically similar AI implementations produce dramatically different organizational outcomes across contexts.

Problem Statement

Despite growing recognition of sensemaking's importance in technological change, three critical gaps constrain current understanding of how managers navigate AI integration. First, existing research has primarily examined sensemaking in relation to discrete crisis events or strategic jolts rather than the sustained, ambiguous transitions characteristic of AI implementation (Maitlis & Sonenshein, 2010; Stigliani & Ravasi, 2012). AI integration unfolds gradually through multiple phases—exploration, experimentation, scaling, and embedding each presenting distinct sensemaking challenges as initial enthusiasm confronts implementation realities (Benbya et al., 2020; Gregory et al., 2021). Managers must continuously update their interpretations as AI technologies evolve, organizational contexts shift, and stakeholder responses emerge, yet research offers limited insight into these dynamic, processual aspects of sensemaking during extended technological transitions.

Second, current literature inadequately addresses the paradoxical and contradictory demands managers encounter when integrating AI technologies. Managers simultaneously face pressure to embrace AI's transformative potential while maintaining operational stability, to augment human capabilities while managing workforce anxieties about displacement, and to implement standardized AI systems while accommodating diverse local practices (Jarzabkowski et al., 2013; Smith & Lewis, 2011). These tensions require sophisticated sensemaking capabilities that enable managers to hold contradictory interpretations simultaneously, construct integrative narratives that accommodate conflicting demands, and facilitate organizational acceptance of ambiguity rather than premature closure (Lüscher & Lewis, 2008; Putnam et al., 2016). However, research has insufficiently examined how managers engage in this paradoxical sensemaking work, leaving practitioners without empirically grounded guidance for navigating AI's inherent contradictions.

Third, while scholars acknowledge that sensemaking constitutes a fundamentally social process involving interactions among multiple organizational actors (Weick, 1995; Maitlis, 2005), research on AI integration has predominantly adopted individualistic perspectives that overlook collective sensemaking dynamics. Managers do not interpret AI technologies in isolation but through conversations with colleagues, negotiations with technical specialists, interactions with subordinates, and engagements with external stakeholders, all of whom contribute divergent perspectives, expertise, and interests (Stigliani & Ravasi, 2012; Sonenshein, 2010). Understanding how managers orchestrate these social sensemaking processes facilitating dialogue, mediating conflicting interpretations, and constructing shared narratives remains critically important yet empirically underexplored (Bartunek et al., 2006; Vlaar et al., 2008).

A fourth challenge emerges from the specific characteristics of AI technologies that distinguish them from previous waves of organizational technology adoption. Unlike conventional information systems with transparent input-output relationships, AI systems employ machine learning algorithms that produce decisions through processes opaque even to technical experts, creating what scholars' term "algorithmic opacity" or the "black box problem" (Burrell, 2016; Pasquale, 2015). This opacity fundamentally challenges managers' traditional sensemaking strategies, which rely upon understanding causal relationships between actions and outcomes (Weick, 1995). Managers must somehow construct meaningful interpretations of AI systems whose decision-making logic remains inaccessible, assess their reliability when conventional verification methods prove inadequate, and maintain accountability for outcomes they cannot fully explain (Kellogg et al., 2020; Lebovitz et al., 2021). This unprecedented interpretive challenge requires novel sensemaking strategies that current research has yet to adequately characterize or theorize.

Addressing the Research Gap

To address these interconnected challenges, this study poses the central research question: How do managers make sense of AI integration during organizational transitions, and what sensemaking processes enable them to navigate the ambiguities, paradoxes, and identity challenges accompanying AI implementation? Answering this question requires moving beyond descriptive accounts of AI adoption toward processual understanding of the interpretive work through which managers construct meaning, focusing specifically on: (1) the temporal dynamics of sensemaking as managers' interpretations evolve throughout extended implementation processes; (2) the strategies managers employ to navigate paradoxical demands and construct integrative narratives; (3) the social processes through which managers facilitate collective sensemaking among diverse stakeholders; and (4) the novel interpretive approaches managers develop to accommodate AI's algorithmic opacity. By illuminating these processes, this research contributes theoretical refinement to sensemaking literature while offering practical insights for managers and organizations navigating AI-driven transitions.

Research Objective

The primary objective of this study is to develop a comprehensive understanding of the sensemaking processes through which managers interpret, navigate, and facilitate organizational transitions during AI integration, with specific focus on identifying the cognitive schemas, social practices, and narrative strategies that enable managers to transform technological ambiguity into actionable organizational frameworks.

Literature Review

Sensemaking Theory and Organizational Change

Sensemaking theory, rooted in Weick's (1995) seminal work, provides a foundational framework for understanding how organizational members construct meaning from ambiguous, equivocal, or confusing situations. Weick conceptualizes sensemaking as comprising seven distinctive properties: it is grounded in identity construction, retrospective in nature, enactive of sensible environments, social in character, ongoing without clear temporal boundaries, focused on extracted cues rather than comprehensive information, and driven by plausibility rather than accuracy (Weick, 1995; Weick et al., 2005). This framework has proven particularly valuable for examining organizational change contexts where established routines and interpretive frameworks become disrupted, requiring organizational members to actively construct new understandings that enable coordinated action (Maitlis & Christianson, 2014). Empirical research has demonstrated that successful organizational transitions depend critically on leaders' capacity to facilitate collective sensemaking processes that generate shared interpretations of change imperatives and legitimate new organizational directions (Gioia & Chittipeddi, 1991; Rouleau, 2005).

However, debates persist regarding the relationship between individual and collective dimensions of sensemaking, with scholars disagreeing about whether sensemaking originates primarily in individual cognition and subsequently becomes socialized, or whether it constitutes an inherently social process from its inception (Maitlis, 2005; Weick et al., 2005). Research by Weick (1995) emphasizes individuals as the primary locus of sensemaking, with social processes serving to validate, elaborate, or contest individually generated interpretations. Conversely, scholars adopting social constructionist perspectives argue that meaning emerges through conversational and interactional processes, with individuals participating in collective sensemaking from the outset (Maitlis & Sonenshein, 2010; Stigliani & Ravasi, 2012). This theoretical tension holds practical implications for understanding managerial work during AI integration, as it shapes whether interventions should focus on developing individual managers' interpretive capabilities or on facilitating organizational dialogue and collective meaning construction (Bartunek et al., 2006).

Technology Implementation and Organizational Sensemaking

The intersection of technology implementation and organizational sensemaking has generated substantial scholarly attention, with research demonstrating that technological artifacts do not possess fixed meanings but rather become interpreted and appropriated in diverse ways across organizational contexts (Orlikowski, 2000; Barley, 1986). Orlikowski and Gash's (1994) concept of "technological frames" illuminates how stakeholders develop shared assumptions and knowledge about technology's nature, purpose, and use, with incongruent frames across organizational groups creating implementation challenges. Empirical studies have shown that successful technology implementation requires active sensegiving by change agents who articulate compelling narratives linking technologies to organizational objectives, legitimate their adoption, and address stakeholder concerns (Bartunek et al., 2006; Fiss & Zajac, 2006). Research by Griffith (1999) demonstrated that technology implementation outcomes depend substantially on how managers frame technologies' meanings, with different frames leading to divergent adoption patterns despite identical technical artifacts.

