Reimagining Organizational Learning in the AI Era: A Conceptual Synthesis of Argyris & Schön, March, and Senge

Alexandra P. Maranger

A Thesis in
The Department of Education

Presented in Partial Fulfillment of the Requirements
For the Degree of
Master of Arts (Educational Technology)
at Concordia University
Montreal, Quebec, Canada

March 2025

CONCORDIA UNIVERSITY
School of Graduate Studies

This is to certify that the thesis prepared

By: **Alexandra P. Maranger**

Entitled: Reimagining Organizational Learning in the AI Era: A Conceptual Synthesis of Argyris & Schön, March, and Senge

and submitted in partial fulfillment of the requirements for the degree of

Master of Arts (Educational Technology)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

____________________________________ Chair

____________________________________ Examiner
Arpi Hamalian, Ph.D.

____________________________________ Examiner
Florent Michelot, Ph.D.

____________________________________ Thesis Supervisor(s)
Steven Shaw, Ph.D.

Approved by ____
Chair of Department or Graduate Program Director

______________2025 ______________________________________
Dean of Faculty

Abstract

Reimagining Organizational Learning in the AI Era: A Conceptual Synthesis of Argyris & Schön, March, and Senge

Alexandra P. Maranger

As organizations increasingly adopt artificial intelligence (AI) to enhance efficiency and decision-making, a critical question arises: How does AI shape the deeper processes of organizational learning? Drawing on Argyris and Schön's (1978) distinction between single- and double-loop learning, March's (1991) exploration-exploitation framework, and Senge's (1990) systems thinking, this thesis develops a conceptual model that illuminates AI's potential to both streamline surface-level corrections and catalyze more profound, transformative change.

A literature review spanning human resource development, knowledge management, and organizational behavior reveals that while AI often yields short-term productivity gains, scholars rarely connect these implementations to fundamental learning dynamics such as reflective inquiry, strategic balancing of efficiency and innovation, or system-wide adaptation. Moreover, existing research underscores an array of moderating factors – including leadership style, organizational culture, ethics, and digital maturity – as pivotal in determining whether AI fosters genuine adaptation or merely reinforces existing norms.

By synthesizing classical learning theories with four key AI applications – machine learning/automated decision-making, human-AI collaboration, big data/real-time analytics, and algorithmic feedback – this thesis provides an integrated framework. The model details how AI can facilitate deeper reflection, sustain ambidexterity, and strengthen systemic feedback loops, contingent on contextual moderators and boundary conditions. In so doing, it aims to offer a more holistic lens for scholars and practitioners.

Acknowledgements

I owe a sincere thanks to my supervisor, Steven Shaw, Ph.D., for the balance of guidance and freedom he provided. His Knowledge Management course sparked my interest in Organizational Learning, his feedback during the completion of my reading course helped refine my thoughts, and his trust allowed me to find my own path at my own pace. Whether it was sharing a quick insight or letting me run with my ideas, his calm confidence gave me the space (and the nudge) to dive deeper.

Thank you to my committee members, Arpi Hamalian, Ph.D. and Florent Michelot, Ph.D., for their feedback, their time, and their support during my defense.

And finally, thank you to Matthew Fishman, MBA, for affording me the opportunity to go on leave to complete this degree, and for enthusiastically encouraging me to pursue graduate studies.

Dedication

To my husband, Brad Aeon, Ph.D., whose unwavering guidance made this entire journey possible. Your expert time management skills kept me (mostly) on schedule. Your honest feedback, unfailing support, and infectious humor made every milestone feel less daunting. Thank you for reminding me to take breaks and for showing me that even the most meticulously color-coded calendar can be infused with laughter and spontaneity.

And to my mother, who I can only aspire to emulate, and who has always said that education is the greatest investment.

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

In today's rapidly evolving digital landscape, artificial intelligence (AI) stands out as both a powerful technological catalyst and a subject of intense scholarly debate. Many organizations have already adopted AI-driven solutions – ranging from machine learning-based decision making (Balasubramanian et al., 2022; Banasiewicz, 2021; Bohanec et al., 2017; Booyse & Scheepers, 2024; Davenport & Ronanki, 2018) to algorithmic feedback systems (Faraj et al., 2018; Grønsund & Aanestad, 2020) – to increase operational efficiency and automate routine tasks (Brynjolfsson & Mitchell, 2017; Wamba-Taguimdje et al., 2020) . However, while these initiatives often yield short-term productivity gains, there is comparatively little research on how AI might influence deeper organizational learning processes – shaping not only what organizations learn but also how they reflect, adapt, and transform. This gap between technical implementation and holistic organizational learning forms the core motivation for this study.

Classical theories of organizational learning, particularly Argyris and Schön's (1978) emphasis on single- vs. double-loop learning, March's (1991) focus on exploration-exploitation, and Senge's (1990) systems thinking, offer crucial insights for understanding how organizations adapt and evolve. Yet to date, these theories have rarely been directly linked to AI's growing role in areas like human-machine collaboration (Bienefeld et al., 2023; Engström et al., 2024; Herrmann & Pfeiffer, 2023; Jarrahi, 2018; Jarrahi, Askay, et al., 2023; Makarius et al., 2020; Olan et al., 2022; Puranam, 2021; Sturm et al., 2021), big data and real-time analytics (Banasiewicz, 2021; Chen et al., 2023), and automated decision-making ((Banasiewicz, 2021; Benbya et al., 2020; Bohanec et al., 2017; Booyse & Scheepers, 2024; Jarrahi, 2018). A synthesis of these domains can reveal how and why AI might reinforce superficial, efficiency-driven practices in some instances while catalyzing deeper, system-wide reflection in others.

Although AI is increasingly woven into organizational processes, existing scholarship has focused largely on technical integration rather than the learning transformation that AI could facilitate. Research on AI in organizational contexts often addresses individual skill development (Dwivedi et al., 2021; Jarrahi, Askay, et al., 2023; Kar et al., 2021; Li & Yeo, 2024; Makarius et al., 2020) or knowledge management (Alavi et al., 2024), overlooking the broader, collective learning processes that Argyris and Schön, March, and Senge conceptualized decades ago. As a result, there lacks a clear theoretical framework that shows how AI specifically impacts organizational-level learning, including the role of leadership (Bevilacqua et al., 2025), culture (Bley et al., 2022; Rožman et al., 2023), ethics (Katirai & Nagato, 2024; Leslie, 2019), and digital maturity (Ladu et al., 2024) as moderating influences.

Given this research gap, the central question guiding this thesis is: Which theoretical perspectives best explain AI's role in enabling (or hindering) organizational learning? Sub-questions include how classical theories of learning account for new AI mechanisms (e.g., algorithmic feedback, real-time analytics), which moderating factors shape AI's effectiveness in fostering deeper reflection, and what boundary conditions – such as industry context or technical infrastructure – constrain or enhance AI's transformative potential.

Research Purpose and Objectives

The purpose of this thesis is to develop a conceptual framework that integrates classical organizational learning theories with contemporary AI practices, illuminating how AI may serve as either a catalyst or barrier to deeper learning across organizations. More specifically, the objectives are to:

1. Analyze AI mechanisms (machine learning/automated decision-making, human-AI collaboration, big data/real-time analytics, and algorithmic feedback) through established

theoretical lenses (single-/double-loop learning, exploration-exploitation, systems thinking).

2. Identify moderating factors (leadership, culture, ethics, digital maturity) that shape whether AI initiatives reinforce superficial routines or spark genuine adaptation
3. Examine boundary conditions (organization size, industry context, technical infrastructure, workforce capability) that influence AI's role in learning outcomes
4. Contribute to the organizational learning literature by extending classical theories into modern AI contexts, proposing a framework that future empirical work can test and refine.

By bridging Argyris & Schön's single- vs. double-loop learning, March's exploration-exploitation model, and Senge's systems thinking, the framework proposed here aims to revitalize organizational learning discourses in the era of AI. It extends these theories by incorporating AI's unique capabilities and by examining how these capabilities shift learning processes. This thesis employs a conceptual research design, integrating classical theories with literature on AI in management, human resources development, and knowledge management. A lack of direct studies linking AI and organizational learning further justifies a theoretical synthesis approach, where each AI mechanism is mapped to the relevant learning dimension and contextual moderators. As a conceptual study, the scope is to propose and refine a framework rather than empirically test it, though future validations are anticipated.

Chapter 2. Literature Review

This review examines how AI influences organizational learning processes through three foundational theoretical lenses: Argyris and Schön's (1978) single- and double-loop learning, March's (1991) exploration-exploitation framework, and Senge's (1990) systems thinking approach. As organizations increasingly integrate AI capabilities, understanding their impact on knowledge creation, sharing, and application becomes crucial. While these established theories emerged before widespread AI adoption, they offer valuable frameworks for analyzing how AI shapes organizational learning dynamics. This review first examines each theoretical perspective's core tenets and evolution, then explores AI's current organizational applications and implementation challenges. Finally, it considers how leadership, culture, and ethics moderate AI's influence on learning outcomes. By synthesizing these perspectives, the review aims to illuminate both opportunities and tensions in AI-enabled organizational learning.

Foundational Theories of Organizational Learning

Single- and Double-Loop Learning

Argyris and Schön's (1978) seminal work frames organizational learning as the interplay between espoused theories (stated beliefs) and theories-in-use (actual actions), highlighting how these underlying assumptions guide an organization's behavior. Their Theory of Action argues that every deliberate human action rests on cognitive foundations – norms, strategies, and assumptions – which can be revealed and tested to foster change. They propose two interrelated models of individual theories-in-use: Model I, centered on attaining goals and maintaining control, and Model II, based on valid information, free choice, and reflective commitment.

These frameworks feed into distinct organizational learning systems, Model 0-I and Model 0-II, reflecting how an organization's structures and processes either inhibit or enable deeper adaptation. Model 0-I systems emphasize single-loop learning, where errors are remedied without questioning core values or norms, thereby preserving the status quo. While this process can maintain stability, it often leads to superficial fixes, defensiveness, and a lack of awareness about deeper systemic issues. In contrast, Model 0-II systems promote double-loop learning, in which members confront and restructure the very norms and assumptions that foster errors, enhancing the capacity for genuine adaptation. This shift entails open dialogue, valid information sharing, and a collective commitment to continuous improvement.

Argyris and Schön also stress mapping as a central mechanism for understanding and shaping an organization's theory-in-use. By capturing both tacit and explicit knowledge, mapping illuminates underlying beliefs and practices, guiding future actions. Additionally, they focus on how single- and double-loop learning differ in scope: the former addresses immediate mismatches between expected and actual results, while the latter transforms the organization's guiding principles. Double-loop learning thus calls for a willingness to challenge entrenched approaches, adopt rigorous inquiry, and redefine objectives based on broader reflection and collaboration. Ultimately, their core assertion is that organizations thrive not by merely correcting errors but by reexamining the deeper beliefs driving their actions, enabling lasting flexibility, adaptability, and the emergence of a more reflective, resilient culture.

While Argyris and Schön's (1978) distinction between single-loop and double-loop learning remains one of the most influential frameworks in organizational learning literature, scholars have identified several key challenges in applying this framework both theoretically and practically. These challenges can be broadly categorized into conceptual complexity, measurement difficulties, and implementation barriers. Scholars note that despite its widespread citation, Argyris and Schön's framework has left a "superficial impact on the literature and practice" (Auqui-Caceres & Furlan, 2023, p. 741). As Lipshitz (2000) argues, this limited influence stems partly from the inherent complexity of the framework's core concepts. The distinction between espoused theories and theories-in-use, while theoretically elegant, proves challenging to operationalize in organizational settings. Jaaron and Backhouse (2017) characterize double-loop learning as an "inherently complex concept" that many practitioners struggle to fully grasp and apply.

A significant criticism centers on the difficulty of measuring double-loop learning in practice. Mazutis and Slawinski (2008) indicate that most empirical studies rely heavily on questionnaires and interviews, which are inadequate for capturing the actual transition from Model I to Model II theories-in-use. This methodological limitation stems from the fact that "theory-in-use and their governing variables must be inferred from actual behaviors or routines of individuals, teams, and organizations" (Auqui-Caceres & Furlan, 2023, p. 751). The lack of validated measurement tools has led to considerable variation in how researchers operate and assess double-loop learning outcomes.

Perhaps the most significant challenge lies in implementing double-loop learning within organizations. Multiple scholars (Bochman & Kroth, 2010; Henderson, 1997; Lipshitz, 2000) characterize the development of double-loop learning capabilities as "extremely difficult" and "problematic." These difficulties stem from several factors. Organizations and individuals often employ defensive routines that inhibit the questioning of underlying assumptions and values (Mazutis & Slawinski, 2008). Simultaneously, successful implementation of double-loop learning requires committed leaders who can facilitate authentic dialogue and reflection – a combination of skills that remains rare in practice (Witherspoon, 2014). Moreover, the transition from Model I to Model II behaviors necessitates sustained effort over extended periods – often 18 to 24 months or longer (Auqui-Caceres & Furlan, 2023). Compounding these challenges, organizational cultures that prioritize efficiency and quick fixes can hinder the deeper reflection and questioning crucial for genuine double-loop learning (Lipshitz, 2000).

Argyris and Schön's (1978) framework has been widely revisited and expanded upon since its original publication. Some authors propose a third learning loop where the core principles upon which an organization is founded are brought into question, this level of learning involves questioning the company's position in the outside world, its intended role, and its identity (Hawkins, 1991; Swieringa & Wierdsma, 1992). This later interpretation of Argyris and Schön's (1978) framework has been wrongly attributed to the authors, and has been criticized for lacking empirical validation, having poorly defined terminology, conflating different theoretical perspectives, and promoting an uncritical assumption that higher levels of learning are inherently more valuable for organizations (Tosey et al., 2012).

Exploration-Exploitation

March's (1991) framework on organizational learning highlights the fundamental tension between exploration – pursuing new ideas, innovations, and risk-taking – and exploitation – refining existing capabilities for efficiency and reliability. Both processes are vital for long-term success, yet they compete for finite resources and demand conscious trade-offs. Exploitation can drive immediate gains by standardizing practices, enhancing productivity, and stabilizing performance, but an overreliance on exploitation risks locking organizations into suboptimal routines and limiting adaptability. When environments shift or technologies evolve, excessively exploitative organizations may struggle to respond effectively.

In contrast, exploration calls for variation, discovery, and openness to new knowledge, enabling organizations to innovate, adapt, and stay competitive amid change. However, exploration poses significant challenges: benefits often emerge later, its returns are uncertain, and it can be more difficult to measure or justify in resource-allocation decisions. Organizations must therefore balance exploration's potential breakthroughs with exploitation's dependable outcomes, recognizing that each approach serves different time horizons and risk profiles.

Maintaining this balance often requires deliberate resource allocation, cultural encouragement of experimentation, and an awareness of how turnover, diversity, and socialization patterns shape learning behaviors. A moderate influx of fresh perspectives can spark exploration without destabilizing core operations. Ultimately, March contends that organizational learning hinges on how managers navigate the tension between short-term refinement of existing competencies (exploitation) and the longer-term pursuit of novel possibilities (exploration). Achieving an appropriate balance is vital for both adaptability and sustained competitive advantage.

The evolution of March's (1991) exploration-exploitation framework has been marked by significant theoretical developments, particularly in understanding how organizations can simultaneously pursue both modes of learning. While March originally conceptualized exploration and exploitation as competing activities that create inherent trade-offs in resource allocation, subsequent research has challenged and refined this view through the lens of organizational ambidexterity (O'Reilly & Tushman, 2013; Raisch et al., 2009)

The concept of organizational ambidexterity, first introduced by Duncan (1976) and later expanded by Tushman and O'Reilly (1996) represents a crucial advancement in understanding how organizations can manage the exploration-exploitation paradox. Ambidextrous organizations develop the capability to simultaneously explore new possibilities while exploiting existing competencies (O'Reilly & Tushman, 2013). This dual capacity has become increasingly critical in modern organizational contexts, where rapid technological change and market dynamics demand both efficiency and innovation (Birkinshaw & Gupta, 2013).

Recent literature has identified several distinct approaches to achieving ambidexterity. Structural ambidexterity, as described by O'Reilly and Tushman (2004), involves creating separate organizational units for exploration and exploitation activities, each with its own processes, structures, and cultures. This approach allows organizations to maintain different operational logic simultaneously while preserving overall strategic integration. The temporal dimension of ambidexterity has also received attention, with scholars examining how organizations can sequentially alternate between periods of exploration and exploitation (Siggelkow & Levinthal, 2003). This sequential approach suggests that organizations might benefit from rhythmic switching between these modes rather than attempting to maintain them simultaneously. However, in increasingly dynamic environments, the luxury of temporal separation may be diminishing, pushing organizations toward more simultaneous approaches to ambidexterity (Boumgarden et al., 2012).

Empirical studies have provided evidence for the performance benefits of ambidexterity, while also highlighting its contextual nature. Meta-analyses suggest that the relationship between ambidexterity and performance is positive but moderated by environmental and organizational factors (Junni et al., 2013). This indicates that the optimal balance between exploration and exploitation may vary across contexts and over time, requiring organizations to develop dynamic approaches to managing this tension.

The emergence of new organizational forms and technological capabilities has not eliminated the fundamental tension that March identified but rather has created new ways of managing it. As organizations continue to evolve in response to technological and environmental changes, our understanding of how to effectively balance exploration and exploitation must similarly evolve. Future research might examine how emerging technologies, and organizational forms affect the nature of this balance and the mechanisms through which organizations can achieve ambidexterity in increasingly complex and dynamic environments.

Systems Thinking

Senge's (1990) systems thinking is framework that views the organization as a dynamic and interdependent system – where decisions or changes in one area can have far-reaching consequences elsewhere. Instead of managing activities in isolation, systems thinking emphasizes identifying patterns, feedback loops, and the underlying structures that drive behavior over time. Organizations comprise of multiple, interlocking processes and relationships, no parts function truly independently.

Senge (1990) describes five learning disciplines that are key to building a learning organization. These disciplines are systems thinking, personal mastery, mental models, building shared vision, and team learning. Systems thinking is referred to as the "fifth discipline" as it integrates all others, acting as a conceptual cornerstone. A key principle of systems thinking is that structure influences behavior – when placed in the same system, people tend to produce similar results. It directs us to look at the underlying structures that shape individual actions and create the conditions where certain events are likely. Personal mastery involves continually clarifying and deepening personal vision, focusing energies, developing patience, and seeing reality objectively and is considered the spiritual foundation of the learning organization. Mental modes entail working with our internal pictures of the world, bringing them to the surface, and holding them up for scrutiny. The ability to surface and challenge mental models is key to adapting to change. Building a shared vision involves creating a shared picture of the future – it requires a long-term commitment and helps to bind individuals together around a common identity and sense of destiny. Finally, team learning is a discipline that focuses on the ability of groups of individuals to look for the larger picture beyond individual perspectives, it involves practices such as dialogue, reflection, and a willingness to expose the limitations in one's thinking. It is important to note that these disciplines are not meant to be applied separately, but as an ensemble.

Feedback is a key concept in systems thinking, referring to any reciprocal flow of influence in which every influence is both a cause and an effect. Two broad types of feedback processes exist: reinforcing feedback, often seen as the engine of growth, and balancing feedback, which underpins goal-oriented behavior. Many feedback processes contain delays – interruptions between actions and their consequences – and minimizing these delays is a high-leverage strategy for improving overall system performance. Systems archetypes, meanwhile, are recurring structures that reveal an elegant simplicity beneath management complexity; by recognizing these archetypes, individuals can recondition their perceptions to identify leverage points that transform system behaviors.

