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Evolution of a New Strategic Orientation in the AI Era: Exploring the Determinants of AI Orientation

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**Evolution of a New Strategic Orientation in the AI Era:
Exploring the Determinants of AI Orientation**

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Doctor of Business Administration with an emphasis in Strategic Management

December 2025

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Abstract

The field of AI has undergone significant evolution over the past few decades. While AI is heralded as one of the most transformative technologies, scholars caution that its strategic impact may still not be fully realized. Given the strategic importance of AI in today's firms, it is essential to consider AI as a strategic orientation and understand its determinants in detail. Our study examines AI Orientation, defined as a firm's deliberate application of AI technologies to achieve its strategic objectives. Drawing on multiple theoretical perspectives, this study investigates the determinants that shape a firm's AI orientation. This study employs a qualitative research approach based on 20 semi-structured interviews with senior AI leaders across various industries. This study makes three interrelated contributions. First, it presents a revised theoretical model of AI Orientation by integrating RBV, UET, ABC, TOC, and LOC, refining six determinants (leadership influence, AI capability, enterprise alignment, AI scalability, AI governance and organizational learning orientation) and documenting sub-themes to illustrate how organizations can apply AI towards its strategic goals. Second, it demonstrates a hybrid methodological approach by combining traditional manual coding in Quirkos with AI-assisted analysis through QualiGPT, illustrating how human–AI collaboration can enhance triangulation and analytical depth. Finally, the study provides a practical framework for leaders seeking to strengthen AI Orientation, especially in organizations where AI adoption remains fragmented or disconnected from strategic priorities.

Keywords: AI Orientation, AI Governance, AI Capabilities, Strategic AI Orientation

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Chapter 1: Introduction

“At one point, within the next 100 years – and possibly the next 50 – computers, unaided by human controllers, would be capable of producing prose on the level of Shakespeare.” –Marvin Minsky, an MIT professor, made this bold statement in a conference in 1982, and the audience reacted with disbelief (Amabile, 2020). The rapid advancements in electrical and computer engineering and the understanding of the human brain have contributed to making this a reality. Recent years have witnessed significant progress toward artificial intelligence (AI) technologies.

Motivation

Artificial Intelligence (AI) technology is “a broad collection of computer-assisted systems for task performance, leveraging machine learning, automated knowledge repositories, image recognition, natural language processing, and large language models” (Von Krogh, 2018). AI has progressed through several waves, moving from the early rule-based expert systems (Simon & Newell, 1958, Yoo et.al, 1995) to machine learning and deep learning approaches (LeCun, Bengio, & Hinton, 2015) fueled by advances in computing power, data availability and technological innovations. The emergence of foundation models, generative AI, agentic AI (Schneider, 2024, 2025) and physical AI (Liu et.al, 2025, Boussetouane, 2025) marked a paradigm shift in the applications of artificial intelligence. These advancements have enabled AI to evolve as a transformative innovation that can compel organizations to reinvent their business models to endure, maintain operations, and achieve competitive advantages (Davenport et al., 2020). AI is becoming increasingly relevant in solving operational problems, and an increasing

number of firms are integrating it into their strategies (Wilson & Daugherty, 2018, Accenture Report, 2024).

There are many positive benefits of AI for enhancing efficiency, such as creating new opportunities, reducing man-made errors, undertaking the responsibility of solving complex problems, and carrying out routine tasks. AI technologies are different from other forms of digital technologies because they offer novel, distinctive opportunities and pose new significant challenges (Benbya et al. (2021). Businesses and governments will decide to introduce and control the AI technologies that can impact our lives (Jones et al., 2018). This is bringing a significant shift in how organizations must evolve their workforce, which includes human and digital workers. Although enterprises believe in the transformational potential of AI, employees are concerned about the uncertainty around the ethical, sociopolitical, and economic impact of AI on the future of mankind (Huang & Rust, 2018). Because of its significant potential upsides and downsides, developing a strategic position to govern AI effectively is an important challenge for leadership teams across firms (Hang & Chen, 2022).

While AI is heralded as one of the most transformative technologies, scholars caution that its strategic impact may still not be fully realized. In a recent MIT Sloan Management Review study, Wingate, Burns, and Barney (2025) argue that AI alone cannot offer a sustainable competitive advantage, as the technology can be a source of homogenization. It is essential to find novel and strategic ways to use AI, leveraging human creativity, as enterprises strive to capture enduring value from AI. MIT's GenAI Divide study (MIT NANDA, 2025) finds that 95 percent of enterprise generative AI pilots fail to deliver measurable returns, indicating that organizations lack the integration,

adaptation, and learning necessary to realize value. Emerging academic research points to strategic AI Orientation (AIO) as the construct to address this gap.

Given the strategic importance of AI in firms today, it is essential to consider AI as a strategic orientation (Li et.al., 2021) and understand the determinants in detail. Firms with high AI Orientation are not just doing the simple siloed implementation of AI, they go beyond with a broader strategic vision and embrace AI as a transformative strategy (Li, Pan, Wang, & Zhang, 2023). Recent research shows that AIO positively influences innovation (Eicke et al., 2025), operational efficiency (Yao et.al., 2025) and value creation through global collaboration (Huang et al., 2025).

For the purpose of this study, we define *AI Orientation (AIO) as a firm's deliberate application of AI technologies to achieve its strategic goals*, drawing on the Resource-Based View (RBV) theory and Treacy and Wiersema's (1993) value disciplines. Firms can use the value discipline lens of customer intimacy, product innovation, and/or operational excellence (Treacy & Wiersema, 1993; Zacharias et.al., 2016) while deciding their strategic goals. Previous studies have established the positive impact that strategic orientations have on firm performance (Schweiger et al., 2019). Strategic orientations are valuable, rare, inimitable, and non-substitutable resources that provide a sustained competitive advantage (Barney, 1991).

Research Gap

Although research about the significance of AI and its impact on firm performance is rapidly increasing, the extant literature lacks holistic concepts that can capture the determinants of a firm's AI Orientation and lead to value delivery.

Recent research studies have focused mainly on the effect of top management on AI Orientation. For example, Li et.al (2021) established the impact of top management and board on the development of AI Orientation. Their study highlights that CIOs and Boards must collaborate closely to ensure AI technologies enhance long-term value creation while managing associated risks and ethical challenges. Another study by Pinski et.al (2024) explored how the AI Literacy of a company's top management team influences its AI Orientation and AI implementation capability. These studies measure a firm's AI Orientation from its annual reports (for public firms) and external communications (for private firms) leveraging AI skill and competencies taxonomy (Pinski et al., 2024, Li et al., 2021). These measures are based on external-facing firm data and do not capture how firms internally manage AI and how that impacts their AI Orientation. Given the significance of AI as a strategic orientation, it is essential to understand its determinants within firms. This knowledge can be useful for practitioners striving to advance their organizations' AI journey.

Previous literature extensively studies IT orientation in general. The firm's IT orientation was viewed as either strategic, promoting innovative uses of technology to advance long-term objectives, or utilitarian, focusing primarily on maintaining operational efficiency through structured support functions. (Sobol et al., 2009). It is considered a firm-level capability, a business culture that focuses on the right technologies to maintain high levels of business performance. Despite being technology-based, AI Orientation warrants specific focus compared to traditional IT orientation, as the top management team and board play a more active role in developing a company's AI Orientation (Li et al., 2021). While the relevance of AI Orientation is broadly

accepted in both research and practice, academic inquiry into what drives it in organizations remains surprisingly underexplored. This leaves a critical gap in understanding how organizations strategically harness AI for value creation.

Over the years, research has focused on the evolution and advancement of artificial intelligence technologies and their growing influence across industries. As the popularity of AI has increased in recent years, academic research has proliferated across various aspects of AI. Mikalef and Gupta (2021) defined AI capability and developed an instrument to capture it. However, AI is a technology that can only deliver its full potential when combined with other factors like leadership influence, organizational governance, etc. The adoption and value realization of AI technologies has a socio-technical nature, which implies the influence of changes at the individual, social, and institutional levels (Nambisan et.al, 2019). Though many industry-driven studies are trying to explore how firms are being successful in their AI advancements, academic research studies are still limited to exploring how firms manage AI internally holistically to scale and deliver value and how they are trying to establish AI as a strategic orientation. Given AI Orientation is an emerging phenomenon, we argue that more academic research is needed to understand how firms capture the strategic value of AI, and the experiences undergone by senior leaders as their firms advance in this journey.

Strategic IT-Business alignment has consistently been identified as a top IT management issue by chief information officers (CIOs) and senior IT leaders in SIM IT Issues and Trends Study by MIS Quarterly Executive (Johnson et al., 2025; Kappelman et al., 2014). Researchers have highlighted its significance over the past many decades (Wu et al., 2015). Luftman and Kempaiah (2007) proposed six components of the IT-

business strategic alignment maturity model: communication, value, governance, partnership, and architecture (Luftman & Kempaiah, 2007). This strategic alignment becomes even more critical in this new AI era when organizations are racing to respond to the rapid changes AI brings to their operating models. With the increased anxiety across employee levels about the consequences of AI adoption (Kaya et.al, 2022), getting the right levels of strategic alignment across multiple departments is crucial to the success of the organizational AI journey. This study explores the nuances of AI-driven IT-business alignment and validates the underlying alignment components that can impact the strategic AI Orientation as organizations advance in their AI journey. Limited research focuses on how proactive enterprise alignment can enable value delivery from AI implementation.

Previous studies have shed light on how CIOs can promote strategic alignment to increase technological investment and organizational performance, leveraging their business and technology skills, shared cognition, and trust among members of the upper echelon (Banker et al., 2022; Carter et al., 2011; Enns & McDonagh, 2008; Gerow et al., 2015; Karahanna & Preston, 2013; Liang et al., 2017; Peppard et.al.,2010; Sobol & Klein, 2009). A recent study by Li et al. (2021) highlights the importance of CIO presence on top management teams, which can facilitate firms' AI Orientation. Recent industry surveys and practitioner feedback indicate that more focus is needed to bring the right level of strategic alignment to ensure the success of AI programs. According to a recent Gartner poll, 55% of organizations recognize the need for a strategic alignment among multiple departments and a specialized governance structure ("Gartner Leadership Driving AI Revolution in the Boardroom," n.d.).

Prior research demonstrates that IT governance mechanisms play a critical role in facilitating strategic alignment of information systems (IS), thereby enhancing organizational performance—particularly in dimensions such as operational excellence and customer responsiveness (Wu et al., 2015). IT governance frameworks provide a structured approach to decision rights and accountability—clarifying who makes decisions, what is decided, and how these decisions are enacted—to ensure that IT investments support and extend business objectives (Tiwana et al., 2013). Building on this foundation, recent work has sought to extrapolate the IT governance cube to encompass AI governance, examining its antecedents and consequences (Schneider et al., 2023). Effective AI governance practices are increasingly viewed as essential for ensuring that AI initiatives deliver measurable business value in terms of performance and productivity (Zhang et al., 2021).

A well-designed AI governance framework not only safeguards ethical implementation but also seeks to align AI technologies with broader business strategies and organizational goals. Although research on AI governance is expanding rapidly, there is limited empirical work on how AI governance can be integrated seamlessly into overall organizational governance structures to drive value delivery. Some scholars argue that organizational AI governance should be conceptualized systemically, leveraging existing governance mechanisms to avoid redundancy and fragmentation (Mäntymäki et al., 2022). Others highlight the need for more research to identify the key dimensions of AI governance that enable accountability and business value realization from AI initiatives (Benbya et al., 2021). Despite these differing perspectives, a common theme emerges across the literature: AI governance must be strategic in nature. It should not merely

function as a compliance-oriented mechanism but as a dynamic, value-enabling capability that aligns AI initiatives with the firm's broader strategic objectives and performance outcomes.

As organizations advance in their AI journey, more want to move beyond proof of concepts and scale AI implementations to realize value. AI scaling is challenging, especially for large firms that are not digitally native. This can lead to unforeseen barriers that can hinder value realization (Sagodi et al., 2024). More academic research in this field can help build theory-based knowledge that practitioners can leverage as they continue to develop their firm's AI Orientation.

Research Question

What are the determinants of a firm's AI Orientation (AIO)?

Expected Contributions

This research will be beneficial to both researchers and practitioners in this era of AI based reinvention.