Yet, existing research exhibits an important limitation: most studies examine relatively transparent technologies—enterprise systems, communication platforms, or business intelligence tools—where stakeholders can directly observe and comprehend technological functionality (Leonardi, 2011; Vaast & Walsham, 2005). These technologies' relative transparency enables stakeholders to develop technological frames grounded in empirical observation and experiential learning (Orlikowski, 1996). AI technologies, however, introduce unprecedented interpretive challenges through their algorithmic opacity, adaptive capabilities, and autonomous decision-making (Burrell, 2016; Lebovitz et al., 2021). Kellogg and colleagues (2020) found that algorithmic systems' opacity fundamentally disrupts conventional sensemaking processes, as managers cannot access the causal logic underlying system outputs. This opacity gap represents a critical theoretical and practical challenge that existing technology implementation literature has inadequately addressed.

AI Integration and Managerial Challenges

Recent scholarship on AI integration has begun documenting the distinctive challenges confronting organizations and managers, emphasizing that AI implementation differs qualitatively from previous technological transitions (Davenport & Ronanki, 2018; Ransbotham et al., 2020). Research identifies multiple interconnected challenges: technical complexity and the scarcity of specialized expertise (Fountaine et al., 2019), data quality and availability issues (Günther et al., 2017), organizational inertia and cultural resistance (Jarrahi, 2018), ethical concerns regarding fairness and accountability (Mittelstadt et al., 2016), and workforce anxieties about job displacement (Brougham & Haar, 2018). Studies by Lebovitz et al. (2021) examining AI implementation in healthcare revealed that physicians struggled to incorporate algorithmic recommendations into clinical practice when they could not understand the reasoning underlying those recommendations, leading to resistance and workarounds rather than acceptance. Similarly, research by Kellogg et al. (2020) found that workers actively "rebelled" against algorithmic management systems they perceived as incomprehensible or unfair, developing elaborate strategies to circumvent or manipulate algorithmic controls.

These empirical findings highlight managers' critical role in mediating between technological capabilities and organizational realities, yet research has predominantly focused on documenting challenges rather than examining how managers successfully navigate them. Notable exceptions include Beane's (2019) ethnographic study demonstrating how surgical residents developed novel learning practices to accommodate robotic surgical systems, and Raisch and Krakowski's (2021) conceptual framework identifying "artificial intelligence and management" challenges around purpose, principles, processes, and people. However, these studies have not explicitly theorized the sensemaking processes enabling managers to construct workable interpretations of AI technologies. Furthermore, existing research exhibits geographic concentration in Western contexts, with limited empirical attention to how cultural, institutional, and organizational contexts shape AI sensemaking in emerging economies (Amankwah-Amoah et al., 2021), representing an important gap this study addresses through its Malaysian focus.

Identity Work and Technological Change

Technological change frequently triggers identity questions for organizational members whose self-conceptions become disrupted by altered work roles, competencies, and organizational positions (Petriglieri, 2011; Pratt et al., 2006). Research demonstrates that identity threats emerge when technologies challenge individuals' sense of competence, autonomy, or professional worth, provoking defensive responses that impede implementation (Ashforth & Mael, 1989; Barley, 1996). Particularly relevant to AI integration, studies show that technologies perceived as substituting for human judgment—rather than augmenting it—trigger stronger identity threats and resistance (Lebovitz et al., 2022; Raisch & Krakowski, 2021). Beane and Orlikowski's (2015) research on surgical robots revealed that experienced surgeons initially resisted robotic systems they perceived as deskilling their craft, only accepting them after reframing robots as tools extending rather than replacing surgical expertise. This identity reconstruction work proved essential to successful technology adoption.

However, scholarly debate continues regarding whether managers' identity work primarily involves defensive responses to identity threats or proactive identity elaboration that enables novel self-conceptions (Kreiner et al., 2006; Petriglieri, 2011). Brown (2015) argues that organizational change contexts require individuals to engage in adaptive identity work that balances continuity with change, maintaining coherent self-narratives while accommodating new realities. Applied to AI integration, this perspective suggests managers must construct identity narratives that preserve valued aspects of managerial expertise—strategic thinking, interpersonal skills, contextual judgment—while incorporating new technological competencies and altered decision-making roles (Curchod et al., 2020). Yet, empirical research examining managers' identity work during AI integration remains limited, with most studies focusing on frontline workers rather than managerial populations (Lebovitz et al., 2021; Kellogg et al., 2020). Understanding how managers navigate identity challenges while simultaneously facilitating others' identity work constitutes an important research gap.

Paradox Theory and Technological Implementation

Paradox theory offers valuable insights for understanding how organizational members navigate the contradictory demands accompanying major organizational changes (Smith & Lewis, 2011; Putnam et al., 2016). Paradoxes represent persistent contradictions between interdependent elements that appear logical individually but inconsistent when juxtaposed, requiring acceptance rather than resolution (Lewis, 2000; Schad et al., 2016). AI integration generates multiple organizational paradoxes: tensions between efficiency and innovation as standardized AI systems constrain creative improvisation (Jarzabkowski et al., 2013), between control and autonomy as algorithmic management systems simultaneously enable surveillance and worker empowerment (Kellogg et al., 2020), and between human and machine agency as organizations must decide which decisions to automate versus retain for human judgment (Raisch & Krakowski, 2021). Research demonstrates that organizational effectiveness depends on leaders' capacity to engage these paradoxes through both/and thinking rather than either/or choices, developing integrative responses that accommodate contradictory demands simultaneously (Smith & Tushman, 2005).

However, tension exists in the literature regarding whether paradoxes should be actively engaged or strategically avoided. While paradox theory advocates direct engagement with contradictions (Smith & Lewis, 2011), organizational identity literature suggests that strategic ambiguity—leaving contradictions unresolved—sometimes facilitates adaptation by permitting diverse stakeholders to maintain distinct interpretations (Eisenberg, 1984; Gioia et al., 2000). Research by Abdallah and Langley (2014) found that managers sometimes deliberately cultivate ambiguity during change processes, allowing multiple interpretations to coexist rather than forcing premature consensus. This strategic ambiguity approach may prove particularly valuable during AI integration's exploratory phases when technological capabilities, organizational implications, and appropriate applications remain uncertain. The debate between active paradox engagement and strategic ambiguity maintenance holds important implications for understanding optimal sensemaking strategies during different AI implementation phases, yet empirical research examining these dynamics remains limited.

Research Gaps and Study Contributions

Synthesizing the reviewed literature reveals three critical gaps that this study addresses. First, while sensemaking theory and technology implementation research have developed separately, their integration remains theoretically and empirically underdeveloped, particularly regarding AI technologies whose distinctive characteristics—opacity, adaptability, autonomy—challenge conventional sensemaking processes. Second, existing research has insufficiently examined the temporal, processual dimensions of sensemaking during extended technological transitions, with most studies offering static snapshots rather than dynamic accounts of how interpretations evolve. Third, current literature inadequately addresses the social, collective dimensions of managerial sensemaking work, particularly how managers orchestrate diverse stakeholders' meaning construction processes. This study contributes to addressing these gaps by providing rich, processual accounts of managers' sensemaking practices during AI integration, illuminating the cognitive, social, and narrative strategies enabling managers to transform technological ambiguity into organizational action while navigating identity challenges and paradoxical demands inherent in AI implementation contexts.