At the organizational boundary level, the principle of system boundary insists that attention must be directed to the most significant interactions affecting an issue, regardless of departmental or hierarchical divisions. In applying systems thinking, the emphasis should remain on the desired result rather than on presumed processes or means; this perspective fosters a continuous learning approach rather than the pursuit of static "perfect plans." Mental models, especially those shared by key decision makers, are instrumental in shaping organizational action, with leaders' effectiveness linked to the continual improvement of their own mental models. Ideally, these mental models guide self-concluding decisions and create space for openness and systemic inquiry, both of which are vital in complex environments where there is rarely a single "right answer." A shared vision emerges when individual visions harmonize within a broader organizational purpose, helping local decision makers avoid missing interdependencies beyond their immediate spheres of influence. Ultimately, the question is where organizations choose to focus their attention – on events, on repeating patterns of behavior, on the systemic structures underneath, or on a unifying "purpose story" – and how well each individual's mental models align with that overarching direction.

Some critics argue that Senge's systems thinking lacks engagement with the fundamentals of systems theory, relying heavily on traditional system dynamics while neglecting power processes (Flood & Finnestrand, 2020; Kiedrowski, 2006; Örtenblad, 2020). Without clear guidelines, organizations may apply Senge's ideas superficially, embracing the language of systems thinking but overlooking deeper issues of power and dialogue. Additionally, Senge's model is said to focus too heavily on individual cognition, glossing over collective, embodied, and cultural dimensions of learning (Örtenblad, 2007, 2020). Scholars have also faulted it for an individualistic rather than a holistic organizational view, failing to address how dominant groups might shape or suppress certain visions and mental models (Flood & Finnestrand, 2020; Kiedrowski, 2006). As a result, critics describe the framework as utopian and idealistic, contending that it is not always grounded in the practical realities of organizational life and can serve managerial interests at the expense of true collaboration (Kiedrowski, 2006). Finally, they assert that Senge provides insufficient practical guidance for building learning organizations, framing him more as a practitioner who repackages basic theory into accessible language than as a theoretician offering robust, operationalizable methods (Flood & Finnestrand, 2020).

Digital Transformation of Learning Theories

The digital transformation of organizational learning theories has evolved significantly from early technological implementations to modern AI-enabled systems. Kane and Alavi's (2007) analysis of IT-enabled learning mechanisms laid the groundwork for understanding how technology shapes organizational learning through Knowledge Repositories and Portals (KRPs), Virtual Team Rooms (TRs), and Electronic Communities of Practice (ECOPs). This foundation has expanded considerably with modern digital transformation, as identified by Argote et al. (2021), who highlight three fundamental shifts: the unprecedented acceleration of organizational learning speed, the dramatic expansion of learning scale, and the broadening scope of what organizations can learn. Johnson et al. (2022) further develop this understanding by demonstrating how digital technologies, particularly AI, enable real-time learning through continuous data collection and automated knowledge synthesis, fundamentally altering traditional organizational learning mechanisms and creating new pathways for knowledge creation and transfer.

AI's impact on traditional learning frameworks represents a paradigm shift in both exploitation and exploration capabilities, transcending previous technological advancements. In terms of exploitation, AI enables process optimization and efficiency gains through automated workflows and enhanced decision-making processes (Wamba-Taguimdje et al., 2020), while fostering novel forms of human-AI collaboration that augment existing capabilities (Makarius et al., 2020). Puranam's (2021) Human-AI Collaborative Decision-Making framework illustrates how AI transforms exploitation activities through real-time feedback processing and pattern recognition. Simultaneously, AI has emerged as a powerful tool for exploration, serving as a strategic asset for innovation (Jarrahi, Askay, et al., 2023) through sophisticated data analysis capabilities (Kakatkar et al., 2020) and pattern recognition (Soni et al., 2020). This dual enhancement challenges the traditional notion of trade-offs between exploration and exploitation, as AI enables organizations to transform resource allocation (Berente et al., 2021), make real-time adjustments (Engström et al., 2024), and leverage AI-enabled transactive memory systems (Bienefeld et al., 2023).

Digital transformation has introduced new possibilities for managing the exploration-exploitation tension. Technological advances, particularly in data analytics and artificial intelligence, have created opportunities for organizations to pursue both activities more efficiently (Kane & Alavi, 2007; Verganti et al., 2020). Digital technologies can reduce the traditional resource constraints that March (1991) identified as central to the exploration-exploitation trade-off, enabling organizations to process information more efficiently and experiment with new possibilities while maintaining operational excellence (Berente et al., 2021).

Machine learning models and transparent explanations can be powerful enablers of both single- and double-loop learning in organizations (Bohanec et al., 2017). Predictions and data-driven insights enhance existing processes – a hallmark of single-loop learning – by identifying inefficiencies, streamlining operations, and aligning actions more closely with established goals. ML-driven explanations can reveal deeper insights that prompt decision-makers to question underlying assumptions, thereby engaging in double-loop learning, which involves modifying the organization's very norms and mental models. By encouraging discussion around why a model produced certain results, these explanations facilitate reflection, reduce subjective biases, and prompt re-evaluation of initial forecasts or business strategies.

Jarrahi, Kenyon, et al.'s (2023) framework for mutual learning between AI and humans closely aligns with the concepts of single- and double-loop learning by offering a dual pathway for organizational improvement and transformation. AI-driven insights can refine existing processes and correct errors within familiar norms and objectives – reflecting single-loop learning, where the emphasis is on sustaining current performance. AI's capacity to uncover novel patterns and suggest new ways of working can prompt organizations to question deep-rooted assumptions, thus engaging in double-loop learning, where core strategies and values are reexamined. In this ongoing feedback loop, humans contextualize AI's outputs, while AI systems adapt based on human input, ultimately supporting both operational efficiency and the reinvention of organizational norms.

The integration of AI and knowledge management into organizational systems presents an opportunity to examine the adaptability of established theoretical frameworks. Herrmann and Pfeiffer (2023) and Jarrahi, Askay, et al.'s (2023) work demonstrates alignment with Senge's systems thinking principles, yet also reveals areas where traditional frameworks may need expansion. While both works validate Senge's emphasis on feedback loops, integrated systems perspectives, and organizational learning, they also introduce novel considerations specific to AI capabilities. Herrmann and Pfeiffer's (2023) four distinct organizational loops in AI implementation – use, customization, original tasks, and contextual changes – extends beyond Senge's original conceptualization, suggesting the need for more nuanced theoretical frameworks that can accommodate AI's unique characteristics. Similarly, Jarrahi, Askay, et al.'s (2023) exploration of human-AI symbiosis introduces dynamics not fully captured in traditional systems thinking models, particularly regarding the recursive learning relationship between human and artificial agents. This emerging scholarship suggests that while Senge's fundamental principles remain relevant, there may be a need to evolve systems thinking frameworks to fully encompass the distinct properties and implications of AI systems, particularly their capacity for autonomous learning and decision-making within organizational contexts.

These foundational theories underscore the multifaceted nature of organizational learning. Argyris and Schön's emphasis on single- versus double-loop learning highlights the importance of both routine process optimization and deeper reexamination of norms, while

March's exploration-exploitation framework brings into focus the tension between incremental improvement and more radical innovation. Senge's systems thinking adds a holistic viewpoint, underscoring the complexity and interdependence of organizational elements. Recent scholarship and digital-era transformations demonstrate that these theories, though seminal, benefit from ongoing refinement to fully capture how AI, machine learning, and other advanced technologies alter organizational knowledge flows. As organizations increasingly combine human expertise with AI-driven insights, the interplay among single- and double-loop learning, exploration-exploitation, and systemic feedback loops becomes more dynamic, calling for theoretical frameworks that can accommodate new modes of inquiry and collaboration. Ultimately, the convergence of these foundational perspectives with contemporary digital innovations paves the way for richer, more adaptive learning processes in modern organizations.

AI in Organizational Contexts

The following section provides an overview of AI's historical trajectory and current applications in organizational settings. Early efforts focused on automating basic tasks and calculations, while modern AI initiatives have become increasingly complex, involving real-time data analysis, machine learning, and strategic innovation. Researchers underscore that effective AI implementation now demands not just technical enhancements but also social and structural changes—ranging from leadership engagement to team-based knowledge exchange. Ultimately, these developments shift AI's role from a simple efficiency tool to a transformative force that reshapes how organizations learn, adapt, and innovate.

Historical and Current AI Adoption

AI's evolution reflects a progression from theoretical concepts and mechanical automation (Nilsson, 2009) to sophisticated systems embedded in everyday life (Brynjolfsson &

McAfee, 2014). Early iterations of AI centered on building machines to handle well-defined tasks – such as automating basic calculations, payroll processing, and information handling – through rule-based approaches (Brynjolfsson & McAfee, 2014). Concurrently, pioneering efforts in symbolic processing, heuristic search, and neural networks laid the groundwork for AI's eventual leap beyond theoretical problems into real-world applications (Nilsson, 2009). By the 1970's and 1980's, government and commercial support propelled AI toward practical endeavors, culminating in expert systems, computer vision, and natural language interfaces (Nilsson, 2009). This shift has enabled AI to tackle increasingly complex tasks and to function in partnership with human expertise, requiring organizational co-inventions (Brynjolfsson & Mitchell, 2017) that reshape business processes and management structures. The consistent theme has been a growing potential to move beyond basic efficiencies, facilitating profound changes in how organizations learn, adapt, and reinvent their core operations.

Earlier research noted technology's potential to drive organizational learning, as initial inquiries into enterprise resource planning systems (Robey et al., 2002) and knowledge management systems (Alavi & Leidner, 2001) demonstrated how IT can foster knowledge-sharing and training. However, AI surpasses these earlier technologies in both scale and sophistication. The evolution of AI in organizational contexts demonstrates a marked progression from simple automation to sophisticated, strategically oriented deployments. Data analytics capabilities have moved beyond basic descriptive methods to advanced pattern recognition and real-time data processing (Kakatkar et al., 2020; Soni et al., 2020), enabling organizations to leverage actionable insights from large datasets. Machine learning applications now include sophisticated algorithms – such as decision trees, Bayesian networks, and deep learning systems – that bolster both operational efficiency and strategic innovation (Johnson et al., 2022).

Similarly, automation has evolved from routine task execution to intelligent process optimization and dynamic resource allocation (Wamba-Taguimdje et al., 2020), while predictive modeling has advanced to permit real-time forecasting and strategic planning (Berente et al., 2021).

Initially, AI implementations centered on achieving efficiency gains through exploitative, task-specific uses (Brynjolfsson & Mitchell, 2017). However, by the 2020's, organizations began adopting human-AI collaborative models that balance exploitation with exploration capabilities, reflecting an emphasis on enhanced decision-making and strategic innovation (Engström et al., 2024; Kakatkar et al., 2020). More recent developments, especially from 2022 onward, underscore real-time learning and adaptation, along with the necessity of addressing implementation hurdles such as employee resistance, team dynamics, and structural adaptation (Booyse & Scheepers, 2024), AI systems place growing importance on knowledge creation and transfer, marking a departure from earlier efficiency-focused applications and highlighting the need for comprehensive, systematically managed approaches that blend technical, social, and organizational considerations (Jarrahi, Kenyon, et al., 2023).

Implications for Organizational Learning

This section examines how artificial intelligence (AI) reshapes the landscape of organizational learning. From knowledge management systems that embed both tacit and explicit insights (Argote et al., 2021) to collaborative frameworks that emphasize mutual learning between human teams and AI agents (Bienefeld et al., 2023; Jarrahi, 2018) researchers increasingly view AI as a transformative force for enhancing decision-making, innovation, and the capture of organizational know-how. These studies also illuminate the social, ethical, and strategic complexities inherent in implementing AI, underscoring the importance of systems thinking, team dynamics, and sociotechnical frameworks.

Argote et al. (2021) observe that AI-enhanced knowledge management systems and machine learning algorithms can significantly enrich organizational learning by capturing both tacit and explicit knowledge, thereby uncovering insights that might otherwise remain unseen. These tools not only streamline knowledge sharing, reduce search costs, and accelerate new employees' path to productivity, but also hold promise for helping organizations adapt to rapidly shifting market demands. Agrawal et al.(2024) caution that AI's impact often extends beyond isolated tasks, underscoring the importance of a systems-thinking perspective in contexts where interdependent decisions exacerbate organizational complexity. Within the healthcare sector, for example, Bienefeld et al. (2023) emphasize the utility of incorporating AI agents into a team's transactive memory system to strengthen collective expertise, while also demonstrating the need to balance trust – neither over- nor under-reliance – to ensure consistent, high-level performance. At the individual level, Jarrahi (2018) highlights the productive synergy that emerges when human discernment pairs with AI-driven data processing, a concept advanced further by Johnson et al. (2022), who regard AI as a collaborator that fosters more profound exploration and innovation, rather than simply automating standard procedures.

Sturm et al. (2021) expand this discussion through agent-based simulations, illustrating that organizations must involve humans in configuring machine learning systems to maintain an equilibrium between exploration and exploitation. Their findings resonate especially in uncertain or dynamic settings, where imperfect data quality and swiftly evolving conditions require diligent human oversight and flexible cooperation. This "mutual learning" paradigm, as conceptualized by Jarrahi, Kenyon et al. (2023) depicts AI as a partner that brings substantial analytical capacity, while humans contribute contextual insight and nuanced decision-making. One illustrative example is the United Parcel Service's AI-empowered network planning tool, in which human feedback loops iteratively refine AI outputs, generating "artificial capital" that aligns with the organization's distinctive culture and strategic objectives. Such patterns of reciprocal interaction underscore how continuous feedback between algorithms and people drives sustained gains in efficiency, innovation, and learning.

Finally, Jarrahi, Askay, et al. (2023) examine AI's broader function in knowledge management and workforce development, showcasing MITRE's, a federally funded US based research organization, strategy of pro-actively mapping employee expertise with AI to minimize knowledge silos. In addition to identifying overlooked connections in extensive datasets – for instance, a deep-learning algorithm revealing new correlations in materials science – AI can enable ongoing, iterative learning experiences. Previously, Orlikowski (1992) and Leonardi (2013) investigate the continual sociotechnical interplay between organizational structures and technology, but their analyses typically address broad conceptual changes rather than focusing on reflective practice, systems thinking, or the exploration-exploitation tension. Makarius et al. (2020) and Li and Yeo (2024) ushering the notion of a sociotechnical structure into the 2020's, asserting that this framework is essential, ensuring that social, cultural, and managerial processes advance in tandem with AI adoption, thereby bolstering psychological safety and personalized learning opportunities. Under conditions of supportive leadership, robust infrastructures, and carefully designed protocols, AI and human expertise can collectively generate "sociotechnical capital": a strategic advantage arising from the integrated interplay between machine intelligence and employee capabilities in highly dynamic, knowledge-driven environments.

Ardichvili (2022) warns that AI's automation of knowledge work can inadvertently curtail employees' opportunities for skill development by minimizing their engagement with progressively complex tasks and limiting social interactions that foster collaborative learning.

When tasks are broken into micro-components, workers may experience reduced autonomy, job engagement, and a reliance on automated advice that promotes cognitive complacency and deskilling. Dwivedi et al. (2021) echo these concerns, noting that an overdependence on AI can diminish employee motivation, cause alienation, and compromise job satisfaction. They also emphasize transparency and accountability issues: "black box" algorithms complicate the tracing of AI outputs back to human decisions, and organizations often grapple with the quality of data used to train AI models. These challenges reveal a broader tension between AI's potential to streamline operations and the risk of eroding both worker agency and shared organizational knowledge.

In Industry 4.0 contexts, rapid digital transformation can intensify these tensions. Malik et al. (2022) show how employees may struggle with the pace and complexity of AI-based tools, leading to "technostress" manifested in reduced job satisfaction, increased anxiety, and concerns about job security. Alongside data privacy and system integration risks, these factors underscore the need for holistic change-management strategies, particularly when employee workloads and expectations escalate. Wilkens (2020) further points out that AI can reinforce single-loop rather than double-loop learning, narrowing the scope of organizational reflection and inhibiting more dynamic, non-linear thinking. Although AI can offer remarkable gains in efficiency and insight, the literature collectively stresses that these benefits must be weighed against their potential downsides—from skill attrition to mistrust of opaque algorithms—calling for implementation strategies that safeguard both long-term learning capacity and workforce well-being.

Implementation Barriers

The adoption of AI often encounters resistance due to psychological and professional barriers at the individual level. Employees may view AI in abstract, complex terms and become passively engaged with new technologies rather than proactively learning to use them (Engström et al., 2024). Knowledge workers, in particular, may see AI as a threat to their professional autonomy and expertise, leading to concerns about maintaining a sense of agency in decision-making (Booyse & Scheepers, 2024). Such apprehensions about role displacement and diminished control can in turn reduce motivation and engagement, illustrating how employees' reluctance to upskill or collaborate with AI hinders successful implementation (Booyse & Scheepers, 2024; Shrivastav, 2022).

Beyond the individual, AI adoption introduces a range of group-level complexities that revolve around team coordination, reconfigured workflows, and evolving leadership roles. Poor interdepartmental coordination, inconsistencies in processes, and misaligned goals can disrupt collective efforts to integrate AI smoothly (Engström et al., 2024; Kar et al., 2021). Transformations in team interaction - prompted by the introduction of AI-augmented tasks - require revisions to leadership responsibilities and accountability structures. These shifts can create resistance or confusion among teams, especially where cultural norms and process ownership conflict with new AI-driven practices (Booyse & Scheepers, 2024). Moreover, AI adoption necessitates a broader cultural transformation, and teams may resist changes to long-established patterns of communication and decision-making (Engström et al., 2024; Kar et al., 2021). As a result, effective AI integration calls for robust change management, collaborative support, and clear delineations of responsibilities

On an organizational level, AI implementation is frequently constrained by strategic, structural, and contextual issues that demand more systemic solutions. Many organizations struggle to shift from AI experimentation to full production, as doing so necessitates integrating novel tools into existing infrastructures and practices, reskilling staff, and addressing ethical concerns (Benbya et al., 2020; Kar et al., 2021; Shrivastav, 2022). A scarcity of AI professionals compounds these difficulties, particularly outside the tech sector, where attracting and defining roles for AI talent proves challenging (Benbya et al., 2020; Shrivastav, 2022). Meanwhile, the "black box" nature of certain algorithms raises accountability questions and fosters apprehension around ethically charged issues such as bias or discrimination (Booyse & Scheepers, 2024). Organizations also face knowledge-sharing hurdles and resource limitations that can impede AI's ability to learn from past projects or fully capitalize on tacit knowledge (Olan et al., 2022). Overall, the successful integration of AI ultimately depends on supportive leadership, coherent cultural norms, and a well-structured environment that collectively address these sociotechnical barriers.

Moderating Factors

In exploring how AI shapes organizational learning, three key elements – leadership, culture, ethics, and digital maturity – emerge as crucial moderators. Leaders occupy a central position by defining strategic objectives, allocating resources, and guiding cultural transitions that help employees view AI as an enabler rather than a threat. Organizational culture, understood as the collective beliefs that distinguish one organization from another (Bley et al., 2022), can either facilitate or stifle AI's integration by influencing how teams collaborate, share knowledge, and adapt to new technologies. Moreover, ethical considerations ensure AI adoption aligns with values of accountability, fairness, and social responsibility, creating a framework for responsible innovation.

Leadership

Bevilacqua et al. (2025) emphasize that top managers guide AI adoption by shaping strategic objectives, defining the cultural climate for AI use, and allocating necessary resources.

In a complementary vein, Divya et al. (2024) reveal that leadership not only amplifies AI's direct positive effect on engagement but also sustains it by aligning AI initiatives with organizational objectives and preserving employee motivation. Their distinction between AI-supported and AI-led leadership underscores the need for human leaders to remain central in decision-making, thereby preventing a purely technology-driven approach that might erode social identity.

Peifer et al. (2022) highlight how leaders help organizations shift from experimental AI use to systematic deployment, often requiring them to reskill in data management while keeping team needs at the forefront. Leaders are also responsible for fostering a culture of learning and inclusion – one that accommodates mistakes and embraces AI's advantages – while maintaining vigilance over ethical or discriminatory outcomes that AI systems may produce. Wijayati et al. (2022) add that leaders serve as vital change agents who must articulate a shared vision of AI's benefits, support employees' emotional needs during the transition, and harmonize AI capabilities with broader strategic imperatives. Together, these studies depict a multifaceted leadership role in which vision-setting, resource stewardship, employee support, and ethical oversight converge to determine whether AI truly elevates organizational learning, performance, and engagement.