For Researchers:

1. This research expands on the literature on AI Orientation, building on the growing research on the leadership and governance elements of AI. Strategic orientation literature is constantly evolving, and given AI's significance today, it is essential to understand how firms can develop AI as a strategic orientation. This study advances the conceptualization of AI Orientation as a strategic construct.
2. This research unearths the experiential nuances firms experience in their AI journey through in-depth interviews of senior leaders influencing AI-related

decisions. This contributes to upper echelon's theory and governance literatures by examining how these are impacting AI Orientation

3. This qualitative research explores the challenges and best practices that firms experience in their AI journey. Existing literature studies AI Orientation based on annual reports and other external-facing documents. These often take a quantitative approach towards AI Orientation. Our research takes a qualitative approach and can complement the current studies around AI Orientation.

For Practitioners:

1. As firms advance from experimenting with AI technologies to scaling AI across the board, they must have a well-researched and holistic framework to govern AI and track progress. By exploring determinants of AI Orientation, this study equips practitioners with an executable playbook to govern and advance AI initiatives and position AI for long-term value delivery.
2. The study serves as a practical guide for top-level management, most of whom have low technical knowledge, but are becoming increasingly aware of the risk of not addressing the AI opportunity. The study offers a framework for pursuing AI Orientation by aligning the key determinants inside the organization. Drawing on Treacy and Wiersema's value disciplines, it suggests that firms can direct AI Orientation toward operational excellence, customer intimacy, or product innovation, depending on their competitive positioning. This guidance enables organizations to make deliberate choices about where AI should create value, rather than dispersing investments without clear strategic logic.

3. Firms face many unforeseen barriers that can hinder value capture from AI initiatives, considering these are emerging technologies. This study explores the constraints, best practices and challenges in realizing value from AI projects and shares how firms developed strategies and tactics to address their constraints. This can provide actionable insights to senior leaders as they take AI-related decisions in their firms.

Chapter 2: Literature Review

Artificial Intelligence (AI) has emerged as the top technology priority for organizations in recent years. The emergence of foundation models and Generative AI has positioned AI as a technology with applications across industries and functions. Its implications for firm production and operations are huge, as it can impact how firms make decisions and offer customization and optimization opportunities (Davenport & Ronanki, 2018). While these developments signal AI's transformative potential, scholars caution that AI technologies have to be combined with the correct organizational elements to capture sustainable value from those implementations. This perspective underscores the importance of examining AI technologies and how organizations strategically orient themselves towards applying AI for business value delivery.

What is Artificial Intelligence?

Artificial Intelligence systems can be broadly defined as systems designed to perform actions that, if performed by humans, would be considered intelligent (Hammond, 2024). Artificial Intelligence (AI) technology is “a broad collection of computer-assisted systems for task performance, leveraging machine learning, automated knowledge repositories, image recognition, natural language processing, and large language models” (Von Krogh, 2018). The term artificial intelligence was first coined by Stanford Professor John McCarthy in 1955 and defined as “the science and engineering of making intelligent machines” (Stanford Institute for Human-Centered Artificial Intelligence [HAI], 2020). Li et al (2021) define AI systems as technologies that leverage machine-based intelligence and advanced computing capacity to mimic human

‘cognitive’ functions (Li et al. 2021). Benbya et al. (2021) summarized AI technologies and their domain of applications as follows:

Technology	Brief description	Example application
<i>Machine learning</i>	Learns from experience	Highly granular marketing analyses on big data
	Learns from a set of training data	
	Detects patterns in data that are not labeled and for which the result is not known	
<i>Deep learning</i>	A class of machine learning that learns without human supervision, drawing from data that is both unstructured and unlabeled.	Image and voice recognition, self-driving cars
<i>Neural networks</i>	Algorithms that endeavor to recognize the underlying relationships in a set of data through a process that mimics the way the human brain operates.	credit and loan application evaluation, weather prediction
<i>Natural language processing</i>	The ability of a computer program to understand human language as it is written or spoken	speech recognition, text analysis, translation, generation
<i>Rule-based expert systems</i>	A set of logical rules derives from human experts	Insurance underwriting, credit approval
<i>Robotic process automation</i>	Automates structured digital tasks and interfaces with systems	Credit card replacement, validating online credentials
<i>Robots</i>	Automates a physical activity, manipulates and picks up objects	Factory and warehouse tasks

The field of AI has evolved significantly over the past few decades, creating machines capable of executing tasks that mimic human cognitive abilities. The pivotal moment in the evolution of AI was in late 2022 with the democratization of Generative AI through the launch of ChatGPT. Generative AI uses generative modeling, compared to discriminative modeling (Ng and Jordan 2001) often used in data-driven decision support. The advancements in supporting infrastructure and computing mechanisms facilitated rapid developments in the field of AI.

While AI can be defined and categorized based on various characteristics like underlying technology or application function, the more relevant categorization for this study is on the basis of business value derived from its application in organizations. AI can be classified as AI for automation and AI for augmentation based on its applications

in organizations. Automation refers to situations where machines fully assume tasks previously carried out by humans, whereas augmentation describes a collaborative dynamic in which humans and machines work together to accomplish a task. (Wilson & Daugherty, 2018; Raisch & Krakowski, 2021; Queiroz et al, 2023). Previous studies argued that organizations should prioritize augmentation and provided managers with directions to develop and implement an augmentation strategy.

More recent studies focus on Agentic IS, which refers to IS artifacts such as AI systems and other technologies that can have the capacity to learn, adapt, and act autonomously without being prompted by human agents (Baird & Maruping, 2021, Queiroz et al, 2023). As Agentic AI is gaining momentum in the industry, more organizations want to leverage AI for operational decision-making. Organizations are seeking to employ AI agents to automate repetitive tasks—such as customer service, smarter software development, data analysis, and report generation (Gross & Korolov, 2025; Murugesan, 2025). The advanced computing and machine intelligence in AI systems allow high-intelligence algorithms to analyze data and make autonomous decisions (Davenport et al., 2020; Simon, 1995).

How is AI different?

Berente et al. (2021) argue that artificial intelligence (AI) represents a new class of emerging computing capabilities that differs from traditional IT in three fundamental ways: its learning capacity, its sociotechnical nature, and its autonomy. Unlike conventional IT systems, it learns and evolves from data rather than following fixed rules, which means its behavior evolves over time. Its performance is shaped by human-machine interaction, and functions with a degree of autonomy that shifts decision-making

and accountability within organizations. These characteristics collectively make AI qualitatively different from earlier IT innovations, demanding new orientations, capabilities, and governance mechanisms to ensure that AI delivers strategic and ethical value (Berente et. Al, 2021).

The transformative potential of artificial intelligence (AI) to fundamentally reshape business processes and organizational dynamics is widely recognized and expected to intensify in the years ahead (Holmström, J, 2022); Jorzik et.al, 2024). AI fundamentally differs from previous generations of Information Technologies as it can learn, adapt, augment, and make autonomous decisions based on data and context (Brynjolfsson & McAfee, 2017). This capability of autonomy and learning elevates AI from a simple tool to a digital coworker, and hence, the introduction of AI in enterprises requires rethinking of organizational practices, culture, structure, governance, and leadership (Schneider et.al, 2023).

The advent of Artificial Intelligence (AI) technologies in organizations demands a new leadership landscape that necessitates orchestrating human-AI collaboration, strategic change and cultural transformation (Myszak, 2025). AI is a dynamic phenomenon, and leaders need to be cognizant of the emerging complexities and utilize and adaptive, collaborative and iterative approach towards AI implementation (Goryunova, 2025). AI-enabled systems learn, adapt, and make autonomous decisions, which requires leaders to bridge technical expertise with human insight, and evolve from control-oriented managers into orchestrators of intelligence, AI-persona management, culture, ethics, and strategy (Hoque & Davenport, 2025).

What is AI Orientation?

For the purpose of this study, we define *AI Orientation (AIO) as a firm's deliberate application of AI technologies to achieve its strategic goals*, drawing on the Resource-Based View (RBV) theory and Treacy and Wiersema's (1993) value disciplines. Firms with high AIO are not just doing the simple siloed implementation of AI, they go beyond with a broader strategic vision and embrace AI as a transformative strategy (Zhang et al., 2025). Recent research shows that AIO positively influences innovation (Eicke et al., 2025), operational efficiency (Yao et.al., 2025), and value creation through global collaboration (Huang et al., 2025). AI differs from conventional IT because it leverages data for automatic self-learning and decision-making and performs tasks on behalf of individuals or organizations (Faraj et al., 2018). Li, Li, Wang, and Thatcher (2021) argue that firms need a strategic orientation on AI to navigate the complexities of AI deployment.

AI Orientation can be understood as a type of strategic orientation that goes beyond implementing AI in isolated tasks to encompass a firm's broader commitment to embedding AI into its mission, goals, and values (Chan et al., 1997; Gatignon & Xuereb, 1997; Li et al., 2021). It reflects both the acquisition of AI-related knowledge and the diffusion of AI innovations across the organization, fostering a culture and readiness to fully leverage AI (Li et al., 2021). In this way, AI Orientation reshapes how firms allocate and deploy resources within their operational systems to achieve strategic advantage (Berente et al., 2021; Dubey et al., 2020; S. Li et al., 2023).

Firms with high AI Orientation apply AI to their strategic goals. There is increasing evidence that firms using AI strategically capture greater benefits. Industry

reports highlight that companies that pursue AI-enabled growth strategies stand to outperform their peers (Accenture, 2024; McKinsey& Company, 2023). Academic research highlights that the strategic deployment of AI creates substantially greater and more sustainable benefits than using AI tactically. Krakowski, Luger, and Raisch (2022) demonstrated that competitive advantage emerges when AI is strategically integrated to complement human judgment and reshape sources of value, rather than simply automate tasks. Ruokonen (2025) further emphasizes that aligning AI with strategic goals and innovation agendas is critical to achieving enduring long-term success. Collectively, these studies reinforce the importance of conceptualizing AI Orientation as a strategic construct—one that distinguishes between organizations that merely use AI in silos and those that apply AI to pursue strategic goals.

Treacy and Wiersema (1993) determined three value disciplines to focus the organization's activities based on companies that have taken leadership positions in their industries: Customer Intimacy, Operational Excellence, and Product Development. AI Orientation enables firms to go beyond applying AI for specific siloed tasks and consider it a transformative strategy (Yao et.al., 2025). Firms with high AI Orientation can apply AI technology towards their strategic goals like customer intimacy, operational excellence, or product development. Towards this, AI Orientation requires learning, cultural readiness, and demands restricting the way resources are allocated in a firm.

Theoretical Framework

The academic literature on AI Orientation (AIO) continues to remain fragmented in spite of its growing relevance. Some studies emphasize the role of leadership and governance in shaping how firms direct AI strategically (Li et al., 2021), while others

focus on the outcomes of orientation, such as innovation (Li et al., 2025) or operational efficiency (Yao et al., 2025). Conceptual contributions highlight orientation as a driver of capability development (Mikalef & Gupta, 2024), yet few integrate these insights systematically in the organizational context. Limited qualitative studies exist to understand the experiences that senior leaders are going through as they advance their firm's AI journey. To address this gap, this dissertation draws on five theoretical perspectives—Resource-Based View (RBV), Upper Echelons Theory (UET), Attention-Based View (ABV), Theory of Constraints (TOC), and Simons' Levers of Control (LOC)—to examine the determinants of AI Orientation in organizations.

1. Resource-based view (RBV): The Resource-Based View (RBV) of the firm highlights the significance of valuable, rare, inimitable, and non-substitutable (VRIN) resources in attaining a competitive advantage (Barney & Clark, 2007). The resource-based view of the firm has led to extensive academic research around strategic orientations that represent intangible and inimitable capabilities that can provide sustained competitive advantage (Schweiger et.al, 2019). The application of RBV in IS research provides a unique perspective into how IS resources influence firm performance (Wade & Hulland, 2004). Previous studies suggest that IS assets alone are unlikely to create a sustainable competitive advantage. It is only when IS resources are combined with functional capabilities and complementary resources, including human, technology, process, and relationship resources, that it can deliver a superior result (Mata et al., 1995; Ravichandran & Lertwongsatien, 2005). We propose to extend these findings to AI capabilities as a way to enhance organizational capabilities which form the basis of a company's competitive advantage. In today's AI era, technical AI capabilities are

available to all organizations and, by itself, is not the basis for sustained competitive advantage (Wingate et. al, 2025)]. Although AI technologies can be increasingly commoditized, the way organizations orient towards AI and apply AI towards strategic goals can represent an intangible, inimitable capability that meets VRIN criteria. Conceptualizing AI Orientation as a resource-based capability emphasizes how firms can transform generic technologies into unique, value-creating outcomes. RBV forms a key theoretical foundation as we explore key determinants of AIO, like organizational AI capability and organizational learning orientation.