Methodology

Research Design and Philosophical Approach

This study adopts an interpretive qualitative research design grounded in social constructionist epistemology, recognizing that managers' understanding of AI integration emerges through social interactions and interpretive processes rather than existing as objective phenomena awaiting discovery (Berger & Luckmann, 1966; Creswell & Poth, 2018). This philosophical orientation aligns with sensemaking theory's fundamental premise that organizational realities are enacted through human interpretation (Weick, 1995), making qualitative methodologies particularly appropriate for examining the subjective meanings, interpretive processes, and social constructions through which managers navigate AI integration. The research employed a multi-case study approach, enabling comparison across organizational contexts while maintaining the rich, contextual understanding essential to interpretive research (Eisenhardt, 1989; Yin, 2018).

Research Context and Site Selection

The research was conducted in Malaysia, focusing on organizations in manufacturing and service sectors undergoing active AI integration during the study period (July 2023 - March 2024). Malaysia provides a valuable research context as a middle-income economy investing substantially in AI capabilities through national initiatives like the National Artificial Intelligence Roadmap 2021-2025, while simultaneously confronting infrastructure, expertise, and cultural challenges distinctive to emerging economy contexts (Amankwah-Amoah et al., 2021). Organizations were selected based on purposive sampling criteria: (1) active implementation of AI technologies beyond pilot phase, (2) organizational size exceeding 200 employees to ensure sufficient managerial hierarchy, (3) implementation duration of at least 12 months to enable examination of sustained sensemaking processes, and (4) willingness to provide researcher access to managers at multiple organizational levels. Six organizations meeting these criteria agreed to participate, spanning electronics manufacturing (2 organizations), financial services (2 organizations), logistics (1 organization), and healthcare (1 organization).

Sampling Strategy and Participant Selection

Within participating organizations, managers were selected using purposive and snowball sampling techniques designed to capture diverse perspectives across organizational levels, functional areas, and implementation roles (Patton, 2015). Initial participants were identified through organizational gatekeepers based on their direct involvement in AI implementation, with subsequent participants recruited through snowball sampling as early interviewees identified colleagues with relevant experiences. The final sample comprised 24 managers, including 8 senior managers (director level or above), 10 middle managers (department head or equivalent), and 6 junior managers (team lead or supervisor). Participant characteristics are presented in Table 1.

Code	Gender	Age Range	Management Level	Industry Sector	AI Implementation Role	Implementation Duration
SM1	Male	45-50	Senior	Electronics Mfg	Strategic Sponsor	24 months
SM2	Female	40-45	Senior	Financial Services	Change Champion	18 months
SM3	Male	50-55	Senior	Logistics	Executive Sponsor	36 months
SM4	Male	48-52	Senior	Healthcare	Strategic Lead	20 months
SM5	Female	42-47	Senior	Financial Services	Implementation Director	22 months
SM6	Male	46-51	Senior	Electronics Mfg	Operations Director	28 months
SM7	Female	43-48	Senior	Healthcare	Clinical Director	16 months
SM8	Male	44-49	Senior	Logistics	Technology Director	30 months
MM1	Female	38-42	Middle	Electronics Mfg	Implementation Manager	24 months
MM2	Male	35-40	Middle	Financial Services	Project Manager	18 months
MM3	Female	37-41	Middle	Logistics	Operations Manager	36 months
MM4	Male	36-41	Middle	Healthcare	Department Manager	20 months
MM5	Female	39-43	Middle	Financial Services	Change Manager	22 months
MM6	Male	38-43	Middle	Electronics Mfg	Quality Manager	28 months

Note: Codes preserve participant anonymity while indicating management level (SM=Senior Manager, MM=Middle Manager, JM=Junior Manager). Implementation Duration indicates time elapsed since AI implementation commenced at participant's site.

Data Collection Procedures

Primary data were collected through semi-structured individual interviews ranging from 60 to 120 minutes (average: 85 minutes), conducted in English or Bahasa Malaysia according to participant preference. Interview protocols were developed through iterative refinement, informed by sensemaking theory and preliminary pilot interviews with three managers excluded from the final sample. The protocol explored managers' interpretations of AI technologies, their experiences navigating implementation challenges, the evolution of their understanding over time, interactions with diverse stakeholders, identity implications, and strategies for managing contradictory demands. Sample interview questions included: "How did you initially make sense of what AI meant for your organization?", "Can you describe how your understanding of AI has changed throughout the implementation process?", "What challenges have you encountered in helping others understand AI's role?", and "How have you managed tensions between different demands or expectations regarding AI?"

All interviews were audio-recorded with participant consent and transcribed verbatim, producing 487 pages of single-spaced transcript text. Supplementary data sources included organizational documents (implementation plans, communication materials, training resources), field notes from implementation meetings (where permitted), and reflective memos capturing researcher observations and emerging interpretations. These supplementary data enabled triangulation and provided contextual understanding enriching interview data interpretation (Denzin, 2012).

Data Analysis Procedures

Data analysis followed Gioia methodology's systematic approach to qualitative analysis, moving iteratively between data and emerging concepts while maintaining theoretical sensitivity (Gioia et al., 2013). Analysis proceeded through three interconnected phases. First-order analysis involved open coding to identify participants' lived experiences and interpretations using their own terms and language, producing 127 distinct first-order codes. These codes were systematically organized into 18 second-order themes representing more abstract conceptual categories that captured underlying patterns across first-order codes. Finally, aggregate dimensions were developed by clustering second-order themes into five overarching theoretical constructs: (1) Retrospective Interpretation Processes, (2) Collaborative Meaning Construction, (3) Identity Negotiation Work, (4) Paradox Navigation Strategies, and (5) Opacity Management Approaches. This analytical progression is illustrated in Table 2.

First-Order Codes (Examples)	Second-Order Themes	Aggregate Dimensions
Drawing on past technology experiences	Experience-Based Interpretation	Retrospective Interpretation Processes
Comparing AI to previous systems	Experience-Based Interpretation	Retrospective Interpretation Processes
Referencing historical implementation challenges	Experience-Based Interpretation	Retrospective Interpretation Processes
Learning from previous failures	Experience-Based Interpretation	Retrospective Interpretation Processes
Leveraging Historical Reference Points	Experience-Based Interpretation	Retrospective Interpretation Processes