Within Argyris and Schön's (1978) framework, leadership determines whether organizations engage in single-loop learning – merely correcting surface-level errors – or double-loop learning, which questions underlying norms and fosters deeper change. Similarly, March's (1991) emphasis on exploration versus exploitation hinges on leaders who allocate resources and encourage risk-taking for innovative exploration, rather than fixating on efficient exploitation alone. From Senge's (1990) perspective, leadership drives systems thinking by promoting holistic views of interdependence and enabling teams to recognize and manage the feedback loops central to organizational adaptation. In each case, effective leaders set the tone for inquiry, resource allocation, and cultural openness, ensuring that AI-driven learning is embedded in a broader vision that balances immediate needs with long-term organizational growth.

Organizational Culture

Bley et al. (2022) found that organizational culture exerts a powerful influence on how effectively AI is adopted, deployed, and ultimately leveraged for performance gains. A supportive culture ensures that AI initiatives are approached not merely as technical solutions but as catalysts for deeper organizational change, wherein collaboration, shared objectives, and a data-driven mindset become the norm. In such an environment, tangible resources such as data governance systems, human capital, and intangible resources such as an organizational learning mindset, all converge to build AI capabilities that underpin innovation and competitive advantage.

Bley et al. (2022) emphasize that organizational culture moderates how AI translates into performance gains: even sophisticated AI systems may fail if employees and leadership are unprepared or resistant to change. By cultivating collaboration across departments, embedding data-driven decision-making, and proactively refining work processes, organizations can enhance both social and market outcomes through AI. In parallel, Rožman et al. (2023) underscore the value of a supportive, learning-oriented culture for maximizing AI-driven initiatives, highlighting data-focused values, open collaboration, and a positive stance toward new technologies. Fostering a digital mindset ensures employees are primed for the skill development and procedural shifts AI requires, while leadership alignment and digital literacy reinforce organizational readiness. Ultimately, these studies converge on the conclusion that a flexible, adaptive culture is as essential as technological prowess for lasting success in a rapidly evolving digital organizational environment.

Argyris and Schön's models highlight how cultural assumptions can reinforce Model I (status-quo maintenance) or cultivate Model II (transformative learning), underscoring the impact of an organization's collective mindset on its readiness for AI-driven change. In March's exploration-exploitation framework, a supportive, innovative culture encourages experimentation while preventing stagnation in existing routines. From Senge's systems-thinking lens, culture either fosters open information flow, feedback loops, and collaborative learning or entrenches silos that hinder AI's potential. By embracing shared values around data-driven thinking, risk-taking, and continuous improvement, organizations create an environment where AI initiatives reinforce deeper learning and strategic adaptability.

Ethics

Ashok et al. (2022) stress that ethical AI deployment hinges on aligning social responsibility with stakeholder needs, urging organizations to translate high-level principles into tangible frameworks that address intelligibility, accountability, fairness, and autonomy. Leslie (2019) similarly underscores how these guidelines serve as a moderating force on AI's learning impact by mitigating bias – through representative data use and fairness-aware design –while also strengthening accountability via human oversight, auditability, and autonomy protections. According to Katirai and Nagato (2024) ethical standards help balance critical trade-offs in AI development: safeguarding personal and proprietary information, ensuring diverse voices shape algorithmic decisions, and retaining a human-centric approach even as automation advances. Across these sources, responsible innovation emerges as an ongoing process of reflecting on values, mitigating risks, and orchestrating social and technical elements. Ethical principles thus become integral to organizational learning, preventing unintended harm, promoting transparency, and nurturing a culture in which AI can be harnessed for shared benefit without sacrificing human dignity or collective well-being.

Building on Argyris and Schön's (1978) view of reflective practice, ethical considerations enhance double-loop learning by compelling organizations to question underlying values and biases in AI applications. Likewise, March's (1991) tension between exploration and exploitation raises ethical trade-offs about the societal impact of innovation versus efficiency. From a systems-thinking standpoint (Senge, 1990), ethical frameworks shape the broader feedback loops between AI, stakeholders, and social systems, ensuring that the pursuit of organizational goals does not undermine wider stakeholder wellbeing. By embedding fairness, accountability, and transparency into AI processes, organizations enrich their learning capacity and maintain stakeholder trust, thus grounding AI-driven initiatives in responsible and sustainable practices.

Digital Maturity

Digital maturity refers to the degree to which an organization effectively aligns technology, strategy, workforce, and culture to meet the evolving digital expectations of stakeholders (Kane et al., 2017). Rather than simply installing new digital tools, digitally mature organizations treat technology adoption as part of a systemic transformation that influences how they learn, innovate, and adapt (Kane et al., 2017; Ladu et al., 2024). Recent studies (Akbarighatar et al., 2023; Brătucu et al., 2024) further emphasize that digital maturity not only determines whether organizations integrate AI effectively, but also shapes how deeply AI-driven insights permeate organizational learning processes.

Kane et al. (2017) highlight several core elements that characterize digitally mature organizations. Digitally mature organizations alter organizational structures, workforce development, and cultural norms to support cross-functional collaboration and digital fluency. They encourage small-scale digital experiments and scale successful organization-wide initiatives, reflecting a tolerance for risk and failure. A hallmark of digital maturity is breaking down silos; cross-functional teams tackle digital priorities with shared goals and incentives. Rather than a static endpoint, digital maturity is an ongoing process of adapting to a shifting digital landscape. These elements signal how culture, leadership style, and collaborative structures can all moderate how AI is adopted and how it shapes learning. For instance, if an organization lacks risk tolerance, even the most sophisticated AI models may be relegated to single-loop error-correction; conversely, a culture of experimentation may spur double-loop inquiries that question strategic norms. Moreover, digitally mature organizations are more adept at scaling AI pilots into organization-wide initiatives (Brătucu et al., 2024; Kane et al., 2017). They not only refine routine processes (exploitation) but also create space for exploratory thinking, bridging the tension March (1991) describes between short-term efficiency and long-term innovation.

Akbarighatar et al. (2023) underscore that AI maturity – a subset of overall digital maturity – requires sociotechnical considerations, meaning organizations cannot focus solely on technical aspects of AI without also addressing the human, cultural, and ethical dimensions. Mature AI deployments integrate human-centric design, ethical risk management, and continuous feedback loops to ensure technology aligns with both instrumental and humanistic objectives. This perspective resonates with systems thinking, where success hinges on navigating interdependencies among technology, people, and processes.

Synthesis and Gaps

Collectively, Argyris and Schön's (1978) single- vs. double-loop learning, March's

(1991) exploration-exploitation framework, and Senge's (1990) systems thinking present organizational learning as a complex mix of reflective inquiry, resource trade-offs, and systemic feedback loops. Although AI research has increasingly addressed practical challenges in human resource development and knowledge management (Argote et al., 2021; Booyse & Scheepers, 2024; Engström et al., 2024; Jarrahi, 2018), it rarely connects those insights to the core tenets of organizational learning, leaving open questions about how AI-based practices alter deeper processes tied to norm re-examination, strategic balancing, and system-wide interdependencies.

Several works hint at a more holistic theoretical synthesis. For instance, Sturm et al. (2021) use agent-based simulations to explore how human-machine collaboration simultaneously engages routine exploitation and novel exploration, paralleling March's (1991) concerns about resource allocation trade-offs. Makarius et al. (2020) use a sociotechnical lens that resonates with Senge's (1990) systemic perspective and Argyris and Schön's (1978) notion of questioning organizational routines, whereas Herrmann & Pfeiffer (2023) investigate how AI-enabled loops can potentially extend systems thinking principles. Jarrahi, Askay, et al. (2023) draw attention to AI's role in converting tacit knowledge to explicit forms, echoing Argyris and Schön's call to surface underlying assumptions and Senge's emphasis on collective mental models. Still, these contributions remain fragmented, as none systematically integrate AI's role across all three foundational learning theories.

Further illustrating these gaps, Bevilacqua et al. (2025) and Divya et al. (2024) demonstrate how leadership shapes AI implementation – an aspect relevant to both March's resource-balancing dilemma and Argyris and Schön's insistence on reflective leadership – while Peifer et al. (2022) and Wijayati et al. (2022) highlight leaders as change agents in AI adoption, aligning with Senge's systems orientation. On the cultural dimension, Bley et al. (2022) and

Rožman et al. (2023) emphasize a learning-oriented environment that supports AI initiatives, pointing back to Argyris and Schön's deeper vs. superficial learning and to Senge's systemic feedback loops. Meanwhile, works on ethical considerations in AI – including Ashok et al. (2022), Leslie (2019), and Katirai and Nagato (2024) – bridge fairness and accountability concerns with fundamental calls for questioning assumptions (Argyris & Schön, 1978), balancing efficiency with broader social impacts (March, 1991), and adopting a holistic perspective (Senge, 1990).

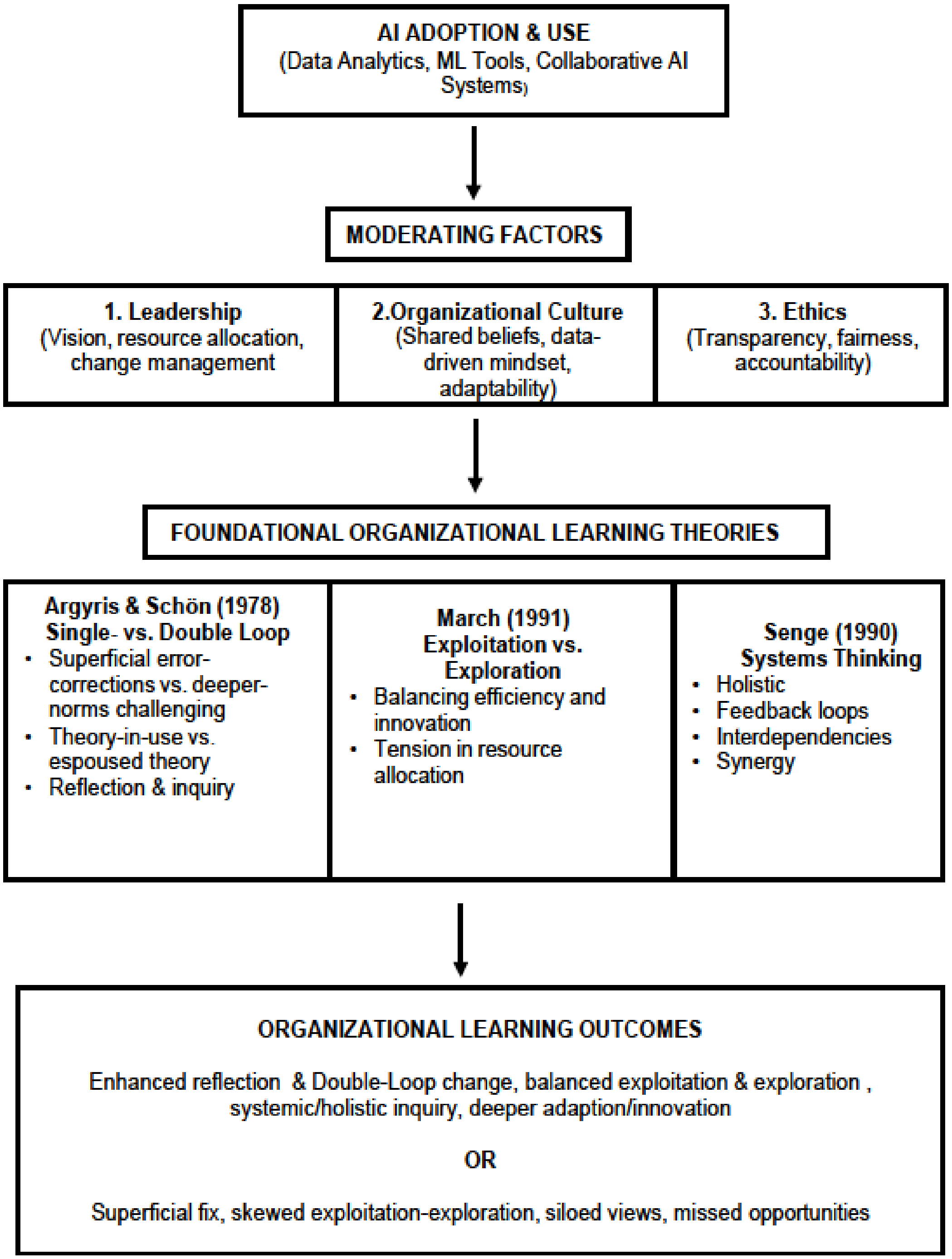
Additionally, Auqui-Caceres and Furlan (2023), Lipshitz (2000), and Mazutis and Slawinski (2008) underscore the implementation difficulties of double-loop learning, suggesting AI might either exacerbate or alleviate the struggle to challenge entrenched norms. Ambidexterity research (O'Reilly & Tushman, 2004, 2013; Raisch et al., 2009; Tushman & O'Reilly, 1996) extends March's (1991) exploration-exploitation framework by illustrating how organizations can deliberately structure and manage themselves to pursue both incremental improvements (exploitation) and more radical innovations (exploration). While these authors do not specifically address AI, their focus on reconciling seemingly opposing activities provides a foundation for understanding why balancing exploration and exploitation can grow more urgent in contexts that integrate powerful new technologies. Critiques of Senge's systems thinking (Flood & Finnestrand, 2020; Kiedrowski, 2006; Örtenblad, 2007, 2020) further complicate the terrain, raising questions about power dynamics, readiness for cultural change, and the risk of superficial "systems" language – challenges that can intensify once AI entangles more organizational feedback loops.

In sum, these observations reinforce the need for a more integrated framework that explicitly examines how AI-driven processes – from algorithmic recommendations to collaborative human-AI work arrangements – reshape the deeper architecture of organizational learning. This thesis endeavors to close these gap by situating AI's potential within Argyris and Schön's (1978) reflective loops, March's resource-allocation tension (1991), and Senge's systemic perspective (1990), illuminating how AI technologies can – if thoughtfully managed and implemented – transcend mere efficiency gains to transform an organization's core learning capacities.

Proposed Conceptual Model

Building on Argyris and Schön's (1978) focus on single- vs. double-loop learning, March's (1991) exploration-exploitation framework, and Senge's (1990) systems thinking, this thesis proposes a conceptual model that situates AI adoption within these three foundational perspectives. Specifically, AI-powered processes such as, machine learning tools, algorithmic insights, human-AI collaborations, are hypothesized to influence an organization's capacity for reflective learning (Argyris & Schön), strategic balancing (March), and holistic feedback loops (Senge). However, leadership, organizational culture, and ethical considerations moderate these interactions. Effective leadership provides a guiding vision, allocates resources, and shapes the cultural climate needed to integrate AI meaningfully; an adaptable culture supports data-driven dialogue and experimentation; and ethical principles ensure fairness, accountability, and transparency in AI deployments. The overarching premise is that AI adoption can either foster deeper organizational learning and adaptability or reinforce superficial, efficiency-driven processes – depending on how well these classic theoretical constructs are integrated with the social, cultural, and ethical dimensions of AI implementation. Figure 1 below illustrates the proposed conceptual model of AI and organizational learning.

Figure 1. Proposed Conceptual Model Integrating AI Adoption with Foundational Organizational Learning Theories



This literature review has highlighted three foundational theories, Argyris and Schön's (1978) single- vs. double-loop learning, March's (1991) exploration-exploitation framework, and Senge's (1990) systems thinking, as crucial lenses for understanding how organizations learn and adapt. Prior research underscores two main observations: firstly, that AI shows tremendous potential to accelerate knowledge creation, process optimization, and decision-making; secondly, that organizational learning in an AI-driven environment remains under-theorized beyond technical or HRD perspectives. While the literature offers valuable insights into skill development, knowledge-sharing, and operational enhancements, little has been established regarding deeper reflection (double-loop learning), balancing exploration and exploitation, or system-wide adaptation in AI-rich contexts. Three critical gaps emerge in current understanding of AI-enabled organizational learning. While AI research addresses functional aspects – such as HRD, knowledge management, and data analytics – it rarely connects to fundamental learning processes described by Argyris and Schön (double-loop inquiry), March (exploration–exploitation tension), or Senge (holistic, systems-level feedback). Few studies examine how AI shapes deeper organizational dynamics like double-loop reflection or system-wide adaptation, resulting in an incomplete theoretical grasp of AI's transformational potential. Existing scholarship primarily conceptualizes AI as a set of tools for efficiency or incremental learning. Discussions on transformative learning remain fragmented or limited to isolated case examples. Although many authors highlight best practices and barriers to AI adoption, few offer a unified theoretical lens that addresses both practical implementation and deeper organizational change. The absence of a comprehensive framework leaves practitioners with limited guidance on orchestrating AI-driven processes that genuinely enhance reflective and systemic learning.

These gaps collectively reinforce the need for a holistic conceptual model that integrates AI's capabilities with the foundational organizational learning perspectives of Argyris and Schön, March, and Senge. Such a model would not only depict where and how AI mediates learning processes at various depths but also why certain moderating factors and boundary conditions determine whether AI remains a tool of superficial fixes or a catalyst for transformative adaptation. The following chapter introduces a conceptual framework that explicitly addresses these gaps, mapping AI mechanisms onto the deeper learning dimensions of Argyris and Schön, March, and Senge to offer a robust organizational learning perspective.

Chapter 3. Conceptual/Theoretical Framework

Context

As AI technologies reshape how organizations gather, share, and apply knowledge, the classical theories of Argyris and Schön (1978), March (1991), and Senge (1990) offer crucial insights for understanding this transformation at a deeper level. While research on AI often focuses on its technical or functional benefits, such as enhanced data processing, workflow automation, and improved decision-making, relatively few studies examine how these innovations impact the fundamental processes of organizational learning. This conceptual framework aims to bridge that gap by situating a range of AI-driven practices within three cornerstone perspectives: single- vs. double-loop learning, the tension between exploration and exploitation, and holistic systems thinking.

This section considers four key AI applications that increasingly shape learning within organizations: machine learning/automated decision-making, collaborative human-AI approaches, big data and real-time analytics, and algorithmic feedback. By comparing, integrating, and extending the classical theoretical lenses in the context of these emerging tools, this section aims to lay the groundwork for analyzing how organizations might leverage −or inadvertently undermine −core learning capacities in the digital era.

The central research question to address is: “Which theoretical perspectives best explain AI’s role in enabling (or hindering) organizational learning?” To explore this question, this chapter will compare and integrate established organizational learning theories—specifically Argyris and Schön’s focus on single- vs. double-loop learning, March’s exploration−exploitation framework, and Senge’s systems thinking—with the above-mentioned AI-enabled practices. By doing so, this framework aims to evaluate how effectively these theories account for AI-specific learning mechanisms, observable outcomes like changes in reflection or innovation capacity, key moderating variables and contextual variations.

AI Tools for Organizational Learning

This section outlines key AI application – machine learning/automated decision-making, human-AI collaboration, big data and real-time analytics, and algorithmic feedback – that will inform the conceptual framework of AI and organizational learning. By briefly describing each technology’s potential to reshape how organizations gather insights, adapt processes, and manage performance, a foundation is established for understanding how AI can either reinforce short-term, efficiency-driven practices or catalyze deeper, system-wide learning. In doing so, these applications are mapped onto the theoretical lenses of Argyris and Schön, March, and Senge, illustrating how reflective inquiry, resource trade-offs, and holistic sensemaking intersect with AI-driven innovations.

Machine Learning and Automated Decision-Making

Machine learning (ML) is a rapidly advancing technology that uses algorithms trained on large datasets to automate tasks by mapping well-defined inputs to outputs (Brynjolfsson &

Mitchell, 2017). It encompasses various approaches, including supervised, unsupervised, semi-supervised, reinforcement, multitask, ensemble, neural network, and instance-based methods, each suited to different tasks such as classification, clustering, and decision-making. Supervised learning uses labeled data to teach models to make accurate predictions on new, unseen data. Unsupervised learning finds patterns in unlabeled data, such as clusters or relationships. Semi-supervised learning blends the two, leveraging a small amount of labeled data with a larger set of unlabeled data. Reinforcement learning involves software agents learning through rewards or penalties. Multitask learning solves multiple tasks at once by sharing insights between them. Ensemble methods combine multiple models for stronger predictions. Neural networks mimic the human brain to learn complex patterns. And finally, instance-based methods classify by comparing new cases to similar examples from their training data (Mahesh, 2020).