2. Upper Echelons theory: Upper echelons theory suggests that the traits and characteristics of top executives significantly impact organizational outcomes and strategic decisions (Carpenter et al., 2004; Hambrick & Mason, 1984). Specifically, strategic outcomes are shaped by decisions made by top executives, which are driven by their values, cognitions, and perceptions (Harrison & Klein, 2007). Upper-echelon leaders are highly motivated to develop AI Orientations because AI can significantly impact power dynamics and organizational culture (Li et al., 2021). Top managers with limited technological expertise may struggle to understand the rationale and processes behind AI-driven decisions, leading to feelings of confusion, uncertainty, and concern about AI. This often drives them to seek support from technologically proficient upper-echelon members (Brock & Von Wangenheim, 2019). Consequently, top managers with extensive technological expertise and experience, such as CIOs, CTOs, or CDOs (Chief Data Officers), are more likely to influence AI Orientation and establish standard operating procedures for AI compliance (Singh & Hess, 2020). The collective AI Literacy of Top Management team in a firm significantly influences its AI decisions

(Pinski et.al, 2024). The UET forms the theoretical foundation of this study as we explore the critical determinants of a firm's AI Orientation, which includes Leadership influence and alignment among various leadership teams to steer the AI journey.

3. Attention-Based View (ABV): The fundamental presumption of this theory is that a firm's behavior is determined by how it divides and channels its attention, along with limited resources. Therefore, the ABV assumes that the more management focuses on an issue, the more resources and support it will receive, resulting in the desired outcomes for the firm (Hambrick & Mason, 1984). It argues that attention drives resource allocation in a firm (Ocasio, 1997). When more stakeholders are AI literate, it drives more attention and power flow towards AI-related initiatives, helping firms advance towards their AI goals (Pinski et.al, 2024). Leaders shape AI Orientation by focusing organizational attention on AI's potential across levels and functions. ABV provides the theoretical foundation to explore further on key determinants of AIO like leadership influence and enterprise alignment.

4. Theory of Constraints (TOC): The Theory of Constraints (Goldratt, 1986) was originally formulated for a production setting as a systematic approach to identify what was preventing a company from achieving its goal of making money. Goldratt (1990b), Klein & DeBruine (1995) & Dettmer (1997) further expanded the theory as an integrated management philosophy and evolved this into a vital problem structuring and solving methodology across various sectors. TOC considers a firm's processes as rings of the same chain and argues that the chain is only as strong as the weakest link. In other words, if a firm wants to improve its performance, it should understand its own structure and processes and identify the weakest link. As enterprises scale AI initiatives, they face

various constraints like talent shortage, data quality, integration challenges, alignment challenges etc. This theoretical framework underscores the importance of organizational AI scalability and enterprise alignment as key determinants.

5. Levers of Control (LOC): Simons (1994) proposes a framework for Management Control Systems to explain the idea of opposing forces that manage tensions. This includes examples like tension between top-down direction and bottom-up creativity, between empowerment and accountability (Simons, 1994). This theory identifies four levers of control to manage these opposing tensions - two positive levers (belief systems and interactive control systems) and two negative levers (boundary systems and diagnostic control systems). When applied to AI, this theory identified enabling and constraining mechanisms. Belief systems inspire opportunities and articulate a vision for AI and interactive control systems stimulate organizational learning and encourage discussions around AI. Boundary Systems establishes ethical and regulatory guardrails and diagnostic control systems monitor the performance and value of AI systems. Together, LOC as a theoretical framework shapes how firms orient strategically toward AI while managing risks and accountability, thus forming the foundation to further explore organizational AI governance as a key determinant. The LOC framework can also help in reinforcing alignment across the organization by minimizing agency problems and activating the control dimension.

Key themes determining a firm's AI Orientation

We synthesized learnings from these theoretical frameworks to identify six (6) key themes that formed the basis of our further exploration and literature review. Consistent with UET and ABV, **Leadership Influence** emerged as a key theme that

shapes AIO and frames AI initiatives as a strategic opportunity or siloed project.

Organization AI Capability and **Organizational Learning Orientation** align with RBV, encompassing tangible (data, technology, talent) and intangible (culture, risk proclivity, knowledge) resources that orient AI applications as a VRIN capability.

Through the ABV and LOC lenses, **Enterprise Alignment** and Leadership Influence are key themes that shape AIO, highlighting leadership attention and cross-functional alignment are important to apply AI towards strategic goals. Building on the foundation of LOC, **Organizational AI Governance** is identified as a key theme, where belief systems, boundary systems, diagnostic controls and interactive controls harmoniously coexist, underscoring that sustained AI Orientation needs this balance. **Organizational AI Scalability** emerged as a key theme for AIO, leveraging TOC's insights that it is important to identify and overcome the systemic bottlenecks to move towards enterprise-wide adoption and ongoing value delivery.

Leadership Influence

Previous studies have used the Upper Echelons Theory (UET) theory to establish the significance of leadership influence on AI Orientation. Li et al. (2021) examined the impact of Chief Information Officers (CIOs) and Boards of Directors on a firm's AI Orientation and emphasized that CIOs are responsible for leading the technical integration of AI, aligning AI initiatives with broader business objectives, and promoting cross-departmental collaboration to enhance AI adoption. They also explored the pivotal role the board of directors played in guiding AI strategy by overseeing resource allocation, managing risks, and ensuring ethical AI implementation. Though the study only explores the external-facing reports to measure AI Orientation and only considers

the role of IT leaders, this is a critical step in understanding the influence of leadership on a firm's AI Orientation.

Pinski et al. (2024) added an Attention-Based View (ABV) to the earlier theoretical framework. They established how more AI-literate executives in the Top Management Team can help find more support for AI Orientation and enhance the ability to implement AI technologies. The findings show that higher AI literacy within the Top Management Team (TMT) enhances both AI Orientation and implementation, with AI Orientation mediating the relationship between AI literacy and implementation capability. This research also contributes to upper echelons theory by emphasizing the importance of AI Literacy as a critical skill for top management in driving AI value generation. AI Literacy is defined as a human's holistic proficiency that enables critical usage and effective collaboration with AI (Cetindamar et al., 2022; Long & Magerko, 2020). Sobol and Klein's (2009) research highlights the impact of a CIO's background on a firm's technology strategy and AI adoption. They argue that a CIO's education (in fields like computer science or business) and professional experience significantly influence their ability to lead strategic technology initiatives. Another study by Banker et.al (2022) explores how CIOs influence a firm's strategy implementation and proposes that a firm's preferences regarding CIO background (business acumen versus technical expertise) depend on their strategic positioning. Understanding how leadership influences AI decisions in a firm is essential, given that it is an emerging technology with significant business implications.

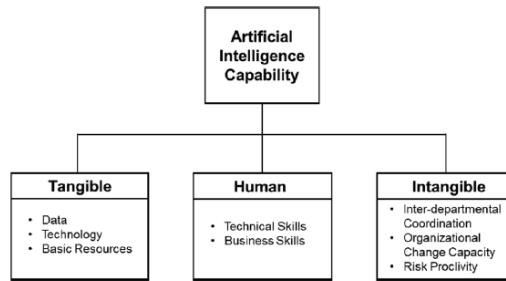
Previous studies have also established that top management can encourage and facilitate artificial intelligence-enabled business model innovation by shaping the firm's

strategic vision, fostering an innovation-oriented culture, and allocating resources toward experimentation (Jorzik, et al, 2023). Other academic research streams are in progress to understand more about emerging roles like Chief AI officer, AI Risk officer, etc. All these studies underscore the importance of the leadership background in shaping a firm's AI Orientation and implementation success.

Organizational AI Capability

Organizational AI capability aligns closely with the Resource-Based View (RBV), which emphasizes that sustainable competitive advantage arises from resources and capabilities that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). In the context of AI Orientation, AI technology in itself cannot offer any competitive advantage. It must be combined with human creativity and organizational innovativeness, encompassing tangible and intangible resources, to transform AI technologies from generic tools into distinctive strategic capabilities (Wingate et.al, 2025).

Mikalef and Gupta (2021) investigate artificial intelligence (AI) capability as a multidimensional construct and its influence on organizational creativity and firm performance. The authors first conceptualize AI capability, defining it as an organization's ability to utilize AI technologies and integrate them into business processes effectively. They develop a robust measurement framework to calibrate AI capability, incorporating dimensions such as technical expertise, data management, and organizational learning. Their empirical results indicate a positive correlation between AI capability and overall firm performance, suggesting that organizations that effectively leverage AI technologies can achieve better operational and financial outcomes.



IS Research has seen extensive academic studies to understand the organizational adoption of several innovative information systems over the years. Jeyaraj, Rottman and Lacity (2006) identified that the best predictors of IT adoption by organizations were Top Management Support, External Pressure, Professionalism of the IS Unit, and External Information Sources. Uren and Edwards (2023) established that given the potential for societal impacts of AI technologies, a socio-technical approach needs to be taken while implementing AI in organizations. Extensive studies have been done on Human-Centered Artificial Intelligence (HCAI) in academia to ensure humans are in the loop as AI technologies advance. HCAI refers to the development of systems that augment rather than replace humans, as HCAI seeks to enhance human performance and human-AI collaboration by integrating artificial and human intelligence (Herrmann et al., 2023). Hartikainen et.al (2023) proposed a HCAI Maturity Model to support AI development practices in firms to build efficient, trustworthy and safe AI solutions.

Enterprise Alignment

The Attention Based View (ABV) emphasizes the role of attention across levels and functions to ensure cross-functional enterprise alignment. Simon's (1994) Levers of Control (LOC) framework helps organizations minimize agency problems (the gap between managerial/employee actions and organizational objectives) and creates an alignment between individual behaviors and strategic goals. Attaining alignment between

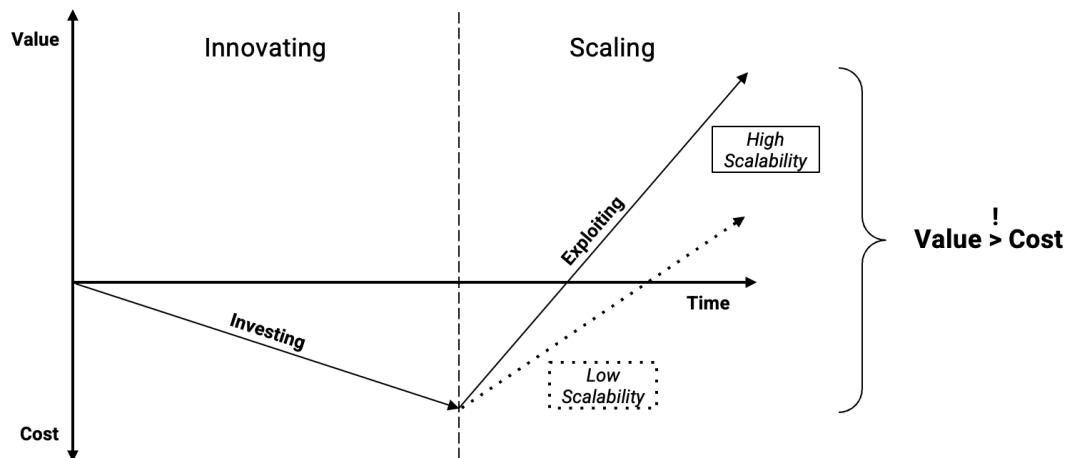
IT and business has been identified as pervasive problem in IS. Society for Information Management (SIM) identifies this as an important problem to be addressed in research. Luftman and Kempaiah (2007) propose that this alignment can be best understood and measured through six interrelated components: communications, value, governance, partnership, scope and architecture, and skills. Their research also found that federated IT organizational structures are linked to higher alignment maturity than centralized or decentralized structures. Previous studies have established that IT resources and capabilities effectively support business objectives, improving operational efficiency and competitive advantage, especially in dynamic and complex situations (Sabherwal et al., 2019). Benbya et al. (2019) curated the extensive research in the alignment space into three categories – (1) strategic, (2) operational, and (3) social. Business-IT alignment and effective IT governance positively influence firm performance, and organizations that excel in both areas achieve more significant performance benefits than those that do not (Chau et al., 2020). Given AI programs need balanced involvement from business and IT, we propose that there has to be a strong alignment across various enterprise functions (business, IT, legal, procurement etc.) on all AI initiatives.