Revisiting initial assumptions	Iterative Sense Revision	Progressive Understanding Development
Updating understanding over time	Iterative Sense Revision	Progressive Understanding Development
Recognizing misconceptions	Iterative Sense Revision	Progress essive Understanding Development
Adjusting expectations	Iterative Sense Revision	Progressive Understanding Development
Facilitating dialogue among stakeholders	Orchestrating Collective Dialogue	Enabling Multi-Stakeholder Engagement
Creating forums for discussion	Orchestrating Collective Dialogue	Enabling Multi-Stakeholder Engagement
Mediating conflicting perspectives	Orchestrating Collective Dialogue	Enabling Multi-Stakeholder Engagement
Building shared language	Orchestrating Collective Dialogue	Enabling Multi-Stakeholder Engagement
Translating technical concepts	Linguistic Bridging Work	Making AI Comprehensible
Creating accessible explanations	Linguistic Bridging Work	Making AI Comprehensible
Using analogies and metaphors	Linguistic Bridging Work	Making AI Comprehensible
Simplifying complexity	Linguistic Bridging Work	Making AI Comprehensible
Questioning managerial relevance	Experiencing Identity Threats	Confronting Competence Challenges
Concerns about deskilling	Experiencing Identity Threats	Confronting Competence Challenges
Threats to expertise	Experiencing Identity Threats	Confronting Competence Challenges
Anxieties about displacement	Experiencing Identity Threats	Confronting Competence Challenges
Reframing managerial value	Reconstructing Professional Identity	Augmentation Narratives
Emphasizing human judgment	Reconstructing Professional Identity	Augmentation Narratives
Positioning as AI collaborators	Reconstructing Professional Identity	Augmentation Narratives
Developing new competencies	Reconstructing Professional Identity	Augmentation Narratives
Managing efficiency-innovation tensions	Engaging Competing Demands	Paradox Navigation Strategies
Balancing control with flexibility	Engaging Competing Demands	Paradox Navigation Strategies
Navigating human-machine boundaries	Engaging Competing Demands	Paradox Navigation Strategies
Reconciling short/long-term demands	Engaging Competing Demands	Paradox Navigation Strategies
Maintaining strategic ambiguity	Productive Ambiguity Cultivation	Temporary Contradiction Acceptance
Allowing multiple interpretations	Productive Ambiguity Cultivation	Temporary Contradiction Acceptance
Deferring closure	Productive Ambiguity Cultivation	Temporary Contradiction Acceptance
Embracing uncertainty	Productive Ambiguity Cultivation	Temporary Contradiction Acceptance
Unable to explain AI decisions	Accommodating Black Box Nature	Trust Despite Opacity

Accepting algorithmic inscrutability	Accommodating Black Box Nature	Trust Despite Opacity
Trusting without understanding	Accommodating Black Box Nature	Trust Despite Opacity
Relying on output patterns	Accommodating Black Box Nature	Trust Despite Opacity
Focusing on system inputs/outputs	Empirical Validation Strategies	Evidence-Based Confidence Building
Monitoring performance patterns	Empirical Validation Strategies	Evidence-Based Confidence Building
Validating through outcomes	Empirical Validation Strategies	Evidence-Based Confidence Building
Establishing verification protocols	Empirical Validation Strategies	Evidence-Based Confidence Building

Analysis was conducted using NVivo 14 qualitative data analysis software, facilitating systematic coding, retrieval, and comparison of data segments. Multiple strategies enhanced analytical rigor, including: maintaining an audit trail documenting analytical decisions, regular debriefing sessions with academic colleagues uninvolved in data collection, negative case analysis to identify data contradicting emerging interpretations, and member checking with selected participants who confirmed interpretations aligned with their experiences (Lincoln & Guba, 1985; Morse, 2015).

Validity and Trustworthiness

Four criteria established by Lincoln and Guba (1985) guided efforts to ensure trustworthiness: credibility, transferability, dependability, and confirmability. Credibility was enhanced through: (1) prolonged engagement with research sites and participants, (2) triangulation across multiple data sources (interviews, documents, observations), (3) peer debriefing with academic colleagues, and (4) member checking with six participants who reviewed and validated interpretations. Transferability was addressed by providing rich, thick descriptions of research context, participants, and findings, enabling readers to assess applicability to other contexts. Dependability was established through detailed documentation of research procedures and maintenance of comprehensive audit trails. Confirmability was ensured through reflexive practices including researcher journaling to acknowledge potential biases and explicit grounding of interpretations in participant data.

Ethical Considerations

The research received approval from the university's research ethics committee prior to data collection. All participants provided informed consent after receiving detailed information about research purposes, procedures, voluntary participation, and confidentiality protections. Participants were assured of anonymity through use of codes rather than identifying information, with organizational and individual identities protected in all outputs. Data were securely stored with access restricted to the research team, and participants retained rights to withdraw from the study without penalty.

Findings

Retrospective Interpretation Processes

Analysis revealed that managers consistently engaged in retrospective sensemaking, drawing upon previous technological experiences to construct interpretations of AI integration. As SM1 explained:

"When we first encountered AI, I immediately thought about our ERP implementation from ten years ago—the chaos, the resistance, the learning curve. That history shaped how I approached AI, recognizing we'd face similar human challenges despite different technology." This retrospective orientation manifested through managers comparing AI to familiar technologies, with MM2 noting: "I kept explaining AI as like our business intelligence system but smarter, more autonomous. That comparison helped people anchor their understanding in something known."

However, managers also recognized that historical analogies sometimes misled understanding, requiring iterative revision of initial interpretations. MM5 reflected: "Initially I thought AI would be like other systems where we configure rules and it executes. Three months in, I realized that was completely wrong—AI learns and adapts in ways we didn't program. I had to completely restructure my mental model." This iterative sense revision process occurred throughout implementation, with managers continuously updating interpretations as practical experiences revealed AI's distinctive characteristics. SM3 described: "Every month brought new surprises that challenged our assumptions. We'd think we understood AI's capabilities, then discover it could do something we never anticipated, or conversely, couldn't handle situations we assumed would be simple."

The temporal evolution of managers' interpretations followed consistent patterns across cases. Initial phases emphasized optimistic, technology-centric interpretations shaped by vendor presentations and senior leadership enthusiasm. MM8 recalled: "At the beginning, everything seemed possible—AI would revolutionize our operations, eliminate inefficiencies, provide perfect predictions. We were drinking the Kool-Aid." Middle phases brought disillusionment as implementation challenges emerged, with managers confronting gaps between promised capabilities and practical realities. JM4 noted: "The shine wore off quickly when we hit real-world complications. Data quality issues, integration problems, user confusion—suddenly AI seemed more burden than blessing." Later phases saw more nuanced, balanced interpretations emerge as managers developed experiential understanding. SM6 explained: "Now we're more realistic. AI does some things brilliantly but fails at others. We've learned its sweet spot and our role is optimizing that match between capability and application."

Collaborative Meaning Construction

Managers served as critical nodes in social sensemaking networks, orchestrating dialogue among diverse stakeholders with conflicting perspectives, interests, and expertise levels. MM1 described this orchestration work: "I spent enormous energy creating spaces where technical people, operations staff, and executives could talk. Each group saw AI completely differently—technologists saw algorithms, operators saw workflow disruption, executives saw strategic advantage. My job was getting them to understand each other's viewpoints." This facilitation work proved essential because AI integration required coordinated understanding across organizational boundaries, yet stakeholders initially lacked shared language or conceptual frameworks.

Linguistic bridging work constituted a critical dimension of collaborative sensemaking, with managers translating technical AI concepts into accessible terms for non-technical stakeholders. MM7 explained: "I became an interpreter, constantly translating between data scientists speaking about neural networks and clinicians caring about patient outcomes. I'd take technical jargon and create analogies they could grasp—explaining machine learning as similar to how doctors develop clinical intuition through pattern recognition." This translation work extended bidirectionally, with managers also conveying practical operational realities to technical specialists. MM10 noted: "The AI team designed beautiful algorithms but had no clue about production floor realities. I had to help them understand constraints they never considered—variability in materials, operator skill differences, equipment quirks. That context fundamentally reshaped their approach."