ML significantly widens the scope of organizational learning by introducing automated decision-making, expanded data capabilities, and new modes of discovering and using knowledge. Unlike traditional human-centric approaches, ML algorithms learn inductively from large datasets, spotting patterns and generating insights that can reshape decision-making processes – effectively challenging the assumption that reflection, resource trade-offs, and systemic awareness are strictly human domains (Banasiewicz, 2021).

Automated decision-making (ADM) refers to systems that not only automate the extraction of insights from data but also include self-contained, autonomous decision engines. While ADM is sometimes viewed as a threat to jobs, its most effective uses amplify rather than replaces human decision-making by combining the speed and scalability of information processing with adaptively creative problem-solving. This synergy shifts the focus of organizational learning from merely acquiring knowledge to exploring competency-enabled creativity, all while highlighting critical issues such as algorithmic bias and the indispensability of human oversight when it comes to ethical judgment (Banasiewicz, 2021).

Nevertheless, ML and ADM also have potential drawbacks: they often favors homogenous decision models that are based on historical data, lack the contextual and causal knowledge that humans naturally bring, and can lead to learning myopia by undervaluing distant or complex interdependencies (Balasubramanian et al., 2022). Moreover, as ML outperforms humans in certain analytical tasks and spawns accountability concerns, particularly when "black box" algorithms obscure decision logic, the interplay of human cognition with AI-driven feedback loops becomes central to whether organizations merely automate existing norms or interrogate them at a deeper, double-loop level consistent with Argyris and Schön's emphasis on questioning underlying assumptions (Bohanec et al., 2017). In addition, data-based creativity and enhanced analytical capabilities require an updated skill set focused on data literacy, algorithmic competence, and collaborative human-machine workflows, echoing Senge's call for systems thinking across departments and capturing potential trade-offs in short- vs. long-term investments (Banasiewicz, 2021). Overall, ML not only automates tasks but also redefines how organizational learning unfolds, highlighting the need for a comprehensive, sociotechnical framework that integrates both human and machine perspectives

Human-AI Collaboration

In an organizational learning context, the interplay between AI technologies and human cognition extends beyond mere task delegation, aiming instead to foster a sociotechnical framework where individuals and algorithms learn reciprocally (Jarrahi, 2018; Makarius et al., 2020). For organizations to successfully implement this framework they must preserve critical human insight by underscoring the organizational rather than purely technical nature of AI integration (Herrmann & Pfeiffer, 2023). While AI excels at processing large datasets and detecting nonobvious patterns, humans contribute contextual understanding, ethical oversight, and creative intuition, qualities essential for deeper reflection and innovation (Sturm et al., 2021).

Organizational design choices thus become pivotal: establishing clear divisions of labor, clarifying interdependencies, and aligning AI workflows with broader strategic goals can help balance the exploitation of current capabilities with exploration of emerging opportunities (Puranam, 2021). By viewing AI as an integral part of interconnected systems (Engström et al., 2024), organizations can encourage team-based sensemaking, minimize siloed decision-making, and ensure that feedback loops support holistic adaptation. The result is a richer approach to learning, one that weaves together double-loop reflection, strategic resource allocation, and systems thinking within a cohesive sociotechnical environment.

Big Data and Real-Time Analytics

Big data is a recent phase in analytics that deals with vast data from sources, requiring advanced processing technologies to reveal insights beyond what smaller-scale data approaches can offer (Calvard, 2016). Real-time analytics (RTA) focuses on the velocity aspect of big data by preparing, processing, and analyzing data as it arrives, thus enabling organizations to generate value in near real-time. Rather than dealing with batch inputs, RTA processes continuous data streams, proactively monitoring events and applying complex event processing to draw meaningful inferences. RTA applications have gained traction in scenarios like financial data quality control, health monitoring, and immediate advertisement recommendations, often incorporating ML or AI to enhance adaptability with minimal human oversight (Chen et al., 2023).

Big data can serve as both a catalyst and a challenge for organizational learning, offering unexpected insights that prompt re-evaluation of existing practices while also requiring robust sensemaking to transform raw information into actionable meaning. On the one hand, big data can instigate higher-order learning – organizations are compelled to confront novel knowledge, reevaluate assumptions, and reconsider entrenched norms. Yet without diligent sensemaking, this influx of information risks overwhelming employees and stifling genuine insight (Calvard, 2016).

Real-time analytics function with an operational focus – generating near-time, functional responses (Banasiewicz, 2021) that align with more exploitative activities (March, 1991), where organizations refine established processes based on incoming data. Yet this same stream of real-time information also supports augmented analytics, creating the potential for open-ended, exploratory questions and simulations that resonate with deeper organizational learning. Such flexible analysis can trigger data-enabled creativity, a dimension of learning that goes beyond immediate, routine corrections (Argyris & Schön, 1978) by prompting organizations to challenge assumptions and envision novel scenarios – effectively balancing single-loop, incremental fixes with double-loop, transformative re-examinations. Moreover, real-time analytics fosters a kind of continuous improvement, encouraging iterative sensemaking (Senge, 1990) as operational teams adapt to near-instant insights while leaders coordinate broader learning loops across the organization. By offering a steady flow of updated knowledge, real-time analytics can thus embed exploration, exploitation, and systemic awareness into daily operations, making organizational learning more adaptive and responsive (Banasiewicz, 2021).

Algorithmic Feedback

Algorithmic feedback – the use of learning algorithms to evaluate and manage performance –

can impose new forms of workplace control by quantifying all aspects of a individual's behavior (Faraj et al., 2018). While these continuous metrics and real-time comparisons promise greater efficiency, they can also narrow employee discretion by emphasizing opaque performance targets that often go unquestioned. This dynamic resonates with single-loop learning (Argyris & Schön, 1978), where workers adapt to the algorithm's directives without fundamentally challenging its underlying goals or assumptions. In some cases, employees even "game" the system – adjusting behaviors simply to satisfy algorithmic benchmarks – revealing how algorithmic feedback not only measures but also shapes behavior in pursuit of organizational objectives. The inherent opacity of many algorithms, however, constrains deeper reflection on whether these metrics truly align with broader strategic values, leaving workers with limited recourse to question or refine the data and assumptions guiding daily tasks (Faraj et al., 2018).

Drawing on a contrasting perspective, Grønsund and Aanestad (2020) describe a human-in-the-loop configuration that allows for reflexivity and scale in organizational learning. This arrangement ties the design and use of algorithms together so that user interactions continuously feed into subsequent improvements, suggesting a potential pathway to more double-loop inquiry (Argyris & Schön, 1978). By positioning humans as "coaches" or "laboratory scientists" who provide ground truths, organizations can regularly audit, adapt, and refine the algorithm in response to shifting operational needs or ethical concerns (Grønsund & Aanestad, 2020). Such human-algorithm synergies align with systems thinking (Senge, 1990) insofar as they acknowledge that algorithmic tools, tasks, and organizational goals form an interconnected feedback loop. When organizations treat algorithms as "lifelong learners," they invest in ongoing improvements – regular feedback, systematic auditing, and flexible adaptation –thus leveraging algorithmic reflexiveness as a strategic capability that can enrich organizational learning and agility (Grønsund & Aanestad, 2020).

In sum, these AI applications both challenge and complement the classical learning perspectives of Argyris and Schön, March, and Senge. While they offer powerful means of generating insights and automating routine tasks, their ultimate effect on organizational learning hinges on whether leaders and teams embrace deeper reflection, balance immediate gains with long-term exploration, and maintain a systemic view of feedback loops. The following section integrates these observations into a comprehensive conceptual framework, showing how AI can be harnessed to enable not just incremental improvements, but also transformative learning across the organization.

Model Development

This conceptual model builds on three core organizational learning theories that frame how AI can influence learning in organizations. By mapping each theoretical framework's core dimensions to specific AI-driven mechanisms, this section sets the stage for understanding how AI might enable or hinder deeper organizational learning. Each perspective addresses a different facet of adaptation: Argyris and Schön focus on error correction vs. norm questioning, March highlights the tension between efficiency and innovation, and Senge underscores interdependencies and feedback loops. Collectively, these models provide a lens through which to analyze AI's influence on organizational learning, covering immediate corrective measures, strategic resource deployment, and holistic, system-wide changes.

Argyris & Schön: Single- vs. Double-Loop Learning in the Age of AI

Argyris and Schön's foundational work distinguishes between espoused theories (what people say) and theories-in-use (what they do), highlighting how an organization's behavior is underpinned by often-unspoken assumptions (Argyris & Schön, 1978). They further propose two models: Model I, which is goal-focused and control-oriented, can inadvertently block deeper reflection; and Model II, which encourages more open inquiry and challenges the status quo. In relation to AI, algorithmic feedback might reinforce single-loop learning if errors are merely corrected without examining underlying norms. Conversely, AI-driven insights can spur double-loop learning by prompting organizations to question entrenched assumptions. This raises the key question: How does AI enable or constrain single- and double-loop learning processes within organizations?

Automated Decision Making in Single-Loop vs. Double-Loop Learning

Automated decision-making (ADM) and ML-based systems can expedite routine corrections. For instance, AI-driven performance dashboards may continuously adjust production metrics in real time (Argote et al., 2021; Johnson et al., 2022; Kane & Alavi, 2007), effectively aligning operations to preset targets. However, simply correcting errors without revisiting the goals or assumptions that underpin those metrics risk entrenching single-loop learning (Ardichvili, 2022; Wilkens, 2020). If no one questions whether goals themselves should be revised, the organization remains in Model I mode. Conversely, AI-driven insights can spur double-loop learning by surfacing previously unchallenged assumptions – such as discovering that a long-held strategy underperforms in newly revealed market segments (Bohanec et al., 2017; Jarrahi, Askay, et al., 2023; Johnson et al., 2022). Under these circumstances, leaders can revisit the underlying rules embedded in the automation, asking whether they align with the organization's broader values and long-term strategies (Bohanec et al., 2017).

Yet a notable limitation is that classical Argyris and Schön theory does not inherently address how AI transparency or human oversight affect deeper reflection. Real-time AI corrections can encourage frequent error fixing but may foreclose deeper inquiry if the organization lacks deliberate checkpoints for questioning AI outputs (Dwivedi et al., 2021; Wilkens, 2020). Without such practices, superficial Model I fixes prevail, preventing true double-loop learning (Ardichvili, 2022; Lipshitz, 2000; Mazutis & Slawinski, 2008).

Machine Learning Enabling/Constraining Assumption Questioning

Machine Learning (ML) can both uncover and entrench assumptions. ML algorithms can mine data to reveal counterintuitive patterns or anomalies, prompting the organization to question standard practices. Conversely, ML models can also reinforce historical biases if trained on unexamined data (Banasiewicz, 2021). In effect, ML can facilitate double-loop learning by flagging when reality diverges from mental models – but only if leaders and teams actively review and question the algorithm's outputs (Bohanec et al., 2017; Jarrahi, Askay, et al., 2023). Otherwise, ML may optimize within the bounds of current assumptions, locking the organization in single-loop behavior.

Human-AI Collaboration in Reflection

Achieving double-loop learning in an AI-rich environment requires intentional human-AI collaboration. While AI yields data-driven insights, human judgment remains critical in deciding whether insights call for altering deeper norms (Engström et al., 2024; Herrmann & Pfeiffer, 2023; Jarrahi, 2018; Makarius et al., 2020; Puranam, 2021). Such collaboration embodies mutual learning between humans and AI, where each improves via iterative interaction (Jarrahi, 2018; Jarrahi, Askay, et al., 2023). This iterative dialogue requires a learning mindset: rather than accepting AI outputs at face value, employees and managers must reflect on why the AI made certain suggestions and what that implies about underlying organizational strategies (Ransbotham et al., 2020). Research shows that AI-human interactions through iterative feedback loops and collaborative learning processes enable deeper organizational adaptation

(Herrmann & Pfeiffer, 2023; Jarrahi, Askay, et al., 2023; Sturm et al., 2021).

Algorithmic Feedback and Norms

Beyond ML and ADM, algorithmic feedback more generally shapes organizational learning by continuously generating performance metrics and alerts (Faraj et al., 2018). If such metrics closely align with existing norms, teams might inadvertently double-down on current practices, thus reinforcing single-loop routines. Yet algorithmic feedback can also challenge the status quo. An anomaly detection system, for example, might flag underperformance in a once-profitable product line, forcing managers to ask "why" and revisit deeply held assumptions. By design, algorithms are "indifferent to organizational norms" (Ransbotham et al., 2020), meaning they often raise inconvenient truths. The organizational response is key: an open culture sees unexpected AI feedback as an opportunity to question and learn, while a defensive culture might dismiss such warnings, forfeiting a chance for double-loop reflection (Bley et al., 2022; Jarrahi, Kenyon, et al., 2023; Rožman et al., 2023).

In sum, across ML, ADM, and algorithmic feedback, AI can either deepen or hinder reflective learning depending on how actively organizations question the embedded assumptions and how willing they are to incorporate disruptive insights into strategic change. The difference between single- and double-loop hinges on the organization's commitment to open inquiry, ethical oversight, and a culture that sees AI's "off-base" outputs not as mere errors, but as signals prompting deeper reflective practice.

Exploration vs. Exploitation with AI

March's (1991) framework focuses on the tension between pursuing novelty, experimentation, and risk, and refining existing competencies for efficiency and stability. Each path competes for scarce resources, compelling organizations to balance immediate gains with long-term adaptability. AI influences this dynamic by potentially channeling resources toward short-term efficiency (exploitation) or unveiling new opportunities for radical innovation (exploration). Advanced data analytics, predictive modeling, and machine learning can optimize routine processes while simultaneously generating novel insights. Therefore, a crucial question emerges: How does AI influence the exploration-exploitation balance, and what factors determine whether organizations lean toward radical innovation or routine efficiency?

Automated Decision-Making and Exploration-Exploitation

Drawing on March's (1991) exploration-exploitation framework, AI implementations reshape how organizations balance short-term efficiency against long-term adaptability. Automated decision-making (ADM) can streamline routine tasks, aligning with exploitation by freeing individuals from low-value labor (Johnson et al., 2022; Makarius et al., 2020). This optimization promises immediate performance gains but can also demand significant investments in data infrastructure and training that potentially divert resources away from experimentation and exploration (Benbya et al., 2020; Kar et al., 2021). Moreover, AI-driven decisions often rely on known patterns, reinforcing incremental improvement strategies (Sturm et al., 2021). Organizations that funnel too much capital toward immediate AI-enabled efficiencies risk neglecting radical innovation, especially if they overly focus on short-term metrics (Berente et al., 2021; Wamba-Taguimdje et al., 2020). The overemphasis on data-driven targets can inadvertently limit the scope of inquiry, undermining deeper strategic reflection and adaptability (Ardichvili, 2022; Wilkens, 2020).

AI's Dual Role in Efficiency vs. Innovation

Machine learning and analytics capabilities enable both process optimization and efficiency gains through automated workflows (Wamba-Taguimdje et al., 2020) while also fostering innovation through sophisticated pattern recognition and data analysis (Kakatkar et al., 2020; Soni et al., 2020). Through AI capabilities, organizations can transform how they allocate resources between routine operations and innovation activities (Berente et al., 2021) and make real-time adjustments to balance both imperatives (Sturm et al., 2021). Via organizational ambidexterity – the ability to simultaneously explore and exploit (O'Reilly & Tushman, 2013) – organizations can leverage AI to both refine existing competencies and pursue novel opportunities. The proposed conceptual model thus posits that AI's strategic value emerges from its capacity to support both incremental improvements and transformative innovation, provided leaders consciously manage this balance.

Real-Time Analytics: Routine vs. Novel Insights

A distinctive feature of AI is real-time data processing, helping organizations dynamically navigate the explore-exploit continuum. On the exploitation side, real-time analytics dashboards allow managers to continuously monitor operations and promptly adjust to deviations, keeping processes within optimal parameters. Simultaneously, real-time data can feed exploration by validating experiments and detecting nascent trends (Shi et al., 2024). Such an approach shortens feedback cycles, enabling faster iteration and adaptation. Research suggests these capabilities help organizations pursue simultaneous exploration and exploitation, meeting immediate operational needs while preserving long-term adaptability (Shi et al., 2024). In essence, real-time analytics AI intensifies the ability to test and deploy improvements swiftly, weaving together existing routines and novel ideas in real time.

Senge's Systems Thinking: Holistic Adaptation and AI's Interconnected Impacts

Senge's systems thinking emphasizes recognizing interdependencies, feedback loops, and collective sensemaking within organizations. By viewing an organization as an interconnected system, leaders and teams can identify underlying structural causes of problems rather than merely addressing surface symptoms (Senge, 1990). AI can bolster this perspective by revealing hidden patterns or, if lacking transparency, undermine it through "black box" processes that obscure broader consequences (Dwivedi et al., 2021; Leslie, 2019). Thus, the central question is: Under what organizational conditions does AI act as a catalyst for systems thinking, and when does it fragment holistic inquiry?

AI-Influenced Feedback Loops

In a digitally enabled organization, real-time analytics and machine learning operate as integral components of the feedback loops that shape adaptive learning (Chen et al., 2023; Grønsund & Aanestad, 2020). By rapidly collecting data on outcomes and feeding it back to decision-makers – or directly into operational systems – AI can tighten the loop between action and response. When well-managed, these AI-driven feedback loops align with Senge's call for holistic adaptation by enhancing responsiveness and resilience. Nevertheless, black box algorithms risk limiting deeper inquiry to surface-level metrics if organizations fail to examine how models arrive at decisions (Bohanec et al., 2017; Leslie, 2019). A human-in-the-loop approach can mitigate this issue, ensuring user oversight continuously refines AI outputs (Grønsund & Aanestad, 2020). In this sense, AI's effectiveness depends on both technical calibration, such as setting thresholds, and organizational readiness, which may manifest as psychological safety and data literacy that enables employees to question and interpret AI's conclusions (Li & Yeo, 2024; Makarius et al., 2020).

Cross-Functional Learning via AI

An essential tenet of systems thinking is recognizing how interdependencies span across departmental or functional boundaries (Senge, 1990). Well-implemented AI can surface systemic bottlenecks – catalyzing cross-functional conversations that lead to more transformative solutions (Agrawal et al., 2024; Bienefeld et al., 2023). Many organizations now form cross-functional AI teams, embedding data scientists with domain experts so that ML-driven insights can be collaboratively translated into process changes (Ransbotham et al., 2020).

This approach fosters collective learning, in which employees from different units learn not only from the AI but also from each other's expertise – essential for understanding how local changes ripple through the broader organizational system. Human-AI collaboration amplifies this effect: while algorithmic feedback might highlight a performance gap, human experts offer contextual knowledge to interpret the gap and adjust workflows accordingly (Engström et al., 2024; Jarrahi, 2018; Jarrahi, Askay, et al., 2023). Over time, the organization develops a unified data culture that sees AI-driven insights as a catalyst for iterative improvement, reinforcing Senge's call to break down silos and cultivate feedback loops that span the entire enterprise. However, incomplete or siloed AI applications risk fragmenting that holistic view, limiting the organization's ability to connect insights across departments (Olan et al., 2022).

Integrating AI-Specific Learning Mechanisms into Organizational Learning

To summarize and visualize these points of intersection between AI and the classical organizational learning theories, Table 1 maps key AI mechanisms to their impact on organizational learning processes, illustrating how each technology can influence single and double-loop learning, exploration and exploitation activities, and system-wide adaptation.