As organizations are increasingly investing in AI initiatives, it is essential to note that more than AI capabilities are needed to create additional business value. Companies need to understand how AI technologies can be commercialized through appropriate AI business model innovation. Astrom et al. (2022) proposed a three-phased process framework that explains the activities companies need to perform for value creation and capture – (1) identifying prerequisites for AI value creation, (2) matching value capture mechanisms, (3) and developing AI business model (Astrom et al., 2022). It is essential

to have upfront alignment on this AI business model approach among the key stakeholders and decision-makers across Business and IT.

Organizational AI Scalability

The Theory of Constraints (TOC)'s insights emphasized the importance of identifying and overcoming systemic constraints to move towards achieving organizational AI scalability which is a key determinant for AIO. According to Gartner: "Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands." Scalable AI is the ability of algorithms, data, models, and infrastructure to operate at the size, speed, and complexity required for the mission (Barmer et al, 2021). Sagodi et al. (2024) established that innovating and scaling are two distinct stages in a firm's AI journey.



Through their detailed case study analysis of how Audi scales AI, they establish that there are three AI specific challenges that organizations need to address in order to create a scalable AI system – (1) Learning requirements which should consider data volume requirements, data quality and continuous user engagement (2) Probabilistic reasoning – performance, accuracy and decision quality of AI systems (3) Data

Processing Requirements – allocation of required resources and integration of AI technologies with legacy landscape. Barmer et al (2021) identify three key areas of focus to advance scalable AI – (1) Scalable management of data model (2) Enterprise scalability of AI development and deployment (3) Scalable algorithms and architecture.

Organizational Learning Orientation

Organizational learning orientation is an intangible capability, aligned to Resource-Based View (RBV), that enhances how firms develop and sustain AI Orientation. Learning orientation empowers organizations to create and sustain competitive advantage by challenging established norms as the environment evolves (Baker & Sinkula, 1999). This ability to adapt to environmental changes is a crucial competency that organizations must develop and maintain to secure competitive advantage and superior performance (Slater & Narver, 1996; Sinkula et al., 1997). Previous research establishes three key components of organizational learning – (1) Commitment to Learning - the extent to which an organization prioritizes learning and sees it as essential for long-term success, (2) Open-mindedness - The willingness of an organization to evaluate critically and, if necessary, abandon existing knowledge or routines in favor of new insights, (3) Shared Vision - A common understanding within the organization of the importance of learning, which ensures that learning efforts are aligned with organizational goals (Sinkula et al., 1997). Organizations need to focus on organizational learning to develop their AI Orientation. AI projects require a substantially different skillset compared to traditional IT, and it demands a mindset change for continuous upskilling. Organizations must be prepared to upskill their existing employees

with the necessary training, so they don't lose business knowledge, and the employees are skilled at leveraging AI tools and techniques (Mikalef and Gupta, 2021).

Organizational AI Governance

Simons' (1995) Levers of Control framework provides a powerful perspective for understanding AI Governance as a strategic control system rather than a restrictive compliance process. Effective AI Governance systems include both enablers (belief systems and interactive control systems) and constraints (boundary systems and diagnostic control systems) to ensure that AI initiatives are both strategically valuable and ethically responsible. Framed through Simon's LOC framework, organizational AI governance emerges as a dynamic balance of control and empowerment, enabling firms to innovate responsibly. AI governance becomes a strategic enabler that ensures that AI Orientation is executed in a manner consistent with the firm's values, culture and long-term vision.

Research has established that organizational IT governance structures, processes, and relational mechanisms enhance firms' performance (Vejseli & Rossmann, 2017). Tiwana et al. (2014) proposed the IT Governance cube as a framework to explore all dimensions of IT governance as organizations go through dynamic environmental complexities. It has three dimensions to indicate who is governed, what is governed, and how it is governed. The "who" dimension represents the scope or expansiveness of governance. This can vary depending on the specific nature of the scope under discussion. The second dimension of "what" pertains to what are the artifacts that need to be governed. The third dimension of "how" represents the mechanisms to govern. As organizations advance in their AI journey, the situational complexities and stakeholder

involvement increase considerably, and more factors can be explored across the three dimensions of the IT governance cube. Attempts have been made to extrapolate the IT Governance cube to include AI governance aspects, understanding the antecedents and consequences (Schneider et al., 2023).

Artificial intelligence (AI) governance is necessary to harness the benefits and manage the risks associated with AI systems (Mäntymäki et al., 2022). It is defined as “a system of rules, practices, processes, and technological tools that are employed to ensure an organization’s use of AI technologies aligns with the organization’s strategies, objectives, and values; fulfills legal requirements and meets principles of ethical AI followed by the organization” (Mäntymäki et al., 2022). Organizational AI governance must consider governance structures, policies and procedures, stakeholder engagement, continuous monitoring, and evaluation. Papagiannidis et al. (2023) establish that AI governance is a complex issue for organizations, encompassing structural, relational, and procedural dimensions of governance (Papagiannidis et al., 2023). It operates across multiple levels, necessitating a structured approach for effective deployment.

As AI technologies are increasingly prevalent in the workplace, it is important to define proper governance mechanisms to have humans in the loop. Benbya et al. (2021) argue that humans must define how machines will be implemented and used and take responsibility for related tasks and outcomes. Previous studies have established that machines do not have any sense of purpose (Braga & Logan, 2017) and machines are incapable of manifesting intentionality (Floridi, 2008). Managing accountability and ensuring AI explainability through a proper AI governance mechanism is critical to implement ethical and responsible AI.

Expert Validation

We validated the themes emerged from our literature review with experts in the field of Artificial Intelligence. Four senior leaders (including practitioners and academicians) known for their contributions to the world of AI were contacted to join the expert validation process. These subject matter experts were identified and recruited using existing networks of contacts and provided context about the research. We conducted a one-hour validation session with each of these subject matter experts to validate the key themes in research model and interview content.

At large, the themes identified from the literature review conformed to the inputs from the subject matter experts. There was terminology changes suggested to align better with the latest research and industry practices. Providing a practical definition and categorization of AI was emphasized in multiple sessions, and hence we decided to include a business-value based AI categorization in the pre-read materials for interview participants. Some experts indicated potential interview feedback that may help us further refine the categorization of determinants or a potential two-sided relationship with AI Orientation. The interview script was refined based on various inputs to improve clarity and simplicity.

Proposed Research Model

Using the above-mentioned categories, our research model and propositions are shown in the below diagram:



Figure 1: Initial Research Model

Research Propositions

1. **Proposition 1 (P1):** Leadership Influence within a firm impacts its AI Orientation
2. **Proposition 2 (P2):** A firm's AI capability impacts its AI Orientation
3. **Proposition 3 (P3):** A firm's Enterprise Alignment impacts its AI Orientation
4. **Proposition 4 (P4):** A firm's ability to scale AI impacts its AI Orientation
5. **Proposition 5 (P5):** A firm's learning orientation impacts its AI Orientation
6. **Proposition 6 (P6):** A firm's AI governance framework impacts its AI Orientation

Key Definitions:

Construct	Description	Examples	Level
AI Orientation	<p>This dissertation defines AI Orientation (AIO) as a firm's deliberate application of AI technologies to achieve its strategic goals.</p> <p>Firms need a strategic orientation on AI to navigate the complexities of AI deployment. AIO guides AI-related strategic decisions, including AI-related investments and management</p>	<p>Li et al. (2021)</p> <p>Pinski et.al (2024)</p> <p>Eicke et al., 2025</p> <p>Zhang et al., 2025</p> <p>Faraj et al., 2018</p>	Firm-level

	<p>practices. AI Orientation has nuances that make it distinctive from conventional IT orientation.</p> <p>AIO positively influences innovation and operational efficiency</p> <p>AI differs from conventional IT because it leverages data for automatic self-learning and decision-making and performs tasks on behalf of individuals or organizations</p> <p>This research highlights why AI needs to be considered as a strategic orientation and its determinants.</p>		
Strategic Orientation	<p>A firm's strategic orientation reflects the strategic directions implemented by a firm to create the proper behaviors for the continuous superior performance of the business. It reflects the firm's philosophy of how to conduct business through a deeply rooted set of values and beliefs that guides the firm's attempt to achieve superior performance.</p>	<p>Slater & Narver (1996)</p> <p>Gatignon & Xuereb (1997)</p>	Firm-level
AI Literacy AI Fluency	<p>A human's holistic proficiency concerning AI that enables critical usage and evaluation of AI as well as effective communication and collaboration with AI</p> <p>AI Fluency is not yet in literature, but industry prefers this that AI Literacy (Anecdotal feedback)</p>	<p>Heyder and Posegga (2021) and Long and Magerko (2020)</p>	Individual level
TMT AI Literacy/ Fluency	The collective AI literacy of the top management team (TMT).	Pinski et.al (2024)	Firm-level
AI Capability	An AI capability is the ability of a firm to select, orchestrate, and leverage its AI-specific resources	Mikalef et.al (2020)	Firm-level
AI Scalability	Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands. The core of sustainable AI-based value generation is a scalable AI system	<p>Sagodi et.al (2024)</p> <p>Someh et.al (2021)</p>	Firm-level

AI Value Capture	Value capture is defined as the mechanisms that ensure an economic return from value creation and that profits are shared throughout the value creation network. It is important to understand how AI creates value, and the firm needs to ensure that complementary products, technologies, and services are available within the value-creation network.	Astrom et al. (2022) Sjödin et al. (2021) Pisano and Teece (2007)	Firm-level
AI Governance	AI governance is a system of rules, practices, processes, and technological tools employed to ensure an organization's use of AI technologies aligns with its strategies, objectives, and values, fulfills legal requirements, and meets the principles of ethical AI followed by the organization.	Mantymaki et.al (2021) Papagiannidis et.al (2022) Schneider et.al (2023)	Firm-level
Learning Orientation	Learning orientation is an organizational characteristic that affects a firm's propensity to value generative and double-loop learning. Such learning will better enable firms to accomplish continuous improvements and breakthrough innovations. Firms that have enhanced learning orientations are more willing to question long-held assumptions about their fundamental operating philosophies	Baker and Sinkula (1997) Slater and Narver (1995)	Firm-level
Business-IT Alignment	Business-IT strategic alignment is defined as the degree to which the mission, objectives, and plans contained in the business strategy are shared and supported by the IS strategy. If alignment and governance are effectively managed, IT may move from being not only an enabler but also a strategic driver of company growth in digital economies. Given the growing dominance of data driven decision making, the alignment between IT and business strategy will become increasingly important. Enterprise Alignment builds in this definition to include all enterprise functions like legal, HR, procurement etc. along with Business and IT	Chau et al. (2020) Chan et al. (1997)	Firm-level

Chapter 3: Method

Overview

The research aims to answer the following question: What are the determinants of a firm's AI Orientation?

Research Method

We performed an exploratory qualitative analysis based on expert interviews to conduct this study. We employed a case study methodology to explore our research questions qualitatively. Case study research was particularly effective for answering "how" and "why" questions about contemporary phenomena within their real-world contexts, according to esteemed case study scholar Robert Yin (Yin, 2009). When the underlying logic explaining such phenomena is unknown, case studies allow researchers to conduct detailed examinations of these "how" and "why" questions (Yin, 2009). According to Yin (2018), "the unit of analysis (the case) could be an individual, an organization, a community, a decision, an event, a program, or a process. What makes it 'a case' is that it is a bounded system—meaning it has clear edges in time and space (e.g., a particular program in one city during a specific period, rather than the concept of 'programs' in general)".