Collective sensemaking processes generated emergent understandings that no single stakeholder could have produced individually. SM2 described: "Through our cross-functional team meetings, we developed shared frameworks that integrated everyone's perspectives. Technical staff contributed algorithmic capabilities, operations added practical constraints, finance provided cost implications, HR addressed workforce impacts. The synthesis created richer understanding than any single perspective offered." However, facilitating productive collective sensemaking required active management of power dynamics and ensuring minority voices received attention. MM3 reflected: "Initially, technical specialists dominated discussions because they controlled the specialized knowledge. I had to deliberately create space for frontline perspectives, which often revealed critical insights the experts missed because they lacked ground-level experience."

Identity Negotiation Work

AI integration triggered significant identity challenges as managers confronted threats to professional competence, autonomy, and organizational value. SM4 articulated this threat: "AI raised fundamental questions about management's purpose. If algorithms could make better decisions than humans, faster and without bias, what justified our existence? That's existentially threatening." These identity concerns manifested most acutely around decision-making authority, with managers questioning their relevance when AI systems could process vastly more information and identify patterns imperceptible to humans. MM6 explained: "I built my career on expertise in quality control—recognizing defects, understanding failure patterns. Then AI came along detecting defects I couldn't see. It felt like my knowledge was suddenly obsolete."

Managers engaged in intensive identity work to reconstruct professional self-conceptions that preserved valued aspects of managerial identity while accommodating AI's capabilities. This reconstruction process frequently involved augmentation narratives that positioned managers as AI collaborators rather than competitors. SM7 described: "I reframed my role from primary decision-maker to decision-architect. AI provides analytical insights, but I supply contextual judgment, ethical considerations, and strategic thinking that algorithms lack. We're partners, each contributing unique value." This augmentation framing proved psychologically protective while enabling productive technology engagement.

However, identity reconstruction work varied by managerial level and functional area. Senior managers more readily adopted strategic partnership frames, emphasizing high-level judgment and vision that AI could not replicate. SM1 noted: "My value lies in setting direction, understanding market dynamics, making judgment calls with incomplete information—all things AI struggles with." Conversely, middle and junior managers whose roles centered on routine analysis and standardized decisions confronted more severe identity threats. JM2 reflected: "My job was reviewing reports, identifying variances, recommending adjustments—exactly what AI does better. I genuinely worried about becoming redundant." These differential identity implications created tension across organizational levels, with senior managers sometimes dismissing concerns that junior managers experienced acutely.

Managers also performed identity work on behalf of their subordinates, constructing narratives that helped staff navigate AI-induced identity threats. MM5 described: "I spent countless hours helping my team process their anxieties. I emphasized that AI handles mundane tasks, freeing them for higher-value work. That reframing helped some staff embrace AI as liberation from tedium rather than threat to employment." However, these sensegiving efforts proved only partially successful when organizational actions contradicted reassuring narratives. MM9 noted: "I kept saying AI would augment not replace people, but then corporate announced workforce reductions in our department. My credibility evaporated—staff stopped believing my reassurances because actions spoke louder than words."

Paradox Navigation Strategies

Managers navigated multiple paradoxes inherent in AI integration, requiring sophisticated both/and thinking that accommodated contradictory demands simultaneously. One prominent paradox involved balancing efficiency imperatives with innovation opportunities. SM3 explained: "Leadership wanted AI to streamline operations, reducing costs and improving consistency. Simultaneously, they expected AI to enable innovation, opening new service possibilities. But standardization and innovation often conflict—how do you optimize existing processes while experimenting with radically new approaches?" Managers addressed this paradox through temporal and spatial separation, dedicating specific teams and timeframes to efficiency optimization while protecting other contexts for experimentation. MM8 noted: "We created dual tracks—one focused on using AI to improve current operations, another exploring innovative applications. Keeping them separate prevented efficiency demands from crushing experimentation."

Another critical paradox emerged around control versus autonomy, with AI systems simultaneously enabling surveillance while promising employee empowerment. MM4 described: "AI gave us unprecedented visibility into operational performance, which tempted management toward micromanagement. But for AI to add value, we needed staff autonomy to adapt systems to local conditions. Finding that balance proved extremely difficult." Some managers deliberately cultivated strategic ambiguity, leaving paradoxical tensions unresolved to permit diverse interpretations. SM5 explained: "I sometimes intentionally avoided clarifying certain aspects because ambiguity served us. Different stakeholders needed different narratives to maintain engagement. Making everything explicit would have forced confronting contradictions we weren't ready to resolve."

The human-machine boundary paradox required managers to determine which decisions should remain human versus becoming automated. SM6 reflected: "Every decision point raised questions: Could AI handle this? Should AI handle this even if it could? We faced constant negotiation about where to draw boundaries." These boundary decisions carried significant implications for organizational structures, workforce sizing, and accountability frameworks, yet clear principles for making them remained elusive. MM10 noted: "We lacked coherent criteria for these decisions. Sometimes we automated because we could, other times we retained human control despite AI's superior performance. The inconsistency created confusion and resentment."

Opacity Management Approaches

AI's algorithmic opacity fundamentally challenged managers' traditional sensemaking strategies, requiring novel approaches to construct workable interpretations despite limited comprehension of system decision-making logic. Managers universally acknowledged their inability to fully understand AI systems' internal processes. SM2 stated bluntly: "I cannot explain how our AI system reaches specific conclusions. It's genuinely a black box—we feed data in, recommendations come out, but the reasoning process remains opaque." This opacity created accountability challenges, with managers responsible for AI-generated decisions they could not fully explain or validate through conventional means.

Managers developed pragmatic strategies to accommodate opacity while maintaining organizational functionality. Primary among these was shifting analytical focus from understanding internal algorithmic processes to monitoring system inputs and outputs. MM1 explained: "Since I can't understand what happens inside the algorithm, I focus on what I can observe and control—input data quality, output patterns, and performance metrics. If inputs are good and outputs prove accurate, I trust the system even without comprehending its internal logic." This empirical validation approach required establishing rigorous monitoring protocols and outcome verification processes. MM7 described: "We implemented extensive tracking of AI recommendations against actual outcomes, building evidence-based confidence through demonstrated performance rather than algorithmic transparency."

However, opacity-induced discomfort persisted despite pragmatic adaptations, particularly when AI systems produced unexpected or counterintuitive outputs. MM6 recalled: "There were times AI recommended actions completely contrary to our conventional wisdom. Without understanding its reasoning, deciding whether to trust those recommendations felt like gambling. Do we follow the AI or override based on human judgment? That uncertainty was extremely uncomfortable." Some managers addressed this discomfort through selective trust, accepting opacity for routine decisions while insisting on transparency for high-stakes choices. SM8 explained: "We established risk-based protocols—for low-consequence decisions, we let AI operate autonomously even without full understanding. For critical decisions affecting safety or major resources, we required explanations, even if that meant simpler, more transparent models."

Organizational culture significantly influenced opacity tolerance, with some contexts accepting algorithmic inscrutability while others demanded transparency. SM4 noted: "In healthcare, algorithmic opacity raised ethical concerns our organization couldn't accept. We needed to explain treatment recommendations to patients and justify decisions to regulators. That requirement shaped which AI applications we could deploy, limiting us to more transparent approaches even when black box models offered superior performance." These variations suggest that opacity management strategies must be contextually adapted rather than universally applied.