Table 1. AI Mechanisms and Learning Outcomes

AI Mechanism	Single-Loop Learning	Double-Loop Learning	Exploration	Exploitation	Systems Impact
Machine Learning	Error correction, Process optimization	Pattern detection challenging assumptions	Novel insights discovery	Routine task automation	Cross-functional data integration
Human-AI Collaboration	Task efficiency	Collective reflection	Creative problem-solving	Knowledge codification	Interdepartmental coordination
Real-time Analytics	Performance monitoring	Strategy questioning	Opportunity detection	Process refinement	Dynamic feedback loops
Algorithmic Feedback	Behavior adjustment	Norm examination	Novel pattern identification	Standard enforcement	System-wide learning

Note. The impacts listed represent potential outcomes dependent on implementation context and organizational factors.

Moderating Effects

As outlined in the Chapter 2, four moderating factors – leadership, organizational culture, ethics, and digital maturity – consistently emerge as pivotal elements that shape how AI tools influence learning processes. Rather than reiterate each detail here, Table 2 provides a concise overview of how each of the four variables influence one another.

Table 2. Moderating Variables Interaction Matrix

Variable	Leadership	Culture	Ethics	Digital Maturity
Leadership	–	Shapes learning mindset	Sets ethical guidelines	Drives tech adoption
Culture	Influences leadership style	–	Ethical norm acceptance	Innovation readiness
Ethics	Guides decision-making	Shapes values	–	Implementation pace
Digital Maturity	Resource allocation	Tech acceptance	Risk management	–

Note. Table entries highlight the directional influence among four organizational variables. A dash (–) indicates no direct cell entry where the same factor would influence itself. This table provides a conceptual overview of how each variable (leadership, culture, ethics, and digital maturity) interrelates to shape organizational learning and AI adoption.

Boundary Conditions

This section outlines several boundary conditions that define where and how this conceptual model of AI-driven organizational learning is applicable, as well as its limitations. These boundary conditions clarify the prerequisites and situational factors for the model, and they highlight areas for further investigation.

Organization Size

Larger organizations typically benefit from greater resource availability, enabling substantial investments in AI infrastructure and the allocation of dedicated teams to research, pilot, and scale new solutions (Benbya et al., 2020). Yet these same organizations face coordination complexity: additional employees, departments, and managerial layers can create knowledge-sharing hurdles that impede AI's ability to learn from past projects (Olan et al., 2022). Even with abundant resources, large companies risk duplicating AI efforts across units if they lack a unifying strategy – highlighting the need for careful governance when moving from experimentation to full production. Smaller organizations may move faster thanks to simpler structures, and may have a more participative culture (Banasiewicz, 2021) but they often face tighter budgets that limit their capacity for sustained AI initiatives. In either case, leaders should align AI adoption with well-defined goals and governance structures that match their organization's size, ensuring that resource strength (or limitations) does not undermine an effective, cohesive approach to AI.

Industry Context

Competitive pressure often acts as a potent enabler, spurring organizations – especially in fast-moving sectors like technology and e-commerce – to adopt AI aggressively for efficiency, innovation, and market differentiation. However, regulatory constraints in healthcare, finance, or public services (Katirai & Nagato, 2024; Leslie, 2019) can significantly complicate or slow AI deployment, given stringent data privacy laws and compliance requirements. Sector-specific needs further shape how AI is applied – whether optimizing supply chains, customizing product recommendations, or automating high-risk operations – underscoring the importance of aligning AI strategies with each industry's risks and demands (Banasiewicz, 2021). Meanwhile, industry dynamics determine whether AI primarily supports short-term operational refinements or continuous discovery (Ladu et al., 2024). Across diverse contexts, organizational culture also plays a crucial moderating role, influencing how effectively AI capabilities translate into performance gains (Bley et al., 2022). Ultimately, successful AI adoption balances the urgency of competitive forces with the vigilance demanded by regulatory landscapes.

Technical Infrastructure

High-quality data and reliable IT systems are vital enablers of AI adoption, allowing machine learning algorithms to generate accurate insights from robust datasets (Kar et al., 2021). In contrast, legacy systems and poor infrastructure integration frequently undermine seamless analytics deployment, creating compatibility issues that lead to disjointed data pipelines (Benbya et al., 2020). Moreover, process inconsistencies and inadequate interdepartmental coordination can further disrupt AI integration, while data quality and transparency problems erode the reliability of AI outputs (Dwivedi et al., 2021; Leslie, 2019). To address these barriers, organizations must align new AI platforms with existing infrastructures – a critical success factor often termed integration capacity. This can involve modernizing data warehousing, unifying data standards, or establishing real-time analytics capabilities. Ultimately, clear data governance and interoperability not only ensure that AI initiatives remain cohesive and scalable but also prevent them from devolving into isolated pilot projects (Benbya et al., 2020; Booyse & Scheepers, 2024; Leslie, 2019).

Workforce Capability

Digital literacy is critical for employees to effectively implement AI tools, interpret analytics, and translate insights into improved workflows; yet many workers view AI as a threat to professional autonomy, resulting in resistance and passive engagement (Booyse & Scheepers, 2024; Engström et al., 2024). This hesitation can undermine AI's potential for fostering organizational learning. Therefore, companies must offer upskilling and training programs (Benbya et al., 2020; Kar et al., 2021; Shrivastav, 2022) and cultivate psychological safety so team members can openly discuss uncertainties (Li & Yeo, 2024). In addition, it is essential to align social, cultural, and managerial processes with AI initiatives, thus ensuring that technical adoption is accompanied by supportive policies, transparent communication, and a learning-oriented culture (Makarius et al., 2020). By proactively addressing concerns, leaders empower employees to build the confidence and skill sets needed to fully leverage AI-driven innovations (Benbya et al., 2020; Booyse & Scheepers, 2024; Engström et al., 2024).

Table 3 outlines key boundary conditions that influence AI-enabled organizational learning, identifying specific enablers and barriers across organizational characteristics. This framework helps leaders assess readiness for AI adoption and anticipate implementation challenges.

Table 3. Boundary Conditions and Implementation Factors

Factor	Enablers	Barriers	Key Considerations
Organization Size	Resource availability	Coordination complexity	Scale of implementation
Industry Context	Competitive pressure	Regulatory constraints	Sector-specific needs
Technical Infrastructure	Data availability	Legacy systems	Integration capacity
Workforce Capability	Digital literacy	Resistance to change	Training needs

Note. This table synthesizes findings from multiple studies examining factors that enable or constrain AI implementation in organizations (Banasiewicz, 2021; Benbya et al., 2020; Bley et al., 2022; Booyse & Scheepers, 2024; Dwivedi et al., 2021; Engström et al., 2024; Kar et al., 2021; Katirai & Nagato, 2024; Ladu et al., 2024; Leslie, 2019; Makarius et al., 2020; Olan et al., 2022). The factors identified represent common patterns across different organizational contexts, though their specific impact may vary based on individual circumstances and implementation approaches.

A Holistic, Multi-Layer Conceptual Model

This thesis proposes a holistic conceptual model that situates four prominent AI tools – machine learning, human-AI collaboration, big data and real-time analytics, and algorithmic feedback – within the theoretical frameworks of Argyris and Schön, March, and Senge. As shown in Figure 2, the model underscores how each AI mechanism can either reinforce existing practices or catalyze deeper, transformative learning, depending on several contextual moderators such as leadership style, organizational culture, digital maturity, and industry regulations. By integrating three classical theoretical lenses – Argyris and Schön's single- vs. double-loop learning, March's exploration–exploitation framework, and Senge's systems thinking – the model captures the depth, focus, and holistic scope of learning processes. Placing key AI tools at the model's core highlights how these technologies can shift organizational learning along multiple dimensions, from superficial, single-loop corrections to deeper, double-loop questioning; from exploitative efficiency to exploratory innovation; and from siloed decisions to system-wide adaptation. Meanwhile, surrounding boundaries and contextual moderators further determine whether AI deployments remain incremental or spark meaningful transformation. Ultimately, this layered design underscores that AI alone does not predetermine outcomes; rather, the organizational environment, theoretical interpretation, and strategic usage of these tools collectively decide whether learning remains narrowly task-focused or evolves into wide-reaching reconfigurations of norms, strategies, and interdependencies.

Outer Boundary Conditions Layer

Encircling the core components of the conceptual model is a boundary conditions layer, which recognizes that organizational learning and AI adoption never occur in isolation. Factors such as organization size, industry context, technical infrastructure, and workforce capability can either catalyze or impede the integration of AI tools. By acknowledging these boundary conditions, the model emphasizes that external and contextual factors must be aligned with internal AI strategies for learning initiatives to achieve their full potential

Contextual Layer

Within the boundary conditions lie the organizational moderators that shape AI adoption. Leadership and culture determine the degree to which employees feel safe challenging AI outputs, reflecting Argyris and Schön's (1978) emphasis on deeper inquiry. Similarly, digital maturity and ethical considerations, can push AI deployments toward short-term efficiency (exploitation) or encourage experimentation (exploration), aligning with March's (1991) exploration–exploitation framework.

AI Tools Layer

Inward from the contextual layer are the four AI applications. Each technology can be deployed in single-loop or double-loop manners (Argyris & Schön, 1978); can bias organizations toward exploitation or exploration (March, 1991); and can unify or fragment system-wide feedback loops (Senge, 1990). For instance, automated decision-making may improve error-correction (single-loop) but also risk entrenching existing assumptions unless consciously evaluated for double-loop potential.

Theoretical Core

At the center of the model are the theoretical lenses that interpret the impact of AI on learning processes.

Argyris and Schön: Does AI use encourage only short-term fixes (Model I) or provoke reflection on deeper norms (Model II)?

March: Are advanced analytics and machine learning deployed for radical innovation (exploration) or merely refining current operations (exploitation)?

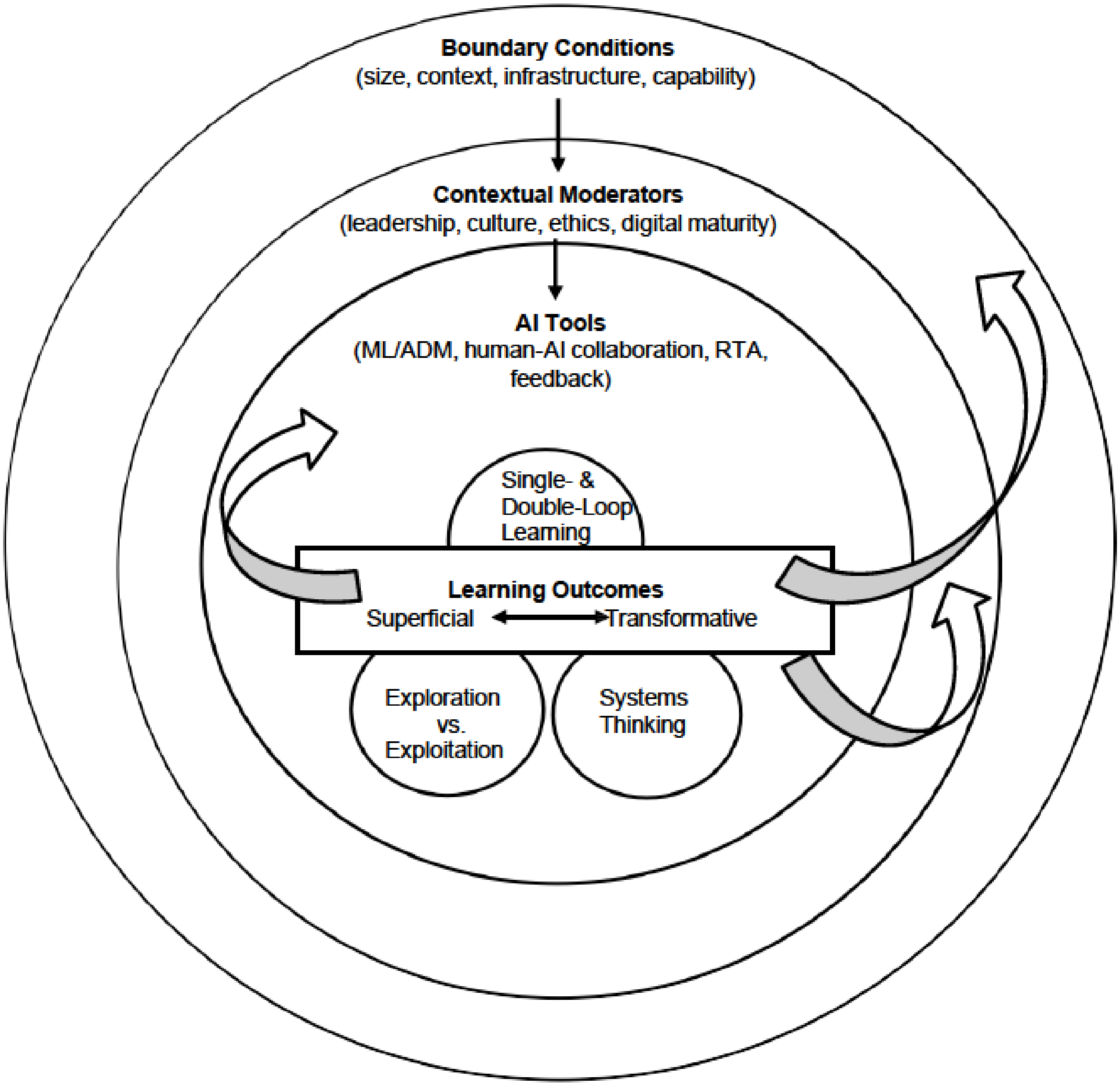
Senge: To what extent do big data systems and collaborative AI help organizations see interdependencies, fostering holistic adaptation versus siloed decision-making?

Learning Outcomes

Finally, the model culminates in a range of organizational learning outcomes, from superficial improvement (single-loop, exploitative, fragmented) to transformative adaptation (double-loop, exploratory, system-wide). By indicating feedback loops – both literal (in big data analytics) and figurative (in reflection processes) – the model shows how initial AI deployments can generate insights that, if harnessed, reshape organizational norms and strategy. Conversely, if leadership or culture suppress broader questioning, AI may simply automate existing routines or performance metrics, hindering transformative learning.

This integrated model aims to address the central research question –"Which theoretical perspectives best explain AI's role in enabling (or hindering) organizational learning?" – by illustrating how Argyris and Schön, March, and Senge each shed light on distinct but complementary dimensions of learning. While AI tools can deliver rapid feedback and high-efficiency operations, their real power lies in sparking double-loop reflection (Argyris & Schön), balancing exploration and exploitation (March), and promoting system-wide sensemaking (Senge). The contextual layer influences whether these potential benefits manifest fully, remain partially realized, or devolve into superficial automation.

Figure 2. Conceptual Model



Note. Adapted from the theoretical foundations of Argyris and Schön (1978), March (1991), and Senge (1990), this conceptual model illustrates how AI tools (machine learning, human-AI collaboration, big data/real-time analytics, and algorithmic feedback) may interact with key contextual moderators (leadership style, organizational culture, ethics, digital maturity) to influence learning outcomes, from superficial, single-loop fixes to transformative, double-loop and system-wide changes. The model is intended as a guiding framework rather than an exhaustive depiction, opening opportunities for future empirical validation and refinements.

In sum, this conceptual framework synthesizes Argyris and Schön's (1978) focus on single- vs. double-loop learning, March's (1991) emphasis on exploration-exploitation, and Senge's (1990) systems thinking, mapping these perspectives to four core AI applications – machine learning/automated decision-making, collaborative human-AI approaches, big data and real-time analytics, and algorithmic feedback. Each AI tool can shape organizational learning in distinct ways, from routine corrective measures to more transformative, system-wide adaptations. Moreover, contextual moderators and boundary conditions influence whether AI-enabled practices reinforce superficial gains or catalyze deeper, reflective change. By integrating these elements into a holistic, multi-layer model, the framework underscores that AI does not unilaterally determine outcomes; rather, successful learning depends on how organizations structure their AI initiatives, manage potential tensions, and embed ethical, leadership, and cultural considerations. The following chapter builds on these insights, detailing how this conceptual model will guide empirical inquiries, practical applications, and further theoretical development.

Chapter 4. Methodology

This chapter outlines the methodological approach used to develop the conceptual framework for understanding how AI tools interact with organizational learning theories. Unlike an empirical study that collects and analyzes primary data, this conceptual thesis draws on extensive literature analysis to identify core constructs, integrate diverse perspectives, and propose a coherent model. The steps below detail how key theories were selected, how AI applications were reviewed, and how these elements were combined to form the final conceptual model.

This research adopts a conceptual design intended to synthesize and integrate existing scholarly work on AI-driven practices and organizational learning theories (Argyris & Schön, 1978; March, 1991; Senge, 1990). Rather than collecting primary data through surveys or interviews, the focus is on critically evaluating and cross-referencing the literature to generate new insights and develop a comprehensive framework.

Rationale for a Conceptual Thesis

When this thesis was initially conceived, the plan was to conduct a systematic literature review focusing on how AI influences organizational learning. Preliminary searches, however, revealed an insufficiency of direct, robust sources that specifically address the intersection of AI and organizational learning theory. Most articles discussing AI's impact tended to focus on human resource development (HRD) or knowledge management (KM) – offering insights into training programs, talent acquisition, and knowledge-sharing systems – but rarely delving into how AI might shape deeper learning processes like double-loop reflection, the exploration-exploitation balance, or system-wide adaptation. As a result, attempts to conduct a standard empirical or systematic review encountered fragmented and siloed pieces of evidence that did not fully illuminate how organizations learn at a structural or cultural level with AI.

Given this gap, a conceptual thesis approach emerged as the most suitable method. Conceptual research allows for theoretical integration when literature on a specific topic – here, AI-enabled organizational learning – is scarce or diffuse. By synthesizing classical organizational learning theories (Argyris & Schön, 1978; March, 1991; Senge, 1990) with emerging AI scholarship from HRD, KM, and broader management contexts, a conceptual framework can be constructed to explain why and how AI technologies might alter the depth, focus, and scope of learning processes across an organization. Rather than gathering new data or statistically verifying existing findings, this conceptual approach positions the study to bridge multiple research domains and propose a cohesive model that future empirical work can test and refine.

Furthermore, designing a conceptual thesis aligns with the goal of theoretical advancement: building on existing theories, highlighting potential gaps, and suggesting new avenues for empirical studies. As literature on AI in organizational settings concentrates heavily on operational gains or knowledge-sharing systems, little attention has been given to deeper organizational transformations like questioning entrenched assumptions or orchestrating system-wide change. Conceptualizing AI's role in these deeper processes thus adds value to both the fields of organizational learning and AI-driven management by offering an integrated lens and hypothesized relationships that future research can explore in more detail.

In short, the lack of direct scholarship specifically addressing AI-enabled organizational learning-beyond HRD or KM contexts necessitated a theoretical synthesis rather than a strictly empirical or purely systematic review approach. This conceptual thesis not only offers a structured framework that combines multiple theories and AI practices, but also helps anchor subsequent empirical inquiries, ensuring that investigators can build on a solid theoretical base when examining how AI truly reshapes how organizations learn, adapt, and innovate.

Scope and Selection Criteria

A wide range of academic and practitioner sources were initially scanned to capture both theoretical and practical dimensions of AI's influence on organizational learning. To maintain rigor and relevance, the following section outlines source search methodology, inclusion and exclusion criteria, quality assessment metrics, and coding methods that were used.

Literature was gathered from academic databases as well as key journals in organizational behavior, education, management, information systems, and AI research. Priority was given to peer-reviewed journals, conference proceedings, and scholarly books that offer academic rigor. Where multiple sources addressed similar topics, those in highly ranked or well-regarded journals were prioritized, ensuring a foundation of established, widely recognized work. Highly cited AI-related articles were prioritized to maintain strong theoretical grounding and capture seminal insights. More recent AI publications with growing citation trends were also examined to capture emerging scholarly discourse. Each source was recorded in Zotero, excluded sources were tagged and briefly annotated with reasons for exclusion and for potential revisitation later. The literature search was conducted using several academic databases, including EBSCOhost (Business Source Complete, Academic Search Premier), ProQuest and Google Scholar.