Our study explored how firms advance their AI journey and understand more about the challenges and best practices around AI Orientation. The emergence of AI as a disruptive technology is relatively recent and has bolstered the transformative potential of AI in all facets of business. This emerging phenomenon needs to be studied through in-depth observations and experience analysis. Our unit of analysis was senior leaders with direct influence on AI-related decisions (such as strategy, recommendations,

technical/value/people suggestions) in large firms. The participants had a minimum of 10 years of work experience in US-based public or privately held companies with at least 100 employees.

Paradigms and Ethics

This research involved interaction with human subjects through remote interviews via conferencing technology, such as Zoom. Interviews were also recorded and transcribed using a professional transcribing service. Thus, we followed a strict code of ethics to protect both the human subjects and the collected data.

As guided by APA ethical standards, we received approval from the University of Missouri - St. Louis Institutional Review Board (IRB) before contacting any potential candidates for interviewing. In the IRB application, we asked for permission to interview up to 30 participants, more than the 20 we interviewed for this research. The IRB Approval letter is provided in Appendix A for reference.

Participant Selection Process

After Institutional Review Board (IRB) approval from the University of Missouri - St. Louis, we launched a website that describes the research objectives, methodology, and recruitment process. The website URL is <https://ai-orientation.com/>, and the screenshots are provided in Appendix B for reference. We leveraged this website as a one-stop shop for research-related information, participant surveys, consent forms, and interview sign-ups. The participant sign-ups were tracked using a Google form linked to the website. This was shared across the research team's professional and personal network, including the UMSL DBA cohorts and social media sites, including LinkedIn

and Facebook. Once we received participant sign-up, we reached out via email to confirm the interview schedule and answer any additional questions they may have.

Research Participants

Our sample selection included 20 senior leaders with direct influence on AI-related decisions (such as strategy, recommendations, technical/value/people suggestions) in the firm. The participants had a minimum of 10 years of work experience in US-based public or privately held companies with at least 100 employees. We selected interview participants from firms where they had a key role in taking AI-related decisions, as firms without clearly defined AI-related roles may not have experiences related to strategic AI Orientation and how AI is associated with the firm's strategic goals. We determined our final sample size at 20 participants, as theoretical saturation had been reached and no new insights were emerging. The table below summarizes the interview participants and their roles. All our participants are part of senior leadership teams in their respective firms engaged in AI-related decisions, and close to strategic business priorities in their firms. This helped us collect rich data about their experiences navigating their firm's AI journey.

#	Company Profile	Role
1	Global Manufacturer of Chemical Products	VP Transformation
2	Retailer of outdoor products, Works with third party manufacturers	CIO
3	Financial Services & Payment Processing company	VP, Data Localization Practice
4	Global Manufacturer of motors	Principal Corporate Lead, Strategic Innovation
5	Engineering & Construction software provider	VP, Product Management
6	Retailer of clothing products, Works with third party manufacturers	Sr. Director, Digital Strategy & Tech Portfolio

7	Retailer of apparel and home products, Works with third party manufacturers	VP, Analytics
8	Global manufacturer of food and beverages	Sr. Manager, Data Insights
9	Global manufacturer of electronic products	VP
10	IT Services & Consulting company for small & medium businesses	Chief Experience Officer
11	Manufacturer of biopharmaceutical products	Senior Director, Manufacturing Systems
12	Manufacturer of measuring instruments	Senior Director, Global IT Operations
13	Manufacturer of pharmaceutical products	Head of E2E Decision Science
14	Retailer of beauty products, Works with third party manufacturers	VP Data and Innovation
15	Management & Strategy Consulting Leader	Chief Technologist, Business Information Security Officer for the Global Defense Sector
16	Global Consulting Firm	Former VP - Trucking, Consulting Leader
17	Global Automotive manufacturer	Head of IT
18	Global Consumer Goods Major	Solution Leader - Enterprise/Corporate Data
19	Global Automotive manufacturer	Global Head of IT
20	Global Mobility Products Supplier	Software Engineering Head

Interview Protocol

The interviews were conducted through the Zoom video conferencing service. The interviews lasted 45-60 mins in most cases, and all interviews were recorded using zoom recording. The interviews were exploratory and included prepared semi-structured questions to probe individuals' experiences with their firm's AI journey. To balance consistency across participants with the opportunity for in-depth insights, we designed an interview guide featuring open-ended questions to structure the semi-structured interviews. The interview protocol process consisted of two parts: a non-recorded part and a recorded part:

Non-recorded Interview Part: 5 minutes

- Introduction (introductory script used during the non-recorded part of the interview)
- Informed consent (informed consent that was distributed to the participants prior to the interview)

Recorded Interview Part: 35 – 60 minutes

- Main questions (25-50 minutes) (list of semi-structured questions)
- Demographic questions (0-5 minutes) (list of demographic questions)
- Summary & wrap-up: 5 minutes

Interview Questions: We formulated our main interview questions aligned to the research propositions and then validated these questions through our expert validation step. The list of questions used for our semi-structured interview process is given in Appendix C for reference.

Research Procedure

All data gathered through the interviews were saved to a folder in the University of Missouri team site. The transcript document file from the Zoom recording served as our primary data file, and other recorded files were used as additional inputs for analysis, as needed. Qualitative data from interviews were then cleaned, transcribed, and redacted.

Filtering the data to focus on Strategic AI Applications:

As our research objective is to explore the determinants of AI Orientation in a firm, we focused exclusively on strategic applications of AI. Our interview protocol was tailored towards this objective, beginning with questions around business priorities and followed by semi-structured discussions. However, some of our interview participants referred to baseline AI applications such as use of copilots for individual productivity or

zoom AI for meeting efficiency. Applying RBV theory and VRIN framework for strategic orientation, we classified them as non-strategic applications or baseline AI applications and excluded them from further analysis or coding activities. This filtering process ensured that our analysis remained centered around data exclusively related to strategic applications of AI, which are more likely to serve as potential sources of competitive advantage

We followed two complementary methodologies to analyze our qualitative data. Our first and primary approach leveraged Quirkos as a qualitative analysis tool to facilitate manual coding with the identification of a priori codes and emerging key themes through researcher-led interpretation. We used this method as our primary approach for analysis, as this is in alignment with established qualitative research practices, and ensures rigor and transparency. The second approach leveraged AI as a supportive researcher through a ChatGPT-based tool named QualiGPT, which provided AI-generated coding through deductive and inductive approaches. This dual approach is noteworthy because it provides additional validation and triangulation, which enhances the robustness of the findings. It also demonstrates the potential of integrating human expertise with AI-assisted analysis. This methodology emphasizes a promising avenue for future qualitative research, where generative AI can augment human judgment, ultimately contributing to methodological innovation in business research.

Data Analysis Approach #1 – Leveraging Quirkos

In the primary analysis approach, we codified the transcripts using a line-by-line technique in Quirkos and assigned the content of the transcript to the previously agreed themes included in the codebook. The codebook used for deductive analysis was derived

based on the initial research model given in Figure 1. We used the codebook below as a priori for Quirkos analysis.

Category	Keywords
Leadership	Top Management Team, TMT, Executive Leadership Team, ELT,
Influence	Leadership Team, LT, TMT AI Fluency, TMT characteristics, TMT AI Vision, Organizational strategic goals, Board Effectiveness, Top Management, Leadership, Executive, CIO, C-Suite, TMT career experience, TMT education, strategy, leadership, leader, leader trust, leader communication, collaboration
Organizational AI Capability	Tangible Resources, Data, Technology, Business Process, Human Resources, Technical skills, Business skills, People, Talent, Intangible Resources, Organizational change, Risk proclivity, Resources
Enterprise Alignment	Business-IT Alignment, Cross-functional alignment, business enterprise, proactiveness, portfolio alignment, AI Value Capture alignment
Organizational AI Scalability	Model Learning Requirements, Decision, Decision Quality, scale, scalability, model learning, partnership, probabilistic reasoning, decision quality, data processing, mainstream infrastructure

Organizational Learning Orientation	Commitment to Learning, Open-mindedness, partnership, shared vision, learning, collaboration, training, learning resources, train the trainer, mentorship, learning circles
Organizational AI Governance	What, Who, How of AI Governance, ai governance, responsible ai, sustainable ai, governance, privacy, who, how, value capture, guardrails, framework, privacy, risk, govern, transparency

As a next step, we also did inductive analysis thereby identifying emergent themes from the interview transcript and documented them as observational findings.

Data Analysis Approach #2 – QualiGPT as a Support Research Tool

As the motivation for this research stemmed from the power of AI in today's world, we were curious to explore AI as a tool in this qualitative research process. Qualitative research is based on experience and subjectivity to understand the human world. Researchers need continuous interpretative and critical thinking for the insights to be relevant and impactful (Zhang, 2025). With the advent of Generative AI that can understand and generate human-like text, qualitative researchers can explore the powerful capabilities of AI in research. However, there are ethical implications for an AI-based research approach for qualitative data. This includes the unintended perpetuation of existing biases, and AI tools may not fully replicate the complex cognitive processes inherent in human analysis (Koivisto & Grassini, 2023). Recent studies suggest that AI tools like ChatGPT can augment and assist in research alongside the human elements like intuition and ethical judgment (Zhang, 2025).

We used QualiGPT as a Collaborative Research Tool as part of our analysis approach #2. QualiGPT is a user-friendly integrated tool built on API and prompt design, specifically tailored for thematic analysis of qualitative data (Zhang, 2024). It allows user-specific input parameters, dynamic prompt generation and presents results in a clear, transferable format. Qualitative analysis inherently has a level of subjectivity, which is a benefit as we analyze experiential data. In traditional qualitative research, multiple human researchers analyze the same text to reconcile and reach a consensus. In our analysis approach, we use QualiGPT as an additional support researcher. We used QualiGPT to analyze the same set of 20 interview data after our primary analysis using Quirkos, using it as a support researcher. The prompts we used for QualiGPT based analysis are given in Appendix D for reference.

After completing both analyses (approach #1 and approach #2), the results from both approaches were collated to produce the final results.

Chapter 4: Results

This section presents our findings, based on the analysis of data collected from 20 interview participants. While the six research propositions remained consistent across the data, the analysis revealed clearer sub-themes within each determinant, providing more nuanced insights into how these factors shape a firm's AI Orientation. In addition, we identified several emergent observational findings from the experiences shared, offering further insights into how organizations are approaching their AI journey. To ensure rigor and triangulation, our findings are presented through two complementary analysis approaches as described in Chapter 3. Firstly, we present our findings from manual coding and thematic coding leveraging Quirkos. Secondly, we present our findings from AI-assisted coding using QualiGPT. At the end of this section, we combine these two findings to present the revised research model based on the revised sub-themes and observational findings. In addition to this, we also present two supplemental findings in Appendix E and Appendix F. Our first supplemental analysis, presented in Appendix E, showcases our findings from the manufacturing industry based on our data analysis, as we believe there are specific industry-related nuances to be highlighted. Our second supplemental analysis, presented in Appendix F, extends a Theory of Constraints tool called Strategy & Tactics tree to discuss how practitioners can use these applied learnings to advance the AI journey in their firms and achieve high AI Orientation.

Findings from Method 1 – Quirkos-based Manual Coding

Proposition 1 (P1): Leadership Influence within a firm impacts its AI Orientation

AI Orientation influences the dynamics of the top management team itself by altering how AI enables strategic objectives, organizational resources are distributed, and

procedures are designed (Li et al., 2021). Our research explored various leadership aspects that can influence and impact a firm's AI Orientation. All of our interview participants (20/20) emphasized the importance of Leadership Influence as a determinant for AI Orientation, indicating broad agreement across the sample.

We found four interconnected leadership dimensions that are key determinants to a firm's AI Orientation. First, **Leadership Sponsorship, Alignment, and Ongoing Engagement** captures the role of C-suite and board-level commitment in sponsoring AI initiatives and ensuring they remain strategically focused over time. Second, **Collaborative Leaders as Culture Catalysts** reflects the ways in which leaders shape openness, trust, and cultural readiness for AI adoption, encouraging cross-organizational collaboration. Third, **Leadership AI Acuity** refers to the sharpness of leaders' strategic insight, encompassing their ability to educate themselves and their organizations on the realities of AI maturity, set a coherent AI vision and link it to enterprise strategy. Finally, **Leadership AI Articulation** emphasizes the importance of clear communication articulating the strategic benefits, establishing ethical boundaries, and risk tolerance, so that the AI journey is viewed as purposeful and responsible.