Discussion

Temporal Dynamics of Managerial Sensemaking

This study's findings illuminate the processual, dynamic character of managerial sensemaking during extended AI implementation, revealing that managers' interpretations evolved through distinct phases as practical experiences challenged initial assumptions. Weick (1995) emphasized sensemaking's retrospective nature, but this study extends understanding by demonstrating how managers engaged in continuous sense revision, iteratively updating interpretations throughout implementation rather than settling on stable meanings. This finding resonates with Stigliani and Ravasi's (2012) research on product designers' sensemaking during innovation, where interpretations evolved through prototyping cycles. However, AI integration's temporal dynamics exhibited distinctive characteristics stemming from the technology's opacity and adaptive capabilities, which continuously generated surprises that disrupted provisional understandings. Unlike conventional technologies where experiential learning eventually produces stable mental models (Orlikowski, 2000), AI's evolving capabilities and context-dependent performance maintained interpretive uncertainty even after extended implementation periods.

The observed pattern of initial optimism, mid-implementation disillusionment, and eventual balanced realism aligns with broader change management literature documenting emotional cycles during organizational transitions (Kanter, 2009). However, this study reveals that these emotional shifts reflected substantive cognitive transformations as managers progressed from abstract, technology-centric interpretations toward nuanced, context-sensitive understandings grounded in implementation experience. This progression parallels Beane's (2019) findings regarding surgical residents' learning with robotic systems, where novices initially focused on technological features while experts developed situated understanding of technology-task fit. Managerial sensemaking during AI integration similarly required moving beyond vendor narratives and technological specifications toward experiential comprehension of situated capabilities and limitations.

These temporal dynamics hold important practical implications, suggesting that organizations should anticipate managers' interpretive evolution and create spaces for collective processing as understanding develops. Rather than expecting stable, consistent narratives throughout implementation, organizations might benefit from explicitly acknowledging sensemaking as an ongoing process, legitimizing interpretation revision as implementation unfolds. This approach contrasts with conventional change communication strategies that emphasize clear, consistent messaging (Kotter, 1996), suggesting AI's distinctive characteristics may require novel communication approaches.

6.2 Social Orchestration of Collective Sensemaking

This study's findings emphasize managers' pivotal role in facilitating collective sensemaking across organizational boundaries, extending existing theory by revealing the specific practices through which managers orchestrated shared understanding among diverse stakeholders. While Weick (1995) and Maitlis (2005) identified sensemaking's social character, research has insufficiently examined the active coordination work required to generate collective interpretations. This study demonstrates that productive collective sensemaking does not emerge spontaneously but requires deliberate orchestration—creating dialogical spaces, managing power dynamics, bridging linguistic gaps, and synthesizing divergent perspectives into integrative frameworks. These practices align with Rouleau's (2005) concept of "middle managers as strategic sensemakers," but extend understanding by specifying the micro-practices enabling cross-boundary sensemaking in contexts of technical complexity and stakeholder diversity.

Particularly significant is the finding that managers performed continuous translation work, converting between technical and non-technical language to enable mutual comprehension. This linguistic bridging function resonates with Carlile's (2004) research on knowledge boundaries, which identified pragmatic translation as essential for cross-domain collaboration. However, AI implementation intensified linguistic challenges because the technology's opacity limited even technical specialists' ability to provide comprehensible explanations. Managers consequently could not rely solely on translating specialist knowledge but had to creatively construct accessible analogies and metaphors, essentially generating new language for discussing phenomena that existing vocabularies inadequately captured. This creative linguistic work represents an undertheorized dimension of managerial practice during technological change, suggesting that communication competencies may be as critical as technical comprehension for effective AI integration.

The finding that collective sensemaking produced emergent understandings transcending individual perspectives offers empirical support for social constructionist accounts of meaning generation (Berger & Luckmann, 1966; Maitlis & Sonenshein, 2010). Managers' descriptions of insights arising through cross-functional dialogue that no single stakeholder could have generated individually illustrate how collective sensemaking creates genuinely new knowledge rather than merely aggregating existing perspectives. However, realizing this creative potential required managing power asymmetries that could silence valuable minority voices, suggesting that inclusive facilitation practices constitute a critical managerial competence. This finding problematizes purely rationalist accounts of AI implementation that emphasize technical expertise, highlighting instead the importance of social competencies enabling diverse stakeholder engagement.

6.3 Identity Work and Professional Self-Reconstruction

This study's findings regarding managers' identity negotiation work contribute to understanding how individuals reconstruct professional self-conceptions when confronted with technological disruption. While existing research has documented identity threats from automation (Barley, 1996; Petriglieri, 2011), this study extends theory by revealing the specific narrative strategies managers employed to preserve valued identity elements while accommodating AI's capabilities. The augmentation framing that positioned managers as AI collaborators rather than competitors proved particularly psychologically protective, enabling constructive technology engagement while maintaining professional self-worth. This finding resonates with Pratt et al.'s (2006) concept of identity customization, where individuals selectively emphasize valued identity elements while downplaying threatened aspects.

However, the study also revealed important variations in identity work by organizational level, with senior managers more successfully constructing augmentation narratives than middle or junior managers whose roles centered on tasks AI could perform. This differential vulnerability suggests that AI integration's identity implications are not uniform but structured by occupational characteristics, with managers performing routine analytical work facing greater existential threats than those in roles emphasizing strategic judgment and interpersonal skills. These findings align with broader discussions of automation's differential impact across occupational categories (Frey & Osborne, 2017), but extend understanding by revealing the psychological and identity implications rather than merely employment effects. Organizations implementing AI should recognize these differential vulnerabilities and provide targeted support for managers in roles most threatened by automation.

The finding that managers performed identity work not only for themselves but also on behalf of subordinates highlights sensegiving as a critical managerial function during technological change. However, the study also revealed the fragility of reassuring narratives when organizational actions contradicted managers' statements, suggesting that successful identity work requires consistency between rhetoric and practice. When organizations simultaneously promoted augmentation narratives while implementing workforce reductions, managers' credibility eroded and staff rejected their sensegiving efforts. This finding emphasizes that effective sensemaking during AI integration requires alignment between communication, decision-making, and organizational actions, with misalignment generating cynicism that undermines change efforts (Kotter, 1996; Ford et al., 2008).

6.4 Navigating Paradoxes Through Strategic Ambiguity

This study's findings regarding managers' paradox navigation strategies contribute to organizational paradox theory (Smith & Lewis, 2011) by revealing how managers employed both direct engagement and strategic ambiguity approaches depending on context. While paradox theory typically advocates confronting contradictions through integrative both/and thinking, this study demonstrates that managers sometimes deliberately maintained ambiguity, allowing contradictory demands to coexist unresolved when premature resolution would have proven counterproductive. This strategic ambiguity approach aligns with Eisenberg's (1984) classic work identifying ambiguity's positive functions in organizational communication, suggesting that clarity is not always optimal during change processes. Applied to AI integration, maintaining interpretive flexibility during exploratory phases enabled diverse stakeholders to sustain engagement based on different understandings, with explicit clarification deferred until organizational learning reduced uncertainty.