Inclusion Criteria

- Primary focus on 2015-2025 literature (with exceptions for seminal works).
- English-language publications.
- Peer-reviewed journals, conference proceedings, and scholarly books.
- Direct connection to organizational learning and/or AI implementation.
- Emphasis on organizational-level analysis rather than individual learning.
- Publications with clear methodology or a robust theoretical framework.

Exclusion Criteria

- Non-scholarly sources (unless representing significant industry insights).
- Studies focused solely on technical aspects of AI without an organizational learning context.
- Papers discussing only individual learning without broader organizational implications.
- Publications lacking clear methodological or theoretical foundations.
- Sources focusing exclusively on AI implementation without learning considerations.

The search strategy focused on three major clusters of terms:

1. **Core Concepts in Organizational Learning and AI**

- "Organizational learning"
- "Learning organization"

2. **Classical Theoretical Lenses**

- “Argyris and Schön” OR “single-loop learning” OR “double-loop learning”
- “March exploration-exploitation” OR “exploration and exploitation”
- “Senge systems thinking” OR “fifth discipline”

3. **AI-Specific Terms**

- “Artificial intelligence” OR “AI”
- “Machine learning” OR “automated decision-making”
- “Big data analytics” OR “real-time analytics”
- “Algorithmic feedback”

Table 4. Examples of Boolean Operators Used

Example Query	Description
"Organizational learning" AND "artificial intelligence"	To capture intersections between general learning processes and AI
("Double-loop learning" OR "reflective inquiry") AND ("machine learning" OR "automated decision-making")	To identify studies discussing deep learning processes in AI contexts
("Exploration and exploitation" OR "ambidexterity") AND ("big data" OR "real-time analytics")	To capture literature on resource allocation and innovation in AI
"Systems thinking" AND ("algorithmic feedback" OR "human-AI collaboration")	To find studies linking systemic feedback with AI tools

Combinations of relevant keywords were used, such as “organizational learning,” “AI,” “machine learning,” “Argyris & Schön,” “March exploration-exploitation,” “Senge systems thinking,” “big data analytics,” and “algorithmic feedback.” Studies were included if they engaged directly with one of the three theories (Argyris and Schön, March, Senge) or discussed AI-driven practices within organizational settings, particularly in relation to learning and adaptation. Empirical, conceptual, and review articles were all considered.

Search Results Summary

Initial Search: Approximately 200 results were identified after removing duplicates.

Title/Abstract Screening: 100 articles were excluded due to insufficient focus on AI in organizational learning or a lack of connection to learning theories.

Final Set: 86 articles were selected for full-text review and conceptual coding.

Conceptual Coding Process

Using an iterative coding process, emergent themes were identified from the literature. Codes were developed for core constructs such as:

1. Learning Processes: Single-loop learning, double-loop learning, exploration, exploitation, and systems thinking.
2. Moderating Factors: Leadership, organizational culture, ethics, and digital maturity.
3. Contextual Variables: Organization size, industry context, technical infrastructure, and workforce capability.

For instance, articles addressing "single-loop error correction" or "routine performance fixes" were tagged under single-loop learning, while those exploring deeper norm questioning were tagged as double-loop learning. Codes for moderating factors were applied when studies discussed the influence of leadership style, cultural readiness, ethical governance, or digital maturity on AI's impact.

Key Journals & Outlets

Priority, when possible, was given to sources from high-impact and widely recognized journals and outlets, including:

- *Management Science*
- *Organization Science*
- *Business Horizons*
- *Information Systems Journal*
- *Journal of Business Research*
- *MIS Quarterly*
- *MIT Sloan Management Review*
- *Academy of Management Review*
- *Harvard Business Review*

Identifying Core Constructs

Building upon the initial literature scan and theoretical review discussed earlier, this research sought to pinpoint the specific elements most relevant to understanding how AI shapes organizational learning. Two main sources guided this process: the classical organizational learning theories of Argyris & Schön (1978), March (1991), and Senge (1990), and the emerging AI-focused literature, which, while fragmented, provided clues to the various mechanisms by which AI can influence deeper learning processes.

Drawing on Argyris and Schön's (1978) distinction between single- vs. double-loop learning, March's (1991) emphasis on exploration vs. exploitation, and Senge's (1990) systems thinking approach, key theoretical dimensions that underlaid organizational learning were identified. For example, error correction vs. norm questioning, short-term efficiency vs. long-term innovation, and local vs. system-wide adaptation emerged as significant axes along which AI might exert its influence. These themes served as a conceptual scaffolding for interpreting how AI tools do more than merely automate tasks.

The second phase involved examining AI-related articles across human resource development (HRD), knowledge management (KM), and broader management domains. While few articles addressed "organizational learning" explicitly, this cross-domain review revealed consistent references to four main AI applications: machine learning (ML) and automated decision-making, human-AI collaboration, big data and real-time analytics, and algorithmic feedback. Each of these applications was repeatedly described as a mechanism through which organizations either expand their knowledge base, reinforce existing routines, or innovate in new directions. Hence, these four AI tools were abstracted as core constructs that capture how AI practically manifests in daily operations and strategic initiatives.

Beyond these theoretical and AI-centric constructs, many studies highlighted contextual factors – for instance, leadership, organizational culture, ethics, digital maturity, and industry constraints – that significantly shape whether AI accelerates deeper learning or reinforces shallow compliance. In parallel, discussions around organization size, technical infrastructure, and workforce capability prompted the inclusion of boundary conditions to account for differences in resources, regulatory pressures, and skill sets. As these factors appeared consistently across diverse sources, they were formalized as additional constructs that situate AI-driven learning within its organizational and environmental context.

Having compiled multiple thematic leads, the final step involved validating these constructs through iterative mapping: each concept or dimension was checked against both the classical learning theories and the AI literature to ensure relevance and coherence. Constructs that lacked direct linkage to the identified theories (for example, purely technical aspects without a learning angle) were either merged into broader categories or excluded. The outcome of this refinement was a concise set of interrelated constructs – theoretical lenses (single-/double-loop, exploration-exploitation, systems thinking), AI mechanisms (ML & automated decision-making, human-AI collaboration, big data & real-time analytics, algorithmic feedback), moderators (leadership, culture, ethics, digital maturity), and boundary conditions (organization size, industry context, technical infrastructure, workforce capability) – which, when integrated, formed the basis of the final conceptual model.

Iterative Refinement

Although the initial methodology outlined a standard review of literature linking AI and organizational learning, early searches and discussions with my supervisor revealed limited direct studies examining how AI interacts with deeper organizational-level processes as defined by Argyris & Schön, March, and Senge. Most articles addressed workplace training or HRD topics – useful but not always aligned with organizational learning constructs like single-/double-loop change, exploration-exploitation, or systemic feedback loops.

Given these constraints, our approach shifted toward a conceptual framework, synthesizing classical theories with AI scholarship from diverse fields. This shift is iterative: each draft of the conceptual model undergoes supervisor review, revealing gaps in the literature or opportunities to incorporate newly surfaced articles. For instance, feedback reiterated that AI-focused research commonly addresses individual skills or learning and development programs, reinforcing the need for a more holistic framework that highlights collective learning dynamics.

Chapter 5. Analysis and Discussion

Building on the conceptual framework outlined in Chapter 3, this section integrates the theoretical lenses of Argyris and Schön (1978), March (1991), and Senge (1990) with the four core AI mechanisms – machine learning and automated decision-making (ML/ADM), human-AI collaboration, big data and real-time analytics, and algorithmic feedback – to examine how organizations learn and adapt in today's digital landscape. While Argyris and Schön highlight how the differences between single-loop (surface-level) and double-loop (transformative) learning, March's exploration-exploitation framework offers insights into balancing short-term operational efficiency with long-term strategic innovation. Meanwhile, Senge's systems thinking underscores the importance of recognizing interdependencies, feedback loops, and collective sensemaking.

This chapter opens with an in-depth look at how each AI mechanism can, in practice, reinforce either superficial or deeper learning behaviors, reviewing Argyris and Schön's emphasis on reflective inquiry, March's tension between exploitation and exploration, and Senge's interconnected systemic view of organizations. It then considers how moderating factors – namely leadership (Bevilacqua et al., 2025; Divya et al., 2024), organizational culture (Bley et al., 2022; Rožman et al., 2023), ethics (Katirai & Nagato, 2024; Leslie, 2019), and digital maturity (Ladu et al., 2024) – shape AI's capacity to prompt constructive examination or entrench existing norms. In parallel, boundary conditions – covering organization size, industry context, technical infrastructure, and workforce capability – further refine our understanding of why AI may spark profound organizational transformation under certain conditions but yield more modest or piecemeal outcomes elsewhere.

As these discussions unfold, it is important to acknowledge certain limitations of this conceptual approach, including the fragmented nature of existing AI scholarship on organizational learning and the lack of direct empirical evidence tying AI to each theoretical lens. These constraints – addressed at the close of this chapter – do not undermine the analysis but rather clarify the need for future validation and adaptation of the proposed model in real-world contexts.

The discussion that follows will synthesize these insights to evaluate the conceptual model's ability to account for AI-specific challenges – such as black-box opacity (Ardichvili, 2022; Banasiewicz, 2021; Bohanec et al., 2017), data-driven routines that shape employee behavior (Banasiewicz, 2021), and real-time analytics that potentially accelerate both exploitation and exploration (Chen et al., 2023; Shi et al., 2024). In doing so, the aim is to clarify whether AI's introduction fosters only incremental, single-loop corrections or encourages a double-loop rethinking of fundamental assumptions. This section also weighs how AI mediates the exploration-exploitation trade-off March originally proposed, and whether Senge's holistic systems thinking can accommodate AI's capacity to rewire feedback loops across departments (Grønsund & Aanestad, 2020). By examining the emergent practices in AI adoption, this chapter will provide theoretical and practical insights on leveraging AI to enhance, rather than merely automate, core learning processes in organizations.

Revisiting AI Tools and Organizational Learning

This section evaluates how each of the four key AI tools – machine learning/automated decision-making (ML/ADM), human-AI collaboration, big data and real-time analytics, and algorithmic feedback – can enable or hinder deeper organizational learning. The analysis connects each tool to the three foundational learning theories to illustrate whether AI fosters superficial or transformative learning, promotes short-term efficiency or long-term innovation, and breaks silos or reinforces them.

Machine Learning and Automated Decision-Making

ML systems can expedite error correction by continuously adjusting processes to align with preset objectives (Bohanec et al., 2017; Johnson et al., 2022; Wamba-Taguimdje et al., 2020). This rapid alignment supports single-loop learning, whereby deviations are swiftly remedied without necessarily questioning underlying goals or assumptions (Ardichvili, 2022; Wilkens, 2020). Conversely, ML-driven insights – especially when unexpected or counterintuitive – can highlight deeper flaws in strategic direction or entrenched routines, prompting double-loop inquiries (Bohanec et al., 2017). Whether such transformative learning occurs depends on the presence of organizational checkpoints that challenge the boundaries of routine, single-loop corrections (Dwivedi et al., 2021).

ADM often focuses on exploiting known patterns and refining existing processes, supporting short-term productivity gains (Banasiewicz, 2021; Bohanec et al., 2017). Yet well-designed ML systems can simultaneously feed exploration by detecting novel correlations, suggesting product innovations, or revealing untapped customer segments (Berente et al., 2021). The organization's success in balancing these modes depends on leadership and resource allocation: while overemphasizing exploitative efficiency can sap resources from radical innovation (Berente et al., 2021; Dwivedi et al., 2021; Wamba-Taguimdje et al., 2020; Wilkens, 2020), strategic budgeting for ML experimentation can catalyze new organizational possibilities (Jarrahi, Kenyon, et al., 2023; Johnson et al., 2022; Kakatkar et al., 2020; Sturm et al., 2021).

By rapidly processing large data sets and feeding the results back to operators, ML/ADM tools can form integral parts of feedback loops that transcend departmental silos – improving real-time decision quality in manufacturing, supply chain management, or customer service. However, opacity – commonly referred to as the "black box problem" (Ardichvili, 2022; Banasiewicz, 2021; Bohanec et al., 2017) – may obstruct a holistic understanding of how decisions are reached, undermining the systemic clarity crucial to Senge's emphasis on interdependencies and collective sensemaking. If ML outputs are taken at face value without reflection on root causes or system-wide impacts, the broader potential for holistic learning may remain untapped.

Human-AI Collaboration

Collaboration between human experts and AI agents can be a major enabler of deeper reflection, provided organizational structures encourage critical dialogues around AI-generated recommendations (Engström et al., 2024; Herrmann & Pfeiffer, 2023; Jarrahi, 2018; Jarrahi, Kenyon, et al., 2023). In many cases, collaborative AI allows humans to refine or question AI outputs, potentially challenging underlying norms or assumptions (Bohanec et al., 2017; Grønsund & Aanestad, 2020; Jarrahi, Askay, et al., 2023). If, however, human-AI interaction is merely used to validate existing routines or to expedite repetitive tasks, the outcome may default to single-loop corrections, limiting the scope of reflective inquiry (Ardichvili, 2022; Sturm et al., 2021; Wilkens, 2020).

Human-AI teams can sharpen exploitation through more reliable, data-driven decisions and standardized workflows (Berente et al., 2021; Johnson et al., 2022; Puranam, 2021; Wamba-Taguimdje et al., 2020). Human-AI collaboration can foster exploration through creative problem-solving and novel pattern identification (Jarrahi, 2018; Sturm et al., 2021). Such collaborations enable organizations to augment their exploratory capabilities through sophisticated data analysis and strategic innovation (Johnson et al., 2022). The ambidextrous potential (O'Reilly & Tushman, 2013) of AI implementations depends on leadership approaches that balance process optimization with innovation opportunities (Bevilacqua et al., 2025). Rather than confining AI to routine automation, effective leaders guide its application toward both exploitative efficiency gains and exploratory innovation (Divya et al., 2024; Peifer et al., 2022).

Human-AI collaboration enables cross-functional knowledge exchange, where data scientists and domain experts collaboratively translate AI-driven insights into meaningful organizational changes (Ransbotham et al., 2020). This collective sensemaking is exemplified in organizations that form cross-functional AI teams to combine technical and domain expertise (Agrawal et al., 2024; Bienefeld et al., 2023). This cross-functional synergy mirrors the feedback loops in Senge's systems thinking, ensuring that new insights propagate across departmental boundaries. Yet even a well-conceived AI tool can fail to achieve systemic learning if departments remain siloed (Kar et al., 2021; Olan et al., 2022) or if senior leadership does not cultivate an environment for open data sharing (Bley et al., 2022; Rožman et al., 2023). The key lies in designing sociotechnical structures – aligning people, processes, and AI technologies to integrate knowledge system-wide (Li & Yeo, 2024; Makarius et al., 2020).

Big Data and Real-Time Analytics

Real-time analytics can heighten error correction by offering near-instant feedback on operational discrepancies (Banasiewicz, 2021; Chen et al., 2023). This supports single-loop learning, as teams swiftly rectify anomalies based on continuously updated dashboards (Calvard, 2016). More profound double-loop reflection emerges when anomalies challenge deep-seated assumptions (Bohanec et al., 2017), or when real-time analytics uncover systemic process failures that spark reevaluation of strategic goals (Jarrahi, Askay, et al., 2023). Organizations lacking structured reflection practices may never pivot to double-loop inquiry, treating real-time data as a tool for incremental improvement alone (Ardichvili, 2022; Dwivedi et al., 2021; Wilkens, 2020).

Moreover, real-time analytics enable managers to fine-tune day-to-day routines (exploitation) while simultaneously offering a testing ground for experimental changes (exploration) (Johnson et al., 2022; Shi et al., 2024). By minimizing delays between actions and outcomes, data-driven dashboards accelerate learning cycles, letting organizations quickly validate pilot projects or novel solutions (Berente et al., 2021; Sturm et al., 2021). Yet if leadership overemphasizes short-term performance metrics, real-time analytics can devolve into a continuous push toward exploitation at the expense of more daring or strategic experiments (Ardichvili, 2022; Wilkens, 2020).

Big data streams and real-time analytics lend themselves to Senge's notion of feedback loops, potentially making complex interdependencies visible across multiple functional areas (Chen et al., 2023; Grønsund & Aanestad, 2020). However, without organizational mechanisms for cross-functional collaboration (Agrawal et al., 2024; Bienefeld et al., 2023), such data may stay siloed – limiting its impact on system-wide adaptation (Olan et al., 2022). Data alone does not guarantee systems thinking; the organizational culture (Bley et al., 2022) and structure must support the iterative sensemaking and open discussion required to interpret data patterns in a holistic manner (Jarrahi, Kenyon, et al., 2023; Rožman et al., 2023).

Algorithmic Feedback

Algorithmic performance metrics and continuous comparisons can reinforce Model I norms if employees merely adjust behaviors to meet targets without questioning underlying goals (Ardichvili, 2022; Faraj et al., 2018). This scenario often results in single-loop compliance. However, the same algorithmic tools can provoke double-loop inquiries if unexpected feedback challenges established practices and prompts employees to reexamine embedded assumptions (Bohanec et al., 2017; Ransbotham et al., 2020). The organization's stance – whether receptive to "inconvenient truths" or defensive (Li & Yeo, 2024) – often determines whether algorithmic feedback drives genuine reflection or superficial fixes (Bley et al., 2022; Jarrahi, Kenyon, et al., 2023; Rožman et al., 2023).

Additionally, algorithmic feedback typically emphasizes exploitation by providing real-time key performance indicators (KPIs), refining daily routines (Berente et al., 2021; Wamba-Taguimdje et al., 2020). Yet it can also serve an exploratory function if managers leverage insights to pivot resources into new ventures (Kakatkar et al., 2020; Soni et al., 2020). For instance, a feedback system highlighting an unprofitable product might spark radical reinvention or lead to more cautious cost-cutting, depending on leadership's appetite for experimentation versus short-term efficiency (Johnson et al., 2022; Sturm et al., 2021).

By quantifying an individual's or team's performance, algorithmic feedback influences how people perceive interdependencies across the system. Properly designed, these metrics can form part of broader organizational loops – where changes at one node affect another., in a reinforcing or balancing manner (Chen et al., 2023; Grønsund & Aanestad, 2020; Senge, 1990). However, if the organization does not integrate these metrics across departments (Agrawal et al., 2024) or if the algorithmic approach remains opaque (Dwivedi et al., 2021; Leslie, 2019), deeper system-wide insights may be lost, fragmenting the holistic perspective that Senge champions (Olan et al., 2022).

Overall, each AI tool – ML/ADM, human-AI collaboration, big data and real-time analytics, and algorithmic feedback – intersects differently with Argyris and Schön's single- and double-loop learning, March's exploration-exploitation framework, and Senge's systems thinking. The extent to which AI reinforces superficial fixes versus catalyzes deeper transformation depends not only on the technology's design but also on organizational readiness, leadership vision, cultural openness, and ethical oversight. The next section expands on these moderating influences before synthesizing how the interplay among tools, moderators, and boundary conditions shapes final learning outcomes.

Role of Moderators in AI-Enabled Learning

Although the AI tools outlined offer considerable potential to transform organizational learning, their actual impact is heavily shaped by leadership, culture, ethics, and digital maturity (Ashok et al., 2022; Bevilacqua et al., 2025; Bley et al., 2022; Ladu et al., 2024; Leslie, 2019). These moderating factors condition whether AI initiatives reinforce single-loop corrections, double-loop shifts in norms (Argyris & Schön, 1978), a strategic balance of exploration vs. exploitation (March, 1991), and a holistic, system-wide perspective (Senge, 1990).

Leadership

Leaders critically determine whether AI-driven insights remain surface-level fixes or spark deeper questioning of organizational assumptions (Dwivedi et al., 2021). If top managers treat AI outputs as infallible – merely demanding quick responses to red-flag metrics – employees may slip into Model I behaviors, correcting errors without probing root causes. Conversely, Model II leadership fosters open discussions around AI's limitations, data biases, and surprising results (Peifer et al., 2022; Wijayati et al., 2022), thereby prompting double-loop reflection on whether existing strategies align with broader organizational values.