1.a. Leadership Sponsorship, Alignment and Ongoing Engagement

The success of AI initiatives depends on top management sponsorship and their direct involvement. AI is a technology with a lot of potential, but it has associated risks if not implemented carefully. Getting leadership alignment on its strategic potential and potential risks is critical in implementing AI successfully across the enterprise. Our findings indicate that companies with a high AI Orientation have a very involved leadership team that is actively engaged in driving the AI journey in their firms, making

sure it is directly linked to the firm's strategic goals. Gloria and Sam noted the importance of leadership involvement in AI initiatives, especially since there is a lot of hype around it:

“We'll need their sponsorship. And we're going to need them to approve the investment.” – Gloria

“The role of leadership really is sponsorship. You know, creating the environment where these things can happen and enabling the workforce. I think that because of the hype factor around this right now, there is some FOMO (Fear of Missing Out).” - Sam

Andy highlighted how his firm is ensuring leadership involvement in providing broader guidance effectively:

“Everything is based on leadership in the case of AI, because there is so much risk with the potential. The leadership needs to be aware of what is acceptable, what is not, and, more importantly, what will open up liability for companies. I belong to what's called the global leadership team, the top 100 people in the company that basically look at all these things and then determine how we want to use it. So, we work within the framework of the guidance that we have at the top.” - Andy

Our findings also highlight the fact that ongoing engagement from top management teams can encourage increased attention from senior leaders, thereby driving AI applications towards strategic goals and business priorities.

“Getting a buy-in from the C-suite was definitely important for us, and helped our case because as we move through AI, we may have challenges, and we need to

make sure that everyone is engaged? C-suite engagement was critical to push down a lot of that AI execution and our strategy. The willingness to even give us time every 2 months showed how important it was to the company's characteristics.” - Rob

1.b. Collaborative AI Champions as Culture Catalysts

Participants clearly agree that companies must approach AI as a top-down collaboration to impact the organizational culture and develop a high AI Orientation. Firms with a high AI Orientation can fully leverage AI for their strategic objectives by developing a culture and readiness within the organization through learning and diffusion of AI innovations (Yao et.al, 2025, Li et.al, 2021). For examples, Ria and Mia noted as follows:

“AI very, very clearly, so it is more top-down. That's how your culture changes, because we are like an old company. Our culture is not used to these things.” -

Ria

“I think they have a huge role. If you're hearing it from your CEO / CIO, the same message around AI that they are progressing and they want the company to progress in that direction, it gives more encouragement, it encourages more innovation, as well as taking some risks at a level where we are in the company.”

– Mia

Previous research has long established that innovation champions are essential for successful organizational innovation, and they possess a unique combination of vision, persistence, and social influence that enables them to secure organizational support and overcome resistance to change (Howell, 2005, Howell & Higgins, 1990). In the context

of Artificial Intelligence, our participants highlighted that the role of AI Champions goes beyond traditional innovation advocacy. Our findings indicate that leaders with high technology/data fluency inspire trust across the organization as they drive AI initiatives. As AI is evolving quickly, collaborative leaders can motivate their organizations and broader ecosystems through effective knowledge sharing and ways of working.

“I think it's always beneficial to have a leader who has at least some background or some success in that area. Because you got to have some trust in what your leadership is pushing downwards. Also, leaders' community involvement is another characteristic that is very helpful and knowledge-sharing with other companies, specifically around AI. – Dave

1.c. Leadership AI Acuity

Seals (2022) proposed that Digital acuity is a key leadership capability that implies a visionary component to the application of digital technology. Our findings suggest a key leadership skill for advancing the AI journey in their firms - an extension to digital acuity as Leadership AI acuity. We define this as a leadership skill that includes the ability to understand the current state, envision opportunities, and exploit AI as a strategic competitive lever in the context of their business. Previous research established that leaders with high digital/AI acuity are knowledgeable about emerging technologies and have a more strategic view of the implications for their business. This leadership skill allows leaders to envision how to scale and monetize emerging technologies in their business areas (Sainger, 2018, Sutcliff (2019)).

Our findings recognize a key observation that executives and boards often feel pressured to act on AI despite limited knowledge. Due to the lack of time and structured

education in this fast-changing space, this may inadvertently lead to superficial or misinformed decisions. Rob and Ally highlighted the need for leadership to understand the strategic applications of AI as follows:

“It’s extremely important for the C-suite and the senior leadership team to understand where and how AI can be applied across the organization and business functions so that they can get the most benefit out of the AI rather than trying to compete against AI” – Rob

“In my experience. If leaders aren’t talking about AI and how they’re using it and creating ways for their teams to talk about use cases and share ideas. Then it just kind of falls flat. It just can’t happen without executives understanding and helping guide some of those conversations.” – Ally

Participants highlighted the need for leaders to think more as Applied AI, so that there is more clarity on the application of AI for strategic business priorities. For examples, Reema noted:

“The role of C-suite is to critically assess where and how they can take advantage of the AI value prop and ensure. They’re driving the organization with the right ambition, vision strategy to get the value and impact of the technology. But that should be done in a very productive applied way as Applied AI.” – Reema

We also heard that leaders need to be open to learn more about the current state of AI possibilities and be able to make sharp judgments about the strategic potential. Peter and Diana noted this as follows:

“We also need to educate the top management on what the AI possibilities are and why it will benefit the business. The financial metrics need to get approved by the top management, so their commitment is extremely necessary. Their buy-in is very vital right because they have a business vision.” – Peter

“Really the education is very critical, because they're in the board meeting for a short period of time. They have to make key decisions on spending. And if they're not educated enough, they may not make the right decisions.” – Diana

These observations emphasize the need for leaders with high AI acuity to drive AI initiatives in firms. These leaders, with high technology and data fluency, clear strategy, and humility to learn and collaborate, can enable their firm's journey towards high AI Orientation.

1.d. Leadership AI Articulation

While leadership vision has been studied extensively in previous research, our findings indicate that articulating the vision to the broader organization is extremely important for the success of AI initiatives in a firm. Articulation here refers not only to the communication of vision and strategic direction, but also to the explicit framing of risk, ethics, and guardrails around AI adoption. This is theoretically anchored in Simon's Levers of Control (LOC) framework, which conceptualizes how leaders use control systems to balance innovation and accountability. Participants emphasized that without clear articulation, AI efforts may end up being fragmented, hype-driven, and/or can lead to employee anxiety. Saya articulated the need for articulation of value to the broader organization:

“You've given the board the bigger picture, you've told the executives the bigger picture, you owe it to your team to give them the bigger picture, so that they understand what you are doing in the bigger picture, so that when they do that little proof of concept, a little crawl, they feel a part of it.” - Saya

Other participants highlighted the importance of articulating AI's value to a firm's strategic goals without compromising a firm's organizational values. It is to be noted that AI articulation is more effective for managers and employees when it is told not as an abstract technology, but as tangible value creation. For example, Samy, Paul and Kole noted as follows:

“We have, you know, articulated our company's vision towards AI, ensuring that it does not compromise the original value. Since the company is in the business for such a long time, we want to ensure that the past values or the standards by which it stands does not get compromised” – Samy

“The AI vision has been technically a component under decision science or digital which has - how do we help the internal company to achieve an outcome. How do we help our farmers to be more productive? That's the outcome, productivity and sustainability.” – Paul

“The best way to encourage people is by telling them, you know, how it helps them in their future” – Kole

In conclusion, our research data suggests that leadership influence is a key factor impacting AI Orientation, supporting our proposition #1. Additionally, we found 4 interconnected dimensions of leadership that can influence the AI Orientation of a firm. Though our initial objective was to understand more about board influence on AI

Orientation, our sample did not have enough experience with the board. We heard anecdotal evidence about the board's influence being similar to the top leadership impact. However, further research is needed to establish the determinants for AI Orientation from a board perspective.

Proposition 2 (P2): A firm's AI capability impacts its AI Orientation

Participants consistently highlighted the importance of organizational AI capability as a key determinant of AI Orientation. All of our interview participants (20/20) emphasized the importance of Organizational AI Capability as a determinant for AI Orientation, indicating broad agreement across the sample. It was interesting to note the evolution of AI in various enterprises followed different paths. While the ChatGPT launch was a pivotal moment in the AI journey for many firms, experimentation towards AI had started in pockets even before that in many firms. The journey from traditional AI to generative AI to agentic AI capabilities triggered by various internal and external factors was described eloquently by many participants.

Our findings reiterated the importance of considering AI capability as a combination of tangible (data, technology, security) and intangible (human, change) capabilities aligned to existing literature. Additionally, our participants discussed the importance of Strategic AI capability as another important determinant. This encompasses the firm's capabilities to apply AI towards strategic objectives like customer intimacy, product innovation, and operational excellence, aligned to the value disciplines to focus for organizational success (Treacy and Wiersema (1993). We also heard that many firms are challenged with an activation gap when it comes to scaling AI initiatives, even though they have a defined AI vision in place.

Our findings revealed 4 interconnected areas of organizational AI capability. First, **Foundational Readiness** reflects the technical infrastructure required for AI implementation, including the availability of high-quality data, robust technology platforms, and appropriate security controls. Second, **Human Capital and Talent Readiness** capture the people dimension, ranging from talent availability to reskilling for organizational AI adaptability. Third, **Strategic AI Capability** refers to how organizations orient their AI capabilities toward value creation, whether through operational excellence, customer intimacy, or product innovation. Fourth, **Change Management** captures how effectively organizations are capable of managing changes internally.

2.a. Foundational Readiness (Data, Technology, Infra, Security)

Our participants discussed the technical and infrastructural foundation on which AI initiatives can be launched. Without high-quality, accessible data and secure, well-integrated technology, firms cannot implement AI projects. For example, Roy and Dave talked about the importance of data readiness.

“Number one is, there are some foundational elements that we need to have in place before you launch AI capability - it is extremely important to make sure that your data is accurate, rightly classified, rightly tagged. And you have the right permissions for the right people. “ – Roy

“You're as valuable as what the data is, what type of data you collect, or how you keep that data, as well as how you do it. “ – Dave

We also heard about the importance of organization around data. Firms, where data and AI had common ownership, were able to take necessary steps to ensure foundational readiness to advance in their AI journey. As Lila noted:

“One of my advantages is, I own, technology, data & AI and I have the mandate to do this transformation. That makes my life a lot easier, and thereby I'm able to define governance procedures and processes for application use.” – Lila

Security was highlighted as an important, and often understated capability dimension. As Saya articulated:

“And one thing that nobody is thinking about yet, because we are so engrossed in keeping in pace with AI is security. I don't hear a lot of people talking about security with these AI projects, because speed seems to be taking over everything which is not a bad thing, but security is a big thing.”

- Saya

2.a. Talent Readiness

Another important determinant that various participants consistently discussed was talent readiness. The availability of specialized talent and the willingness to reskill existing employees are important factors impacting a firm's AI Orientation. Companies successfully embedding AI literacy programs and Communities of Practice are able to manage organizational change more effectively by enabling their talent with various cross-functional skills required for the successful execution of AI programs.

“The talent is so different in terms of the layers that you go through in AI development. You know, there are different types of gating criteria to manage an AI project. So, each area or each business or a role is going through that transformation. So obviously, it all depends on how you educate yourself, or how you come up to speed. – Dave

Another interesting observation was that AI programs require talent at the intersection of business, technology and AI expertise. As noted by Reema and Lila:

“So having that intersection of product, that leadership, the domain expertise. But then, understanding where AI itself can drive value is a tough intersection of skills to find.” – Reema

“I would have to get people at all different levels in the organization to have the same level of understanding on use, application and concerns. So, upskilling and reskilling the organization through the journey.” – Lila

2.c. Strategic AI Capability

Beyond readiness and execution, participants described how AI capability must orient toward strategic value. This took three main forms: customer intimacy (personalization, enhanced experiences), product innovation (AI-enabled offerings), and operational excellence (process efficiencies), which aligned with the Tracey-Wasserstein (1993) model. Organizations varied in which focus dominated their AI investments according to their business priorities.