However, the study also identified contexts where paradox engagement proved necessary, particularly when contradictions manifested in resource allocation decisions or performance expectations requiring clear choices. The tension between efficiency and innovation imperatives exemplifies a paradox requiring explicit management through structural separation—dedicating distinct teams and resources to competing objectives. This approach resonates with organizational ambidexterity literature's structural solutions to exploration-exploitation tensions (O'Reilly & Tushman, 2013). Yet, implementation proved challenging as efficiency pressures often overwhelmed innovation efforts despite formal separation, suggesting that structural solutions require sustained leadership commitment and protective resources.

The human-machine boundary paradox highlighted by managers—determining which decisions should remain human versus becoming automated—represents a distinctive challenge lacking clear resolution principles. While scholarship on algorithm aversion and automation bias offers relevant insights (Dietvorst et al., 2015; Parasuraman & Manzey, 2010), these literatures provide limited guidance for managerial decision-making about automation boundaries. This study reveals that managers employed inconsistent criteria driven by contextual factors rather than coherent frameworks, creating organizational confusion. Developing systematic principles for human-machine boundary decisions represents an important theoretical and practical challenge for AI integration, requiring interdisciplinary engagement spanning organizational theory, ethics, and human-computer interaction.

7. Conclusion

Theoretical and Practical Contributions

This study advances theoretical understanding of managerial sensemaking during AI integration by illuminating the cognitive, social, and narrative processes through which managers construct meaning from technological ambiguity. By applying sensemaking theory to AI implementation contexts, this research reveals that successful integration depends critically on managers' capacity to navigate unprecedented interpretive challenges—algorithmic opacity, adaptive capabilities, and identity threats—that distinguish AI from previous technological transitions. The study's identification of five key aggregate dimensions—retrospective interpretation processes, collaborative meaning construction, identity negotiation work, paradox navigation strategies, and opacity management approaches—provides a comprehensive framework for understanding managerial work during AI-driven organizational change.

Practically, this research offers guidance for organizations navigating AI implementation. First, organizations should recognize that managers require time and experiential learning to develop sophisticated AI understanding, suggesting that implementation timelines should accommodate interpretive evolution rather than expecting immediate comprehension. Second, organizations should invest in developing managers' facilitation and translation competencies, recognizing that technical AI knowledge alone proves insufficient without social skills enabling collective sensemaking. Third, organizations must address identity implications thoughtfully, providing opportunities for managers to reconstruct professional self-conceptions while ensuring that organizational actions align with augmentation narratives. Fourth, organizations should develop explicit frameworks for navigating AI's inherent paradoxes rather than leaving managers to improvise individual responses. Finally, organizations must acknowledge algorithmic opacity's unavoidable reality, establishing verification and accountability mechanisms that enable confident AI deployment despite limited algorithmic transparency.

Limitations

Several limitations qualify this study's findings and suggest directions for future research. First, the research examined Malaysian organizations, and cultural, institutional, and economic contexts may shape sensemaking processes in ways that limit transferability to other settings. Comparative research examining AI sensemaking across diverse cultural contexts would valuably extend understanding. Second, the study captured managers' retrospective accounts of sensemaking processes, which may be influenced by memory reconstruction and post-hoc rationalization. Real-time observational research tracking sensemaking as it unfolds would provide complementary insights. Third, the research focused on managers' perspectives, excluding other stakeholders whose sensemaking processes may differ significantly. Future research should examine how frontline employees, technical specialists, and executives make sense of AI integration, exploring convergences and divergences across organizational levels.

Fourth, this study examined relatively early-stage AI implementations (12-36 months), and sensemaking processes may evolve as organizations gain extended experience with AI technologies. Longitudinal research tracking organizations through multiple years of AI maturity would illuminate how sensemaking changes as implementations mature. Finally, the research did not systematically examine relationships between specific sensemaking patterns and implementation outcomes, focusing instead on describing sensemaking processes. Future research should investigate which sensemaking approaches correlate with successful AI integration, providing evidence-based guidance for managerial practice.

Future Research Directions

This study opens multiple avenues for future inquiry. First, research should examine collective sensemaking at the organizational level, exploring how shared interpretations of AI emerge and stabilize across organizational populations beyond individual managers' efforts. Second, scholars should investigate sensemaking breakdowns—situations where managers fail to construct workable interpretations—to understand failure mechanisms and protective factors. Third, research should explore how different AI applications (predictive analytics, natural language processing, computer vision, robotic process automation) generate distinctive sensemaking challenges, recognizing AI as a heterogeneous category rather than monolithic technology. Fourth, scholars should examine how organizational culture, structure, and leadership shape managerial sensemaking, identifying contextual factors enabling or constraining productive interpretation. Finally, research should develop and test interventions designed to enhance managerial sensemaking capabilities, translating descriptive insights into prescriptive guidance for practice.

Co-Author Contribution

Author 1 carried out the fieldwork, prepared the literature review and overlooked the whole article's write up. Authors 2, 3 wrote the research methodology and did the data entry. Authors 4, 5, 6 carried out the statistical analysis and interpretation of the results.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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References

Adibah, L. A., Hafizah, Z. (2021). The creativity practice of islamic education teachers in 21st century learning. *ASEAN Comparative Education Research Journal on Islam and Civilization.* 4(1), 40-54. Abdallah, C., & Langley, A. (2014). The double edge of ambiguity in strategic planning. *Journal of Management Studies*, 51(2), 235-264.

Amankwah-Amoah, J., Khan, Z., & Wood, G. (2021). COVID-19 and business failures: The paradoxes of experience, scale, and scope for theory and practice. *European Management Journal*, 39(2), 179-184.

Ashforth, B. E., & Mael, F. (1989). Social identity theory and the organization. *Academy of Management Review*, 14(1), 20-39.

Barley, S. R. (1986). Technology as an occasion for structuring: Evidence from observations of CT scanners and the social order of radiology departments. *Administrative Science Quarterly*, 31(1), 78-108.

Barley, S. R. (1996). Technicians in the workplace: Ethnographic evidence for bringing work into organization studies. *Administrative Science Quarterly*, 41(3), 404-441.

Barley, S. R. (2020). Work and technological change. Oxford University Press.

Bartunek, J. M., Rousseau, D. M., Rudolph, J. W., & DePalma, J. A. (2006). On the receiving end: Sensemaking, emotion, and assessments of an organizational change initiated by others. *Journal of Applied Behavioral Science*, 42(2), 182-206.

Beane, M. (2019). Shadow learning: Building robotic surgical skill when approved means fail. *Administrative Science Quarterly*, 64(1), 87-123.

Beane, M., & Orlikowski, W. J. (2015). What difference does a robot make? The material enactment of distributed coordination. *Organization Science*, 26(6), 1553-1573.

Benbya, H., Nan, N., Tanriverdi, H., & Yoo, Y. (2020). Complexity and information systems research in the emerging digital world. *MIS Quarterly*, 44(1), 1-17.

Berger, P. L., & Luckmann, T. (1966). *The social construction of reality: A treatise in the sociology of knowledge*. Anchor Books.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, 24(2), 239-257.

Brown, A. D. (2015). Identities and identity work in organizations. *International Journal of Management Reviews*, 17(1), 20-40.

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, 3(1), 1-12.

Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science*, 15(5), 555-568.

Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE Publications.

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly*, 65(3), 644-676.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108-116.