Leaders also allocate resources between short-term operational demands and long-term innovation (Berente et al., 2021). By granting teams the freedom to experiment with new AI functionalities or invest in generative analytics, leaders encourage exploration rather than defaulting to routine exploitation (Sturm et al., 2021). A fixation on immediate KPIs may, however, starve those AI initiatives that hold transformative potential (Wamba-Taguimdje et al., 2020), thereby narrowing the organization's strategic horizons.

Finally, leadership is integral to weaving AI data into cross-functional feedback loops that highlight interdependencies across departments (Agrawal et al., 2024). Leaders who champion systemic dialogue – for instance, convening multi-departmental reviews of AI-derived insights – promote a holistic learning culture (Bienefeld et al., 2023). Absent such facilitation, AI data remain siloed (Olan et al., 2022), undermining the broad, system-wide perspective Senge views as essential for enduring adaptability.

Organizational Culture

A learning-oriented culture encourages reflective inquiry – employees are more likely to examine whether AI-based corrections challenge deeper norms (Rožman et al., 2023). Where defensive routines and risk-averse mentalities prevail (Li & Yeo, 2024), single-loop tweaks predominate, foreclosing double-loop reinvention. Conversely, cultures that reward candor, knowledge-sharing, and collaborative critique give AI outputs the chance to provoke meaningful transformation (Bley et al., 2022).

By shaping organizational attitudes toward experimentation, culture influences whether AI serves short-term efficiency or sparks bold ventures (Makarius et al., 2020). A risk-tolerant, innovative culture may encourage employees to repurpose AI dashboards for product prototyping or novel workflows, fueling exploration (Jarrahi, Kenyon, et al., 2023). Where norms and metrics prioritize immediate efficiency, AI tools remain focused on marginal performance gains (Bley et al., 2022).

Cultural openness to collective sensemaking is vital for embedding AI insights into system-wide discussions (Engström et al., 2024). A culture that breaks down siloed mindsets and fosters cross-departmental collaboration ensures that local AI outputs feed broader organizational loops (Ransbotham et al., 2020). Alternatively, siloed or hierarchical cultures inhibit information flow (Olan et al., 2022), stifling the integrated feedback loops essential to Senge's systems perspective.

Ethics

Ethical dilemmas surrounding AI often force organizations to question deep-rooted practices and values (Ashok et al., 2022). Bias in training data or the potential for discriminatory decisions (Leslie, 2019) may prompt double-loop interrogation rather than limiting correction to superficial error fixes. An organization unprepared to confront these issues might revert to single-loop compliance, simply adjusting parameters without addressing core ethical values.

Ethical constraints also influence how far organizations pursue innovative AI applications versus exploit proven solutions (Dwivedi et al., 2021). Organizations with robust ethical oversight can explore advanced AI projects, confident in risk mitigation measures (Leslie, 2019), while those fearing public backlash or regulatory action may rein in certain AI experiments. Hence, ethical guardrails shape the extent and direction of AI-based exploration, balancing innovation with responsible risk management.

From a systems-thinking standpoint, ethical considerations form integral parts of organizational feedback loops. Ethical oversights, such as data privacy breaches, can reverberate widely – eroding trust in AI tools across the organization (Ashok et al., 2022; Katirai & Nagato, 2024; Leslie, 2019). Conversely, transparent ethical guidelines anchor system-wide adaptation (Leslie, 2019), ensuring that all participants align on shared values that support sustainable learning.

Digital Maturity

Organizations with high digital maturity typically have robust data infrastructures, enabling sophisticated AI deployments (Akbarighatar et al., 2023; Kane et al., 2017). This readiness can facilitate deeper reflection, provided employees possess the data literacy to question algorithmic outputs (Brătucu et al., 2024). Whereas organizations with low maturity, however, may implement digital technologies superficially (Kane et al., 2017) (, reinforcing single-loop tasks and rarely generating the feedback channels essential for double-loop re-examination.

Digitally mature organizations are better positioned to experiment with advanced analytics or generative AI, fueling exploration. Conversely, a lower level of digital infrastructure and data governance might limit AI usage to routine automation (Ladu et al., 2024), prioritizing exploitation for efficiency. Over time, bridging digital shortfalls is key (Kane et al., 2017) for sustaining an ambidextrous strategy that balances incremental improvements with radical discoveries.

In Senge's systems lens, integration capacity is vital: advanced analytics, real-time monitoring, and cross-platform interoperability help create cohesive feedback loops that traverse the entire organization. Digital immaturity hampers this holistic adaptation, leading to disjointed or siloed AI pilots (Akbarighatar et al., 2023). Conversely, a well-structured digital ecosystem provides the technical scaffold for collaborative sensemaking and ongoing systemic learning (Kane et al., 2017).

In summary, these four moderators crucially condition whether AI yields incremental or transformative learning. Each corresponds directly to Argyris & Schön's depth of reflection, March's dual modes of adaptation, and Senge's holistic synergy. The next section evaluates boundary conditions – factors like organization size, industry context, technical infrastructure, and workforce capability – and how they further refine AI's organizational impact in tandem with these moderators.

Interplay of Boundary Conditions in the Conceptual Model

While leadership, organizational culture, ethics, and digital maturity shape how AI tools inform organizational learning, four boundary conditions – organization size, industry context, technical infrastructure, and workforce capability – further determine where and under what circumstances AI sparks transformative or superficial effects (Benbya et al., 2020). Large organizations often benefit from abundant resources and analytics expertise (Banasiewicz, 2021), potentially fueling double-loop reflection (Argyris & Schön, 1978) and ambidexterity (March, 1991), yet they also face complex silos that can limit system-wide insight (Olan et al., 2022; Senge, 1990).

Highly regulated or rapidly evolving industries add further constraints or pressures (Katirai & Nagato, 2024; Leslie, 2019), either channeling AI deployments toward compliance-driven, single-loop routines or incentivizing experimentation (Ladu et al., 2024). Meanwhile, robust technical infrastructures – modern data systems and seamless interoperability – let organizations embed real-time analytics and algorithmic feedback across departments, enhancing feedback loops (Kar et al., 2021). Outdated systems, however, isolate AI in siloed pilots (Benbya et al., 2020), curbing exploration and undermining system-wide learning potential. Finally, a capable workforce can critically interpret AI outputs, fostering collaborative innovation and deeper reflection (Li & Yeo, 2024; Makarius et al., 2020), whereas low digital literacy or fear of AI may confine learning to surface-level error correction (Booyse & Scheepers, 2024; Engström et al., 2024). Together, these boundary conditions act as environmental "filters" around the conceptual model, shaping whether AI primarily delivers operational gains or truly enables strategic renewal and continuous adaptation.

Theoretical Synthesis: Integrating Argyris and Schön, March, and Senge

In bringing together Argyris & Schön's (1978) distinction between single- vs. double-loop reflection, March's (1991) balance of exploration and exploitation, and Senge's (1990) systems-thinking principles, this section provides a unified lens on how AI transforms organizational learning. While Argyris & Schön emphasize the depth of learning, highlighting the move from superficial error correction to questioning entrenched assumptions, March underscores how organizations allocate resources toward either short-term efficiency or long-term innovation. Senge, meanwhile, connects these processes to holistic feedback loops, showing that AI's impact often spans multiple departments and stakeholder groups (Agrawal et al., 2024; Chen et al., 2023; Grønsund & Aanestad, 2020). By synthesizing these viewpoints, AI can catalyze either incremental improvements or sweeping organizational change, contingent on leadership vision (Bevilacqua et al., 2025; Divya et al., 2024), cultural readiness cultural readiness (Bley et al., 2022; Rožman et al., 2023), ethical oversight (Katirai & Nagato, 2024; Leslie, 2019), and digital maturity (Kane et al., 2017; Ladu et al., 2024). This integration thus offers a more comprehensive framework for analyzing how organizations truly learn, and potentially transform, in the face of rapid technological advancement.

Complementary Insights

Argyris and Schön differentiate between superficial (single-loop) corrections and fundamental (double-loop) questioning of norms. ADM and algorithmic feedback can inadvertently reinforce single-loop behaviors if employees simply "correct" metrics without reflection (Ardichvili, 2022; Faraj et al., 2018; Wilkens, 2020). Conversely, unexpected AI outcomes or collaborative AI "thought-partner" scenarios can prompt double-loop inquiry, compelling teams to reexamine underlying assumptions (Bohanec et al., 2017; Jarrahi, Kenyon, et al., 2023; Ransbotham et al., 2020). Leadership vision and an open culture stand out as crucial for enabling deeper scrutiny of AI results and thereby fostering double-loop processes (Bley et al., 2022; Peifer et al., 2022).

March's framework emphasizes balancing short-term efficiency (exploitation) with long-term innovation (exploration). Machine learning and real-time analytics typically optimize daily routines (exploitation) (Banasiewicz, 2021; Wamba-Taguimdje et al., 2020) but can also illuminate emerging market needs or encourage experimental uses (exploration)(Kakatkar et al., 2020; Soni et al., 2020), especially when leaders allocate time and resources for novel AI deployments (Johnson et al., 2022; Sturm et al., 2021). Organizational culture (Bley et al., 2022; Rožman et al., 2023), ethics (Katirai & Nagato, 2024; Leslie, 2019), and digital maturity (Kane et al., 2017; Ladu et al., 2024) can enable or constrain the capacity for exploratory AI activities. In high-regulation industries, ethical and compliance concerns might limit radical exploration (Leslie, 2019); in resource-rich tech sectors, AI fosters a more ambidextrous approach (Berente et al., 2021; O'Reilly & Tushman, 2013).

Senge's model underscores interconnected feedback loops across departments and levels of an organization (Senge, 1990). Tools like real-time analytics and human-AI collaboration can supply rapid, data-driven insights that cross departmental boundaries, enhancing system-wide reflection (Agrawal et al., 2024; Chen et al., 2023; Grønsund & Aanestad, 2020). Yet "black box" algorithms (Ardichvili, 2022; Banasiewicz, 2021; Bohanec et al., 2017) or siloed implementations risk fragmenting the organizational perspective rather than uniting it (Olan et al., 2022). Leadership styles that promote collective sensemaking (Bevilacqua et al., 2025; Bienefeld et al., 2023), along with a culture of open knowledge exchange (Bley et al., 2022; Rožman et al., 2023), amplify Senge's feedback loops. Conversely, limited technical infrastructure or workforce capability can hamper broad-based data sharing, diluting system-wide awareness (Engström et al., 2024; Kar et al., 2021).

Points of Tension

Argyris and Schön (1978) advocate challenging entrenched beliefs, but in practice, many AI systems emphasize quick performance fixes (single-loop) to satisfy immediate KPIs (Ardichvili, 2022; Faraj et al., 2018). If leaders fail to install reflection checkpoints, the transformative potential of AI remains underutilized (Dwivedi et al., 2021; Wilkens, 2020). March (1991) warns that organizations fixate on exploitative applications risk stagnation. While real-time analytics or algorithmic decision-making can yield short-term gains (Banasiewicz, 2021; Wamba-Taguimdje et al., 2020), radical AI experiments may be neglected (Berente et al., 2021). Ethical or regulatory concerns can further dissuade exploratory AI usage (Katirai & Nagato, 2024; Leslie, 2019). Senge (1990) highlights system-wide feedback loops that unify organizational learning, yet technical and cultural barriers often silo AI pilots, restricting knowledge flow (Kar et al., 2021; Olan et al., 2022). Incomplete data infrastructures or departmental rivalries can limit AI's impact to isolated pockets (Benbya et al., 2020; Booyse & Scheepers, 2024), preventing a truly holistic transformation.

Synergy of Lenses

Argyris and Schön (1978) sharpen our focus on the depth of learning outcomes, from quick fixes to profound assumption shifts. March (1991) underscores how organizations allocate scarce resources between exploiting known processes and exploring new horizons. Senge (1990) ensures an integrated system-wide lens, emphasizing collaborative sensemaking and interconnected feedback loops. Each AI tool can support either superficial or deeper learning (Bohanec et al., 2017; Jarrahi, Askay, et al., 2023), incremental or radical innovation (Johnson et al., 2022; Sturm et al., 2021), siloed or system-spanning feedback loops (Grønsund & Aanestad, 2020).

Whether these potentials manifest depends on the interplay of organizational conditions and human choices. Leadership sets the vision and resource priorities (Bevilacqua et al., 2025; Divya et al., 2024; Peifer et al., 2022); culture dictates openness to challenge norms (Bley et al., 2022; Rožman et al., 2023); ethics ensures integrity and trust (Katirai & Nagato, 2024; Leslie, 2019); digital maturity supports seamless data integration (Kane et al., 2017; Ladu et al., 2024)/ Together, these shape whether AI fosters double-loop transformations, balanced exploration, or holistic system insights. The broader environment affects how feasible or ambitious AI-driven learning can be (Benbya et al., 2020; Kar et al., 2021). The synergy among boundary conditions, moderators, and AI tools determines how effectively theoretical ideals translate into practice (Banasiewicz, 2021; Dwivedi et al., 2021; Makarius et al., 2020).

Limitations and Future Research

Theoretical Limitations and Underdeveloped Integration

While some studies hint at AI's ability to prompt double-loop changes (Bohanec et al., 2017; Jarrahi, Askay, et al., 2023), the direct linkage between reflective learning frameworks and

AI adoption remains underexplored. As a result, certain propositions – especially those relating to how AI triggers organizational assumptions to be questioned – are extrapolated from fragmented or indirect evidence. Empirical case studies could investigate whether and how specific AI interventions directly stimulate deeper reflection or remain confined to single-loop corrections.

Though Argyris and Schön, March, and Senge provide complementary views on organizational learning, each theory has known critiques such as measurement issues for double-loop (Auqui-Caceres & Furlan, 2023; Lipshitz, 2000; Mazutis & Slawinski, 2008), bounded rationality in exploration-exploitation (source), or simplistic feedback loops in systems thinking (Flood & Finnestrand, 2020; Kiedrowski, 2006; Örtenblad, 2020). Their combined application may oversimplify certain power or political dynamics that often shape AI initiatives (Flood & Finnestrand, 2020). Studies integrating critical or power-based frameworks could deepen understanding of how AI-based changes intersect with organizational politics or resource distributions.

Methodological Constraints

In examining the interplay between AI and organizational learning, this thesis primarily adopts a conceptual orientation rather than relying on newly collected or secondary empirical data. As a result, the methodological focus is on theoretical integration and literature synthesis, which offers broad insights but also introduces limitations regarding validation and real-world applicability.

Conceptual Scope

This thesis adopts a conceptual design rather than collecting new or secondary data. Consequently, its emphasis lies in synthesizing diverse literature rather than validating specific relationships or causal pathways. Empirical mixed-method approaches – longitudinal surveys, interviews, or agent-based simulations (Sturm et al., 2021) – could refine or challenge the proposed model's assumptions by capturing real-world complexities in AI deployments.

Literature Fragmentation

The scarcity of direct scholarship linking AI and organizational learning theories forced reliance on articles from HRD, KM, and management contexts, each discussing partial aspects rather than directly relating to the key learning theories. Targeted reviews or meta-analyses focusing explicitly on "AI and Organizational Learning" could consolidate emerging studies, providing stronger empirical support for the conceptual relationships proposed here.

Practical and Contextual Limitations

Beyond methodological constraints, there are practical and contextual challenges that can affect the generalizability and implementation of the proposed conceptual framework. These include variations in industry conditions, differences in organizational size, and a variety of technological infrastructures, each of which influences how AI-driven learning initiatives unfold.

Generalizability Across Industries and Scales

This thesis' framework posits that boundary conditions crucially affect AI's role in learning. However, variations within and across industries or among small vs. large enterprises are too broad to be fully captured by a single conceptual model, Comparative case studies or industry-specific investigations could reveal more nuanced pathways. Cross-cultural or international research might further show how national regulations, and cultural norms influence AI-driven learning.

Implementation Realities

Many organizations deploying AI face ethical concerns, skills shortages, and organizational inertia, none of which are easily resolved by conceptual alignment alone (Benbya et al., 2020; Booyse & Scheepers, 2024; Engström et al., 2024; Leslie, 2019; Shrivastav, 2022). Real-world constraints such as legacy systems, fragmented data sources, or stakeholder resistance may prevent double-loop transformations, even with visionary leadership (Benbya et al., 2020; Dwivedi et al., 2021; Kar et al., 2021). Action research or participatory approaches where scholars collaborate with practitioners to implement AI across departmental boundaries could provide deeper insights into the day-to-day challenges that hamper or facilitate system-wide adaptation.

Avenues for Further Empirical Validation

Developing scales to measure AI-driven single- vs. double-loop learning or ambidexterity outcomes could yield robust insights, potentially validated through structural equation modeling or multi-level analyses. Tracking organizations over time – before and after significant AI implementations – may highlight learning trajectory shifts, providing evidence for whether AI indeed promotes deeper reflection or remains an operational tool. Field experiments might verify the effect of moderators on AI's learning outcomes. Extending (Sturm et al., 2021) to incorporate aspects of Argyris and Schön's reflection cycles or Senge's feedback loops could help model complex, dynamic AI adoption scenarios under various boundary conditions.

In conclusion, while this conceptual thesis addresses critical gaps by integrating classical learning theories with contemporary AI scholarship, it primarily generates theoretical propositions requiring further empirical scrutiny. By highlighting dimensions such as double-loop learning, exploration-exploitation, and systems thinking, this study underscores the complexity and promise of AI-enabled organizational learning. Future research – both theoretical and applied – can refine these constructs, test their validity in diverse settings, and expand on how AI might become not just a catalyst for efficiency, but a driver of transformative, system-wide learning across organizations.

Chapter 6. Conclusion

This thesis set out to develop a conceptual framework that integrates classical organizational learning theories – Argyris and Schön's (1978) single- vs. double-loop model, March's (1991) exploration-exploitation perspective, and Senge's (1990) systems thinking – with contemporary AI practices. In doing so, it aimed to answer the central research question: Which theoretical perspectives best explain AI's role in enabling (or hindering) organizational learning? The aim was to illuminate how artificial intelligence might act as either a catalyst or barrier to deeper organizational learning, and to understand which factors tip the scales toward surface-level fixes or transformative reconfigurations of norms, strategies, and systems.

By synthesizing these three theories, the thesis provides a multi-lens viewpoint that captures both routine error-correction processes (single-loop) and more fundamental questioning of norms (double-loop), the balancing act between short-term efficiency and long-term innovation, and holistic, interdependent dynamics that bind individuals, processes, and technologies. Central to this contribution is the mapping of four key AI mechanisms – machine learning/automated decision-making (Banasiewicz, 2021; Bohanec et al., 2017) human-AI collaboration (Jarrahi, 2018; Jarrahi, Askay, et al., 2023; Makarius et al., 2020), big data and real-time analytics (Chen et al., 2023), and algorithmic feedback (Faraj et al., 2018; Grønsund & Aanestad, 2020) – onto these organizational learning processes. This model aims to clarify how AI specifically affects reflection, resource allocation, and systemic feedback loops.

Key Theoretical Insights

Drawing on Argyris and Schön, the framework shows that AI can reinforce single-loop learning by automating performance metrics and routine corrections (Ardichvili, 2022; Wilkens, 2020) or enable double-loop reflection if organizations deliberately question the broader assumptions embedded within AI systems (Bohanec et al., 2017). The extent to which AI simply corrects errors or disrupts entrenched mindsets largely depends on organizational willingness to challenge algorithmic outputs (Dwivedi et al., 2021).

From March's exploration-exploitation lens, AI emerges as both a tool for routine optimization (exploitation) and a potential driver of radical innovation (exploration) (Berente et al., 2021; Johnson et al., 2022). By rapidly uncovering patterns in large datasets or offering real-time predictive insights, AI can spotlight new opportunities that foster experimentation (Kakatkar et al., 2020; Soni et al., 2020). Yet without conscious resource allocation and leadership support, organizations may remain locked in exploitative routines, missing the larger adaptive potential AI might enable (Wamba-Taguimdje et al., 2020).