“Our point of view is that AI should enhance our client experience and the experience of our employees, and that we want to use it to deepen human relationships and not replace them.” – Ally

“Where are the opportunities for us if we were to pursue efficiency as a goal. Things that emerge are things like how we make us supply chain more responsive. How do we make order visibility a priority? How do we make sure that our reps have the right knowledge base? So, they can query and get the information so they can talk to customers more intelligently. How do we drive content consolidation content generation in a in a more innovative way?” – Andy

Participants highlighted that strategic AI capability must be inherent in the way AI programs are executed to make sure AI initiatives are being led with strategic value.

“We need to decide how to take advantage of the AI value prop and ensure they’re driving the organization with the right ambition, vision, strategy to get the value and impact of the technology. It can’t be a separate strategy. It really is inherent in everything we do; it should be right” – Reema

2.d: Change Management

Our findings indicate that different parts of the organization go through the change journey differently. However, the human factors around change management are crucial. For example, Andy noted:

“Some people get over it faster because they have more knowledge - maybe the senior managers who see more things. People who are further and further away from that have that ambiguity and that fear. And I think, anytime, people have to change and do something that is radically different - they’re going to question, because it questions their backgrounds and where they come from and their biases. So, it’s natural.” – Andy

“Change is hard, especially on the front line. So, we have, you know, our front line workers have been met with more skepticism.” – Ally

“In the change journey. We’ve had to answer a lot more right at an individual level. What does it mean for me, and you know not. Every organization is like my current employer. You’ve got people who’ve been in tenure for 27 years, 42 years.” - Lila

Participants highlighted the need for transparent communication across levels to enable sustainable change journey, rather than short term benefits. As Diana noted:

“As long as leadership appears transparent and is honest about the journey, it makes employees more willing to trust the process — and in some cases, even take on the risks associated with change. So, whether it’s through open forums or one-on-ones, depending on the individual, the key is ensuring communication stays open throughout the entire process.” – Diana

Another interesting observation is that AI implementation often requires a change in business processes, and there is reluctance to make a change in business processes as it may impact upstream and downstream processes. Hence it is important to communicate the value of change clearly in such cases. For example, Smith noted:

” When implementing AI, we also have opportunities to change the process. So that is another area where we see hesitation in changing the business process as well, where we can automate either certain things or we can where we can systemically perform certain actions rather than having somebody to manually validate it.” – Smith

Change Management impact can sometimes span beyond a firm’s direct employees and extend to the broader ecosystem and partners. In such cases, this effort has to be meticulously undertaken for proper results.

“Some of those challenges around usage and the change journey and Training - we were putting an application in a retail environment that we didn’t own across markets. So, training not just our staff, but training you know, partners and training the end users, right?” – Lila

In conclusion, our research suggests that organizational AI capability impacts a firm’s AI Orientation, supporting proposition #2. Our observations from the interview data further emphasized that organizational AI capability includes the tangible (data, technology,

security), intangible (change), and human (talent and skills). Additionally, we observed that strategic AI capability is a key dimension of AI capability as firms strive for a high AI Orientation. Also, our findings around Change Management pointed towards how it is a required element for scaled AI execution, rather than highlighting it as a capability.

Proposition 3 (P3): A firm's Enterprise Alignment impacts its AI Orientation

Participants described how misalignment between business and technology units, unclear ownership of AI, or fragmented portfolios often resulted in reactive, siloed adoption of AI initiatives. Conversely, where shared accountability structures supported AI strategy, organizations demonstrated a more mature AI Orientation. A Majority (65%) of interview participants (13/20) mentioned Enterprise Alignment as a key determinant.

Our interviews highlighted three interconnected dimensions of enterprise alignment and a few other interesting organizational dynamics around enterprise alignment for AI initiatives. First, *shared sophisticated accountability structures* are essential to support AI strategy and execution, mainly because there is still ambiguity around these initiatives, and a need for sophistication. Second is the role of *proactive internal alignment to prevent shadow IT* and fragmentation. Third, our participants shared their experience with how *alignment can be a key driver for activating and scaling* AI programs. We heard from participants that enterprise alignment functions as an enabling mechanism that strengthens the coherence between leadership intent, technology capability, and organizational execution in AI initiatives. Additionally, we heard from our participants on how this compares to the Business-IT alignment challenges in traditional IT programs.

3.a. Shared Sophisticated Accountability Structures

AI programs succeed when business and IT jointly own outcomes, rather than when accountability is isolated in a single function. We heard from participants on how they use governance and effective communication as an alignment tool. As Diana, Roy, Dave and Andy noted:

“I think the biggest thing is effectively communicating how it's going to drive growth. It's either growth or operational efficiencies. So, it must be very clear which one is going to drive and what metrics have to be in place to show that it actually did impact the specific metrics, or else it dies.” – Diana

“As I said, we built this AI oversight committee. That committee will meet meet with various champions across business, different business groups and they conduct these workshops to really understand their side of the story” – Roy

“But if your business leaders understand what technology can achieve for you, and they have a buy in, then that's an easier conversation” - Dave

“Enterprise alignment is a little bit of hard science and a little bit of soft science. Hard science is, you know, the easier part. The soft science is change management, you know.” – Andy

We further probed the participants to understand if enterprise alignment concerns are different in the case of AI programs, compared to traditional IT programs. However, the responses largely lean towards the fact AI programs have more top-down push compared to traditional IT programs, which helps get better alignment. But in general, the challenges and best practices for better alignment remain the same at large. The key

difference in the case of AI initiatives is the ambiguity regarding expected results, compared to traditional IT programs.

“If I’m implementing oracle, people know what to expect from the implementation.

It’s a joint process of selecting a tool, a problem we want to solve, how we, thinking through some of this. So no, it’s not the same. – Nancy

Additionally, we heard that enterprise alignment needs more sophistication in the case of AI programs due to regulations and scaling aspects.

“I feel like it mandates more sophistication, but it’s not necessarily new, and it demands to do it right now. I think a lot of the contracting complexities and scalability from cost.” - Reema

3.b. Proactive alignment to manage shadow IT

We noticed many creative ways to engage various stakeholders proactively, which helped advance AI programs successfully. Mia, Roy, and Rob described how they have been effectively practicing this in their firms to ensure AI program success.

“One of the things that I’m leading is a bi-weekly meeting with all my sector digital leads to build the alignments across all sectors and drive the global agenda. And so, we’ve been very proactive in you know, starting those conversations with the sector” – Mia

“We want to make sure everyone has their own space to execute. And at the same time one win serves everyone, and it’s going to be everyone’s win. So, you know, making sure our functions also understood that was very critical.” – Rob

If the right level of alignment is not established between business and IT, it can lead to shadow IT organizations, and in the long term prevent organizations from standardized approaches for accelerating AI initiatives. For example, Paul noted as follows:

“As you are developing AI capabilities, you might want to have at that time IT resources or infrastructure that connects you to the enterprise system. If you don't have those resources then, it could likely create the Shadow IT organizations. All of a sudden, that creates another IT organization within the business and create conflicts of alignment, because now it's driven by investments, but not necessarily seeking to have modular and standardized designs” – Paul

3.c. Alignment as a key driver for Scaled Execution

We also noticed that participants consider Enterprise alignment an integral part of scaled AI program activation rather than a standalone determinant. As Gloria, Rob and Dave highlighted,

“I think you need implementers. You need humans on the ground to help with the change management, and who knows the business. These teams don't know the business; they are data scientists. And I think that's off. I put my team in the middle of this to bridge the activation gap” – Gloria”

“I would say, the frequent partnership between enterprise and the functions- the hub and spoke leaders - is important to ensure that we are all moving forward” – Rob
“If you're not aligned with your business, then you're not going to create the value. You don't want to invest a lot of money building and make this a technology play” -
Dave

In conclusion, our research data suggests that enterprise alignment is a key factor that enables better AI execution, which helps firms have a high AI Orientation. More than half of the interview participants highlighted enterprise alignment as an essential factor. However, it was interesting to note that many participants tied this closely to activation excellence across the enterprise, and not as a standalone determinant. Our initial

proposition #3 stated that Enterprise Alignment impacts AI Orientation. While our findings support this, we observed nuances around how better alignment helps with better execution excellence and scalable capability, which can then lead to a high AI Orientation.

Proposition 4 (P4): A firm's ability to scale AI impacts its AI Orientation

Participants highlighted the importance of scaling AI beyond pilots into enterprise-wide adoption. Nearly all interview participants (19/20) emphasized Organizational AI Scalability as central to AI Orientation. As Dave rightly pointed out:

“I think our mantra has been. If you can't scale it, then you should not build it right? So, the scale is always top of mind” – Dave

Our findings around AI scalability indicated 4 interconnected dimensions of AI Scalability. First, **Scaled AI Execution** highlights the importance of scaled implementation to realize the value from AI initiatives and get continued buy-in. Second, **Scalable AI Capability** emphasizes the need to consider scalability alongside when building AI capability and not as an afterthought. Third, the importance of **Leveraging Partnerships to Scale**. Fourth, the presence of **AI Value Creators** or Digital Adopters or Technology Progressives in the firm, as opposed to pocket vetoes.

4.a. Scaled AI Execution

Participants emphasized that moving to scale requires far more than replicating a successful experiment; it involves financial, technical, organizational, and regulatory considerations and confronts the rising cost of ownership. Many leaders indicated that this is still nascent, and they are learning every day. As Lila, Peter and Reema pointed out:

“Work, effort, improvement, metric and we need to get better at transferring

that either into a cost or a revenue outcome. And we haven't cracked the code on it yet. " - Lila

"Starting an AI project is one thing, but how do you scale it in such a way that it aligns with your vision? So that needs to be thought at a top level, how can we take that use case and scale it. Use cases look like they're beneficial, but to be able to scale it to a next level where it affects the top line and bottom line. And it could be because of lack of data or could be because of data not being continuous— Peter"

"Innovation at some point needs to have a practical application and a value proposition. And that's where the economy and scalability of AI investments in a way that truly can be enterprise-grade and hardened with legal involvement is hard, and I think a lot of companies are probably still in the nascent stage of doing it the right way at scale. And there's probably a lot of learning and opportunity still, to get more efficient." – Reema

Many participants highlighted that the activation gap is a key challenge for them as they try to scale. Most of the firms have a defined AI vision and use cases identified. However, they are finding it hard to move towards scaled execution. Companies need special focus to bridge this activation gap to make sure the vision is implemented correctly to reap expected benefits.

"We're developing alignment with the business who did not have the capability. So, at the beginning it was a push. It will push the strategy on the business unit. And the business unit will react towards it. It was reactive. Now that we evolve, and we start creating a more federated system where the capability is not just in it, but is in the business unit" – Paul

4.b. Scalable AI Capability

Our participants emphasized that firms need to consider scalability as part of their capability development itself, and not as a standalone determinant or afterthought. For example, Saya emphasized that:

“Early on, if you do it correctly upfront and set your expectations, then, you will not have surprises on scalability. You won't have surprises on financial leakages. You won't have surprises on resource leakages, etc. People don't think about that upfront because you're just thinking about the next 12 to 18 months. So, it's very important that you think about scalability, not just on infrastructure, but also on your wallet. “— Saya

“It's not just a one-time activity that you clean up your data and then you launch AI, and then you call it a day. It's an ongoing effort to make sure that your data is consistently clean, classified and tagged. So, it is essential to build something more automatic in terms of data, classification and data readiness. Then the respective data owners validate that information before it is released to be available for AI solution to use it to scale” - Roy

4.c. Leveraging Partnerships to Scale

Another important finding from our data was the important role played by the partner ecosystem in enabling enterprises to scale AI. Participants consistently highlighted that partnerships with vendors, technology providers, and external collaborators were central to scaling AI. While organizations often possessed the vision and internal capability to pilot AI initiatives, many lacked the infrastructure or maturity to expand those pilots independently. As a result, scalability was frequently mediated through external partnerships.

“We actually had an external firm review our processes end-to-end and then provide a set of recommendations in the customer value chain on areas that we felt we could pursue efficiency. When we use partners, whether that is our payment partners, experience partners, or even call center people, we have AI built into all their solutions.” – Andy

“We work with external resources, because there are a lot of external experts that are already working on many, many different kinds of use cases” – Peter

Our analysis indicates that firms go through a variety of build vs buy vs blend/partner decisions as they advance their AI journey. This could be to protect their core resources availability or as a conservative approach to invest in AI only after experimentation.