Denzin, N. K. (2012). Triangulation 2.0. *Journal of Mixed Methods Research*, 6(2), 80-88.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114-126.

Eisenberg, E. M. (1984). Ambiguity as strategy in organizational communication. *Communication Monographs*, 51(3), 227-242.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, 14(4), 532-550.

Fiss, P. C., & Zajac, E. J. (2006). The symbolic management of strategic change: Sensegiving via framing and decoupling. *Academy of Management Journal*, 49(6), 1173-1193.

Ford, J. D., Ford, L. W., & D'Amelio, A. (2008). Resistance to change: The rest of the story. *Academy of Management Review*, 33(2), 362-377.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*, 97(4), 62-73.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254-280.

Gioia, D. A., & Chittipeddi, K. (1991). Sensemaking and sensegiving in strategic change initiation. *Strategic Management Journal*, 12(6), 433-448.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods*, 16(1), 15-31.

Gioia, D. A., Schultz, M., & Corley, K. G. (2000). Organizational identity, image, and adaptive instability. *Academy of Management Review*, 25(1), 63-81.

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2021). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review*, 46(3), 534-551.

Griffith, T. L. (1999). Technology features as triggers for sensemaking. *Academy of Management Review*, 24(3), 472-488.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, 18(1), 59-82.

Günther, W. A., Mehrizi, M. H. R., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *Journal of Strategic Information Systems*, 26(3), 191-209.

Hitt, M. A., Keats, B. W., & DeMarie, S. M. (2016). Navigating in the new competitive landscape: Building strategic flexibility and competitive advantage in the 21st century. *Academy of Management Perspectives*, 12(4), 22-42.

IDC. (2022). *Worldwide spending on artificial intelligence*. International Data Corporation.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586.

Jarzabkowski, P., Lê, J. K., & Van de Ven, A. H. (2013). Responding to competing strategic demands: How organizing, belonging, and performing paradoxes coevolve. *Strategic Organization*, 11(3), 245-280.

Kanter, R. M. (2009). *Change is everyone's job: Managing the extended enterprise in a globally connected world*. *Organizational Dynamics*, 28(1), 7-23.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, 14(1), 366-410.

Kotter, J. P. (1996). *Leading change*. Harvard Business Press.

Kreiner, G. E., Hollensbe, E. C., & Sheep, M. L. (2006). Where is the "me" among the "we"? Identity work and the search for optimal balance. *Academy of Management Journal*, 49(5), 1031-1057.

Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2021). Artificial intelligence-driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. *Sustainable Development*, 29(5), 1-18.

Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what. *MIS Quarterly*, 45(3), 1501-1525.

Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. *Organization Science*, 33(1), 126-148.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, 35(1), 147-167.

Lewis, M. W. (2000). Exploring paradox: Toward a more comprehensive guide. *Academy of Management Review*, 25(4), 760-776.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. SAGE Publications.

Lüscher, L. S., & Lewis, M. W. (2008). Organizational change and managerial sensemaking: Working through paradox. *Academy of Management Journal*, 51(2), 221-240.

Maitlis, S. (2005). The social processes of organizational sensemaking. *Academy of Management Journal*, 48(1), 21-49.

Maitlis, S., & Christianson, M. (2014). Sensemaking in organizations: Taking stock and moving forward. *Academy of Management Annals*, 8(1), 57-125.

Maitlis, S., & Sonenshein, S. (2010). Sensemaking in crisis and change: Inspiration and insights from Weick (1988). *Journal of Management Studies*, 47(3), 551-580.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, 3(2), 1-21.

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W. (2021). Algorithmic management of work on online labor platforms: When matching meets control. *MIS Quarterly*, 45(4), 1999-2022.

Morse, J. M. (2015). Critical analysis of strategies for determining rigor in qualitative inquiry. *Qualitative Health Research*, 25(9), 1212-1222.

O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. *Academy of Management Perspectives*, 27(4), 324-338.

Orlikowski, W. J. (1996). Improvising organizational transformation over time: A situated change perspective. *Information Systems Research*, 7(1), 63-92.

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization Science*, 11(4), 404-428.

Orlikowski, W. J., & Gash, D. C. (1994). Technological frames: Making sense of information technology in organizations. *ACM Transactions on Information Systems*, 12(2), 174-207.

Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors*, 52(3), 381-410.

Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press.

Patton, M. Q. (2015). *Qualitative research & evaluation methods* (4th ed.). SAGE Publications.

Petriglieri, J. L. (2011). Under threat: Responses to and the consequences of threats to individuals' identities. *Academy of Management Review*, 36(4), 641-662.

Pratt, M. G., Rockmann, K. W., & Kaufmann, J. B. (2006). Constructing professional identity: The role of work and identity learning cycles in the customization of identity among medical residents. *Academy of Management Journal*, 49(2), 235-262.

Putnam, L. L., Fairhurst, G. T., & Banghart, S. (2016). Contradictions, dialectics, and paradoxes in organizations: A constitutive approach. *Academy of Management Annals*, 10(1), 65-171.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192-210.

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2020). Expanding AI's impact with organizational learning. *MIT Sloan Management Review*, 59(1), 1-17.

Rouleau, L. (2005). Micro-practices of strategic sensemaking and sensegiving: How middle managers interpret and sell change every day. *Journal of Management Studies*, 42(7), 1413-1441.

Sandberg, J., & Tsoukas, H. (2015). Making sense of the sensemaking perspective: Its constituents, limitations, and opportunities for further development. *Journal of Organizational Behavior*, 36(S1), S6-S32.

Schad, J., Lewis, M. W., Raisch, S., & Smith, W. K. (2016). Paradox research in management science: Looking back to move forward. *Academy of Management Annals*, 10(1), 5-64.

Smith, W. K., & Lewis, M. W. (2011). Toward a theory of paradox: A dynamic equilibrium model of organizing. *Academy of Management Review*, 36(2), 381-403.

Smith, W. K., & Tushman, M. L. (2005). Managing strategic contradictions: A top management model for managing innovation streams. *Organization Science*, 16(5), 522-536.

Sonenshein, S. (2010). We're changing—Or are we? Untangling the role of progressive, regressive, and stability narratives during strategic change implementation. *Academy of Management Journal*, 53(3), 477-512.

Stigliani, I., & Ravasi, D. (2012). Organizing thoughts and connecting brains: Material practices and the transition from individual to group-level prospective sensemaking. *Academy of Management Journal*, 55(5), 1232-1259.

Sturm, T., Gerlach, J., Pumplun, L., Mesbah, N., Peters, F., Tauchert, C., Nan, N., & Buxmann, P. (2021). Coordinating human and machine learning for effective organization learning. *MIS Quarterly*, 45(3), 1581-1602.

Vaast, E., & Walsham, G. (2005). Representations and actions: The transformation of work practices with IT use. *Information and Organization*, 15(1), 65-89.

Vlaar, P. W. L., Van den Bosch, F. A. J., & Volberda, H. W. (2008). On the evolution of trust, distrust, and formal coordination and control in interorganizational relationships: Toward an integrative framework. *Group & Organization Management*, 31(4), 407-429.

Weick, K. E. (1995). *Sensemaking in organizations*. SAGE Publications.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization Science*, 16(4), 409-421.

Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.

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