In line with Senge's systems thinking, AI can reconfigure feedback loops across departments and functions (Chen et al., 2023; Grønsund & Aanestad, 2020). Real-time analytics not only provide rapid error-correction but also reveals cross-functional dependencies that encourage team-based sensemaking (Agrawal et al., 2024; Bienefeld et al., 2023). Where data remains siloed, AI's system-wide benefits are limited (Olan et al., 2022); when integrated holistically, AI's capacity for continuous adaptation can significantly heighten organizational agility.

Across all three theoretical lenses, the role of moderating factors is critical. Leadership sets vision and resource priorities (Bevilacqua et al., 2025; Divya et al., 2024), organizational culture determines whether AI insights spark reflection or defensiveness (Bley et al., 2022; Rožman et al., 2023), ethics guide responsible use and mitigate biases (Katirai & Nagato, 2024; Leslie, 2019), and digital maturity ensures the technical and infrastructural readiness to exploit AI's capabilities (Kane et al., 2017; Ladu et al., 2024). These moderators can amplify or suppress AI's potential for catalyzing deeper learning.

Practical Implications

From a managerial perspective, organizations that seek deeper learning outcomes through AI should structure their AI initiatives to move beyond basic automation (Benbya et al., 2020). Cultivating a culture of inquiry, designing deliberate checkpoints for questioning AI recommendations, and encouraging multi-level dialogues can shift AI usage from mere single-loop corrections to genuine double-loop transformations (Bohanec et al., 2017; Jarrahi, Askay, et al., 2023). Additionally, establishing ethical oversight – via transparent governance practices and robust accountability mechanisms – can ensure algorithmic decisions remain aligned with organizational and societal values, enhancing trust in AI-driven processes (Katirai & Nagato, 2024; Leslie, 2019).

Leaders play a crucial role in fostering reflection: they can enable open communication, allocate dedicated resources for experimental AI projects, and champion cross-functional teams that bring diverse expertise to bear on AI insights (Bevilacqua et al., 2025; Peifer et al., 2022). By doing so, they create a conducive environment for ambidexterity (O'Reilly & Tushman, 2013), balancing the exploitation of existing competencies with the exploration of novel AI-driven possibilities. Moreover, investing in digital capabilities, from data infrastructures to employee training (Kane et al., 2017), amplifies AI's systemic impact. High digital maturity correlates with faster scaling of pilot initiatives, more sophisticated risk management, and an organizational habit of iterating toward best practices (Brătucu et al., 2024; Kane et al., 2017; Ladu et al., 2024).

Crucially, implementing the theoretical framework in practice demands acknowledging real-world constraints such as legacy systems, fragmented data silos, or cultural resistance (Benbya et al., 2020; Kar et al., 2021). Transitioning from isolated experiments to system-wide AI integration may require changes to organizational structures (Olan et al., 2022), challenging yet necessary steps if AI is to spur meaningful learning across the organization.

Looking Forward

While this thesis presents a conceptual foundation, it also carries boundaries. The model has not yet undergone empirical validation within specific organizational contexts. Future research can test these propositions, using in-depth case studies or agent-based simulations to observe whether (and how) AI triggers genuine double-loop reflection, fosters exploration, or reconfigures cross-departmental feedback loops.

Moreover, emerging areas, such as generative AI or the increasing integration of AI into strategic decision-making (Agrawal et al., 2024), warrant further study to assess whether the same moderating factors and boundary conditions apply. As technology evolves, so too must our frameworks for understanding AI's influence on reflection, adaptation, and learning.

Ultimately, this thesis underscores AI's transformative potential in organizations, provided leaders, cultures, and systems align to support deeper, systemic learning. By linking the foundational theories of Argyris and Schön, March, and Senge to four contemporary AI mechanisms, it offers both academic and practical pathways for realizing AI as an enabler, not just of incremental optimization but of reflective, transformational learning. If steered responsibly and integrated with thoughtful governance and supportive cultural norms, AI can indeed reshape how organizations adapt, innovate, and thrive in an ever-shifting digital landscape.

References

Agrawal, A., Gans, J. S., & Goldfarb, A. (2024). Artificial intelligence adoption and system-wide change. *Journal of Economics & Management Strategy*, *33*(2), 327–337. https://doi.org/10.1111/jems.12521

Akbarighatar, P., Pappas, I., & Vassilakopoulou, P. (2023). A sociotechnical perspective for responsible AI maturity models: Findings from a mixed-method literature review. *International Journal of Information Management Data Insights*, *3*(2), 100193. https://doi.org/10.1016/j.jjimei.2023.100193

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge management and knowledge management systems: conceptual foundations and research issues. *MIS Quarterly*, *25*(1), 107. https://doi.org/10.2307/3250961

Alavi, M., Leidner, D. E., & Mousavi, R. (2024). Knowledge management perspective of generative artificial intelligence. *Journal of the Association for Information Systems*, *25*(1), 1–12. https://doi.org/10.17705/1jais.00859

Ardichvili, A. (2022). The impact of artificial intelligence on expertise development: Implications for HRD. *Advances in Developing Human Resources*, *24*(2), 78–98. https://doi.org/10.1177/15234223221077304

Argote, L., Lee, S., & Park, J. (2021). Organizational learning processes and outcomes: Major findings and future research directions. *Management Science*, *67*(9), 5399–5429. https://doi.org/10.1287/mnsc.2020.3693

Argyris, C., & Schön, D. A. (1978). *Organizational learning: A theory of action perspective*. Addison-Wesley Publishing Company.

Ashok, M., Madan, R., Joha, A., & Sivarajah, U. (2022). Ethical framework for artificial intelligence and digital technologies. *International Journal of Information Management, 62*, 102433. https://doi.org/10.1016/j.ijinfomgt.2021.102433

Auqui-Caceres, M., & Furlan, A. (2023). Revitalizing double-loop learning in organizational contexts: A systematic review and research agenda. *European Management Review, 20*(4), 741–761. https://doi.org/10.1111/emre.12615

Balasubramanian, N., Ye, Y., & Xu, M. (2022). Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review, 47*(3), 448–465. https://doi.org/10.5465/amr.2019.0470

Banasiewicz, A. (2021). *Organizational learning in the age of data*. Springer International Publishing. https://doi.org/10.1007/978-3-030-74866-1

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3741983

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly, 45*(3), 1433–1450.

Bevilacqua, S., Masárová, J., Perotti, F. A., & Ferraris, A. (2025). Enhancing top managers' leadership with artificial intelligence: Insights from a systematic literature review. *Review of Managerial Science*. https://doi.org/10.1007/s11846-025-00836-7

Bienefeld, N., Kolbe, M., Camen, G., Huser, D., & Buehler, P. K. (2023). Human-AI teaming: Leveraging transactive memory and speaking up for enhanced team effectiveness. *Frontiers in Psychology, 14*, 1208019. https://doi.org/10.3389/fpsyg.2023.1208019

Birkinshaw, J., & Gupta, K. (2013). Clarifying the distinctive contribution of ambidexterity to the field of organization studies. *Academy of Management Perspectives*, *27*(4), 287–298. https://doi.org/10.5465/amp.2012.0167

Bley, K., Brunvand Fredriksen, S. F., Skjærvik, M. E., & Pappas, I. O. (2022). The role of organizational culture on artificial intelligence capabilities and organizational performance. In *The Role of Digital Technologies in Shaping the Post-Pandemic World* (Vol. 13454, pp. 13–24). Springer International Publishing.

Bochman, D. J., & Kroth, M. (2010). Immunity to transformational learning and change. *The Learning Organization*, *17*(4), 328–342. https://doi.org/10.1108/09696471011043090

Bohanec, M., Robnik-Šikonja, M., & Kljajić Borštnar, M. (2017). Decision-making framework with double-loop learning through interpretable black-box machine learning models. *Industrial Management & Data Systems*, *117*(7), 1389–1406. https://doi.org/10.1108/IMDS-09-2016-0409

Booyse, D., & Scheepers, C. B. (2024). Barriers to adopting automated organisational decision-making through the use of artificial intelligence. *Management Research Review*, *47*(1), 64–85. https://doi.org/10.1108/MRR-09-2021-0701

Boumgarden, P., Nickerson, J., & Zenger, T. R. (2012). Sailing into the wind: Exploring the relationships among ambidexterity, vacillation, and organizational performance. *Strategic Management Journal*, *33*(6), 587–610. https://doi.org/10.1002/smj.1972

Brătucu, G., Ciobanu, E., Chițu, I. B., Litră, A. V., Zamfirache, A., & Bălășescu, M. (2024). The use of technology assisted by artificial intelligence depending on the companies' digital maturity level. *Electronics*, *13*(9), 1687. https://doi.org/10.3390/electronics13091687

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science, 358*(6370), 1530–1534. https://doi.org/10.1126/science.aap8062

Calvard, T. S. (2016). Big data, organizational learning, and sensemaking: Theorizing interpretive challenges under conditions of dynamic complexity. *Management Learning, 47*(1), 65–82. https://doi.org/10.1177/1350507615592113

Chen, W., Milosevic, Z., Rabhi, F. A., & Berry, A. (2023). Real-time analytics: Concepts, architectures, and ML/AI considerations. *IEEE Access, 11*, 71634–71657. https://doi.org/10.1109/ACCESS.2023.3295694

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

Divya, D., Jain, R., Chetty, P., Siwach, V., & Mathur, A. (2024). The mediating effect of leadership in artificial intelligence success for employee-engagement. *Management Decision*. https://doi.org/10.1108/MD-01-2024-0213

Duncan, R. B. (1976). The ambidextrous organization: Designing dual structures for innovation. In *The Management of Organization Design, Volume I: Strategies and Implementation* (pp. 167–188). North Holland.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International*

Journal of Information Management, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Engström, A., Pittino, D., Mohlin, A., Johansson, A., & Edh Mirzaei, N. (2024). Artificial intelligence and work transformations: Integrating sensemaking and workplace learning perspectives. *Information Technology & People*. https://doi.org/10.1108/ITP-01-2023-0048

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization*, *28*(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005

Flood, R. L., & Finnestrand, H. (2020). A mighty step: Critical systemic interpretation of the learning organization. In *The Oxford Handbook of the Learning Organization* (pp. 197–214). Oxford University Press USA.

Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *The Journal of Strategic Information Systems*, *29*(2), 101614. https://doi.org/10.1016/j.jsis.2020.101614

Hawkins, P. (1991). The spiritual dimension of the learning organisation. *Management Education and Development*, *22*(3), 172–187. https://doi.org/10.1177/135050769102200304

Henderson, S. (1997). Black swans don't fly double loops: The limits of the learning organization? *The Learning Organization*, *4*(3), 99–105. https://doi.org/10.1108/09696479710182777

Herrmann, T., & Pfeiffer, S. (2023). Keeping the organization in the loop: A socio-technical extension of human-centered artificial intelligence. *AI & SOCIETY*, *38*(4), 1523–1542. https://doi.org/10.1007/s00146-022-01391-5

Jaaron, A. A. M., & Backhouse, C. J. (2017). Operationalising "double-loop" learning in service organisations: A systems approach for creating knowledge. *Systemic Practice and Action Research*, *30*(4), 317–337. https://doi.org/10.1007/s11213-016-9397-0

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons*, *66*(1), 87–99. https://doi.org/10.1016/j.bushor.2022.03.002

Jarrahi, M. H., Kenyon, S., Brown, A., Donahue, C., & Wicher, C. (2023). Artificial intelligence: A strategy to harness its power through organizational learning. *Journal of Business Strategy*, *44*(3), 126–135. https://doi.org/10.1108/JBS-11-2021-0182

Johnson, P. C., Laurell, C., Ots, M., & Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation? *Technological Forecasting and Social Change*, *179*, 121636. https://doi.org/10.1016/j.techfore.2022.121636

Junni, P., Sarala, R. M., Taras, V., & Tarba, S. Y. (2013). Organizational ambidexterity and performance: A meta-analysis. *Academy of Management Perspectives*, *27*(4), 299–312. https://doi.org/10.5465/amp.2012.0015

Kakatkar, C., Bilgram, V., & Füller, J. (2020). Innovation analytics: Leveraging artificial intelligence in the innovation process. *Business Horizons*, *63*(2), 171–181. https://doi.org/10.1016/j.bushor.2019.10.006

Kane, G. C., & Alavi, M. (2007). Information technology and organizational oearning: An investigation of exploration and exploitation processes. *Organization Science*, *18*(5), 796–812. https://doi.org/10.1287/orsc.1070.0286

Kane, G. C., Palmer, D., Phillips, A. N., Kiron, D., & Buckley, N. (2017). *Achieving digital maturity*. MIT Sloan Management Review and Deloitte University Press.

Kar, S., Kar, A. K., & Gupta, M. P. (2021). Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective. *Intelligent Systems in Accounting, Finance and Management*, *28*(4), 217–238. https://doi.org/10.1002/isaf.1503

Katirai, A., & Nagato, Y. (2024). Addressing trade-offs in co-designing principles for ethical AI: Perspectives from an industry-academia collaboration. *AI and Ethics*. https://doi.org/10.1007/s43681-024-00477-8

Kiedrowski, P. J. (2006). Quantitative assessment of a Senge learning organization intervention. *The Learning Organization*, *13*(4), 369–383. https://doi.org/10.1108/09696470610667742

Ladu, L., Koch, C., Asna Ashari, P., Blind, K., & Castka, P. (2024). Technology adoption and digital maturity in the conformity assessment industry: Empirical evidence from an international study. *Technology in Society*, *77*, 102564. https://doi.org/10.1016/j.techsoc.2024.102564

Leonardi, P. M. (2013). Theoretical foundations for the study of sociomateriality. *Information and Organization*, *23*(2), 59–76. https://doi.org/10.1016/j.infoandorg.2013.02.002

Leslie, D. (2019). *Understanding artificial intelligence ethics and safety: A guide for the responsible design and implementation of AI systems in the public sector*. The Alan Turing Institute. https://doi.org/10.5281/ZENODO.3240529

Li, J., & Yeo, R. K. (2024). Artificial intelligence and human integration: A conceptual exploration of its influence on work processes and workplace learning. *Human Resource Development International*, *27*(3), 367–387. https://doi.org/10.1080/13678868.2024.2348987

Lipshitz, R. (2000). Chic, mystique, and misconception: Argyris and Schön and the rhetoric of organizational learning. *The Journal of Applied Behavioral Science*, *36*(4), 456–473. https://doi.org/10.1177/0021886300364004

Mahesh, B. (2020). Machine learning algorithms—A review. *International Journal of Science and Research (IJSR)*, *9*(1), 381–386. https://doi.org/10.21275/ART20203995

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2022). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower*, *43*(2), 334–354. https://doi.org/10.1108/IJM-03-2021-0173

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, *2*(1), 71–87.

Mazutis, D., & Slawinski, N. (2008). Leading organizational learning through authentic dialogue. *Management Learning*, *39*(4), 437–456. https://doi.org/10.1177/1350507608093713

Nilsson, N. J. (2009). *The quest for artificial intelligence* (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511819346

Olan, F., Ogiemwonyi Arakpogun, E., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. *Journal of Business Research*, *145*, 605–615. https://doi.org/10.1016/j.jbusres.2022.03.008

O'Reilly, C. A., & Tushman, M. L. (2004). The ambidextrous organization. *Harvard Business Review*, *82*(4), 74–81.

O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. *Academy of Management Perspectives*, *27*(4), 324–338. https://doi.org/10.5465/amp.2013.0025

Orlikowski, W. J. (1992). The Duality of Technology: Rethinking the Concept of Technology in Organizations. *Organization Science*, *3*(3), 398–427. https://doi.org/10.1287/orsc.3.3.398

Örtenblad, A. (2007). Senge's many faces: Problem or opportunity? *The Learning Organization*, *14*(2), 108–122. https://doi.org/10.1108/09696470710726989

Örtenblad, A. (2020). Contextualizing the learning organization: Towards differentiated standards. In *The Oxford Handbook of the Learning Organization* (pp. 379–392). Oxford University Press USA.

Peifer, Y., Jeske, T., & Hille, S. (2022). Artificial intelligence and its impact on leaders and leadership. *Procedia Computer Science*, *200*, 1024–1030. https://doi.org/10.1016/j.procs.2022.01.301

Puranam, P. (2021). Human–AI collaborative decision-making as an organization design problem. *Journal of Organization Design*, *10*(2), 75–80. https://doi.org/10.1007/s41469-021-00095-2

Raisch, S., Birkinshaw, J., Probst, G., & Tushman, M. L. (2009). Organizational ambidexterity: Balancing exploitation and exploration for sustained performance. *Organization Science*, *20*(4), 685–695. https://doi.org/10.1287/orsc.1090.0428

Ransbotham, S., Khodabandeh, S., Kiron, D., Candelon, F., Chu, M., & Lafountain, B. (2020). *Expanding AI's impact with organizational learning*. MIT Sloan Management Review and Boston Consulting Group.

Robey, D., Ross, J. W., & Boudreau, M.-C. (2002). Learning to Implement Enterprise Systems: An Exploratory Study of the Dialectics of Change. *Journal of Management Information Systems*, *19*(1), 17–46. https://doi.org/10.1080/07421222.2002.11045713

Rožman, M., Tominc, P., & Milfelner, B. (2023). Maximizing employee engagement through artificial intelligent organizational culture in the context of leadership and training of employees: Testing linear and non-linear relationships. *Cogent Business & Management*, *10*(2), 2248732. https://doi.org/10.1080/23311975.2023.2248732

Senge, P. M. (1990). *The fifth discipline: The art and practice of the learning organization* (1st ed.). Currency Doubleday.

Shi, Y., Van Toorn, C., & McEwan, M. (2024). Exploration–exploitation: How business analytics powers organisational ambidexterity for environmental sustainability. *Information Systems Journal*, *34*(3), 894–930. https://doi.org/10.1111/isj.12456

Shrivastav, M. (2022). Barriers related to AI implementation in Supply Chain Management. *Journal of Global Information Management*, *30*(8), 1–19. https://doi.org/10.4018/JGIM.296725

Siggelkow, N., & Levinthal, D. A. (2003). Temporarily divide to conquer: Centralized, decentralized, and reintegrated organizational approaches to exploration and adaptation. *Organization Science*, *14*(6), 650–669. https://doi.org/10.1287/orsc.14.6.650.24840

Soni, N., Sharma, E. K., Singh, N., & Kapoor, A. (2020). Artificial intelligence in business: From research and innovation to market deployment. *Procedia Computer Science*, *167*, 2200–2210. https://doi.org/10.1016/j.procs.2020.03.272

Sturm, T., Gerlacha, 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. https://doi.org/10.25300/MISQ/2021/16543

Swieringa, J., & Wierdsma, A. (1992). *Becoming a learning organization: Beyond the learning curve* (1st ed.). Addison-Wesley.

Tosey, P., Visser, M., & Saunders, M. N. (2012). The origins and conceptualizations of 'triple-loop' learning: A critical review. *Management Learning*, *43*(3), 291–307. https://doi.org/10.1177/1350507611426239

Tushman, M. L., & O'Reilly, C. A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review*, *38*(4), 8–29. https://doi.org/10.2307/41165852

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and design in the age of artificial intelligence. *Journal of Product Innovation Management*, *37*(3), 212–227. https://doi.org/10.1111/jpim.12523

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wijayati, D. T., Rahman, Z., Fahrullah, A., Rahman, M. F. W., Arifah, I. D. C., & Kautsar, A. (2022). A study of artificial intelligence on employee performance and work engagement: The moderating role of change leadership. *International Journal of Manpower*, *43*(2), 486–512. https://doi.org/10.1108/IJM-07-2021-0423

Wilkens, U. (2020). Artificial intelligence in the workplace – A double-edged sword. *The International Journal of Information and Learning Technology*, *37*(5), 253–265. https://doi.org/10.1108/IJILT-02-2020-0022

Witherspoon, R. (2014). Double-loop coaching for leadership development. *The Journal of Applied Behavioral Science*, *50*(3), 261–283. https://doi.org/10.1177/0021886313510032