“It's always a question of does it make sense for us to spend our time and energy? Or is it something that's already been thought through, and somebody already has a heads up. So why waste your time and resources trying to, you know, basically, reinvent the wheel” – Andy

“Ideally, we don't want our best engineers that are good at doing something to jump ship to this AI. We don't even know is going to give us the financial benefits – Peter

“We will never catch up to the tech because we're not a tech company. We're not in the AI race, but we want to ensure we get the best LLMs as they come in right. We are more focused on a framework to use any of them. – Rob

“We shouldn't be building technology. There are people smarter than us who are building technology, better agentic usage. So, your scaling would be better served when you bring in an external agency that is responsible for the forward-looking technology innovation in the AI space. – Lila

However, firms need to ensure that they have in-house capabilities to manage and evaluate the vendors effectively, asking the right questions and through proper change management.

“If you have those innovative vendors providing that capability to you, you still have to understand what they’re bringing in, the associated risks, but that can be a little bit easier, depending on the vendor that you’ve selected, and you’re running on the back end.” - Dave

The varying maturing of AI capability across ecosystem partners can sometimes be a challenge, especially in industries like Manufacturing where there are a lot of physical integration requirements. As Samy explained a challenge in their ecosystem:

“We are not a standalone. Obviously, this is an ecosystem. We have our partners/OEMs, and we need to ensure that this technology or this trend does not negate or does not contradict what has already been set in terms of contracts. As also our own standards in safety and security should not be compromised. One challenge is aligning it with our suppliers as well as our OEMs, whether we are all talking in the same language as we adopt these new tools and these new technologies, and the second part is the safety and security, because the product that we are delivering goes into the hands of the end user”. – Samy

4.d. AI Value Creators / Technology Progressives Vs Pocket Vetoes

One interesting observation from the interviews was the existence of pocket vetoes and technology progressives in enterprises. This highlights the role of individual leadership attitudes in enabling or obstructing scalable AI initiatives. Several leaders described the presence of “pocket vetoes” or leaders who quietly resisted AI adoption and slowed organizational momentum. In contrast, others identified “technology progressives or digital value creators” as critical allies in advancing AI initiatives. These progressives were not

necessarily technical experts but were characterized by their openness to change, willingness to experiment, and ability to champion new ways of working. As Gloria noted:

“The gentleman in charge of equipment won’t budge and won’t move. So, you know. it’s just there are pocket vetoes. We know it. We talked about it. We do a stakeholder analysis on my team. And we identify those pocket vetoes. And we focus on the coalition and the willing. Then we focus on digital adopters. And we give them the technology. We call it a pilot. We let them prove it out” – Gloria

“The story that I’m telling you has been so cohesive and consistent. But I’m not sure if the story would have been the same if we hadn’t those scientists or leaders who were our champions when it came to investing in the technology and bringing the new talent to help drive AI across the whole enterprise”. – Paul

Senior leaders are on the lookout for these technology progressives or AI value creators who and life-long learners and can make an impact in the firm. Unlike traditional expectations, these soft-skill expectations are less well-known to corporate employees, and it will be interesting to highlight the importance of these traits. Kole indicated this as follows:

“I’m always looking for stars, right? Somebody who’s going to rise up. So. Yes, I want to force the whole group to learn a little bit about AI. And I’m going to tell them, yeah, this is good for your career. But I’m going to look for those people who are digging into it more. And they’re figuring out how that works, not just internally to what we want to do, but also, how does that work for the customer?” – Kole

In conclusion, our research data suggests that AI scalability is a key factor that impacts a firm’s AI Orientation, supporting proposition #4. Our findings also indicate that scalability cannot be a standalone determinant. However, firms need to focus on building scalable AI capability and establish a scaled AI activation model.

Proposition 5 (P5): A firm's learning orientation impacts its AI Orientation

Learning orientation indicates the extent to which companies foster continuous learning, experimentation, and adaptation. Participants emphasized that there is a lot of excitement about AI in the firms. Consensus was strong with the majority of interview participants (19/20) highlighting the importance of learning orientation as central to AIO. Within our analysis, four interconnected areas emerged as critical to understanding how organizations learn with and from AI. First, **Human–AI collaboration** reflects how employees and AI systems jointly contribute to tasks, decision-making, and innovation, requiring new forms of learning and role adaptation. Second, **Applied AI learning** emphasizes the need for continuous, hands-on experimentation and integration of AI tools into workflows, which accelerates organizational competence beyond theoretical knowledge. Third, **AI anxiety** and trust capture the emotional dimensions of learning, as leaders need to address employees' fears of replacement, error, or misuse while cultivating trust in AI-enabled processes. Finally, **AI Democratization** highlights the diffusion of AI knowledge, tools, and literacy across the workforce, ensuring that AI capabilities are not confined to technical experts but embedded broadly within the organization.

5.a. Human-AI Collaboration

Organizations with high learning orientation can embed AI into their key strategic programs by enabling employees with the skills required to engage with the new technologies.

“I think when you talk about AI, and especially generative AI in particular, I think there's a lot of excitement across all functions, from top to level right all the way from President all the way down to engineering technicians, that there's a lot of

excitement about that, and that people want to be engaged because of something new and potentially transformative.” – Peter

Considering the human elements behind this transformative AI technology, leaders need to motivate their employees to undergo these upskilling training programs and actively participate in learning initiatives by ensuring that the expected outcomes and value impact are communicated effectively. Lila and Paul talked about how they encourage that in their firms.

“The best way to encourage people is by telling them, you know how it helps them in their future. This is how you move forward in your career, because in the end most people are looking to move forward in their career, and they want to get paid more well. So, you have to engage them.” – Kole

However, there is a word of caution from leaders to use employee’s time more effectively to ensure that learning initiatives are helping employees. Leaders may want to take deliberate steps to help their teams allocate time to learn.

“Everyone's overloaded with commitments and delivery, and a lot of what we've signing up to deliver this year is not necessarily a shiny discovery of new AI. Everyone wants to do it. So, I think if anything, it's creating the space to invest in AI discovery and experimentation and they're hungry for it – Reema

5.b. Applied AI Learning

One interesting observation is that leaders are highlighting the need for employees to learn at the intersection of business, technology and AI, more in an Applied AI fashion.

Right now, we have great data scientists, and we have great developers. But for us to be successful in this world, we need somebody who can do both equally well. I

need people who know data really well. They know how to get the thing. And I need strong developers. I can't have them in segregated groups, and we've not been able to do that fast enough. – Saya

We heard many best practices around this from the participating leaders as quoted below.

“We also have what we call short term assignments and long-term assignments for any individual to engage in a new practice and develop expertise by working or being hands on a problem with some degree of knowledge, quantitative knowledge in the topic to ensure that you can develop models or can develop AI right in a successful manner.” - Paul

“We have monthly lunches and learn. We do run 90-day objectives and many of those we'll have an AI related focus inside of them. So that's part of kind of like the learning and the development on how we're going to do this. And then we just talk about it frequently. So particularly in my team, innovation related to the use of Gen AI is celebrated, and everybody knows that this is the direction and that they should constantly like to experiment and share.” – Ally

5.c. AI Anxiety and Curiosity Fueling Learning

Participants observed that the appetite to learn and experiment with AI varies across employee levels and generational groups. While companies are taking steps to encourage learning and upskilling, the outcomes depend on the individual's motivation and openness to learning and exploring, along with their current job responsibilities. This is driven by curiosity and/or anxiety about the potential of AI.

“So, I feel like, by default, I need to up my game just to sustain right” – Ria

“You can use AI to learn. AI! That's what my colleague was telling me. But again it

comes down with your psychology that comes down to the individual and the drive, and what they value.” – Nancy

“For the technologists or the engineering people, there is a lot of curiosity and enthusiasm at the same time. Also, there is a section of people who are also worried that it overwrites their needs. So, a lot of education goes into ensuring that it complements your work, not to you know, cancel your work.” – Samy

Participants highlighted the importance of leaders articulating the importance of learning initiatives to their team members, giving due importance to their future.

“They're learning something that will help them today and will help them tomorrow. If they decide to take their skills and go somewhere else - As an organization, we should be both comfortable and also supportive of that shift and that also allows people to learn. You'll still get some people who will not be with you, despite all the effort you make. And that's fine and every transformation leave a few people behind.

– Lila

5.d. AI Democratization

We heard about practices like knowledge-sharing sessions and bidirectional mentorships etc. to encourage democratization of AI skillset.

“Our organizations have made it in a way that we try to educate everyone. So, if you have an interest, if you have a passion, then we're trying to make sure that the resources are out there, and you can explore them. So, I was one of them. I even started a POC on my side that benefits my business units.” – Dave

“Training at every level. It is not just about having your analysts learn a new platform upskilling themselves up. It really starts with the C-suite. The training

starts from there and then it goes down. While we're training for the citizen data scientists, we also need to look at how can how functions can benefit from AI. So, we've started this small journey." – Rob

In conclusion, our analysis suggests that organizational learning orientation impacts a firm's AI Orientation, supporting proposition #5. We observed various aspects of learning orientation driven by firms, leaders and employees. Our observations from data analysis indicate that learning orientation overlaps strongly with the human elements as it is dependent on people's curiosity, anxiety and openness and commitment to unlearn and learn.

Proposition 6 (P6): A firm's AI governance framework impacts its AI Orientation

All twenty participants described governance as a cornerstone of AI Orientation in their firms, emphasizing the importance of having them to make AI purposeful, trusted, and sustainable. Most of the organizations started formalizing their AI governance structure post ChatGPT launch, even though they had some form of AI implementations in their firms prior to that. However, the structures and processes are still evolving. Our analysis of interview data indicates four inter-related dimensions of Governance - **AI operating model and governance structure, AI value capture, AI explainability and trust, and responsible and sustainable AI.**

6.a. AI Operating Model & Strategic AI Governance

Participants emphasized the importance of having a clear definition of who owns AI and having a structured governance framework to execute and track value realization. We observed varying levels of maturity in terms of operating model and governance structures across our data. These firms have an AI steering committee/AI council, and

their responsibilities are clearly defined. However, the maturity of processes and their acceptance across the organization are still evolving. As Andy and Peter noted:

“We have a high-level board for AI governance, mostly ethical use of AI, that reports to our top management group. Every IT initiative has to go through the board if it has any AI implications. So, there is a separate organization that's managing all of the AI priorities in the business transformation group. All of those projects have to be submitted for scrutiny and there is a process to manage. This is all driven under this security, plus CTO umbrella.” – Andy

“The steering committee's job is to make sure you engage the top management to make them understand the value you're going to be getting from the AI implementation. So, the steering committee is going to be responsible for you know several things. First, making sure the AI vision and approach are standardized for all the group companies, what we see right now is several use cases being worked by several businesses. They're kind of working independently on it, because, of course, engineers don't want to wait for, you know, big thing to happen” – Peter

“AI governance practices can be understood in 3 components. Governance talks about how we develop models that are reliable, sustainable, and technically useful.”

– Paul

Different firms have different operating models—whether centralized, federated, or hybrid—aligned to their enterprise maturity. For example, Rob and Reema explained the operating model in their firms below:

“One of the 1st things we did was set up an organizational structure. We actually work in a very federated model, and we call it here as a hub and spoke model. The hub is helping to execute AI initiatives and also helping to upskill folks across the

spokes in different functions. Everyone is using the same data platform, rationalizing those tools, ensuring that it's a single platform that everyone uses, and then the capabilities are built by many.” - Rob

“I would say it's pretty federated with the center of excellence that mandates or shares the best practices that are defined mostly by our platform organization. But it's through a federated governance body with this AI center of excellence group where they're setting up standards and kind of expectations/guardrails through a cross functional governance board. It had been our CIO plus for internal use cases, and a platform executive for external use cases under the CEO. So, there is kind of a shared accountability depending on the use case. But then that was managed and governed by the center of excellence.” – Reema

6.b. Ongoing AI Value Discipline

The need for a reliable value realization mechanism for AI initiatives was highlighted by all our interview participants. For example, Paul and Gloria noted as follows:

“The amount of money that we have available to invest became less because of the dynamics of the market. Then the appropriate assessment, the more granular assessment of the return of this investment became important” – Paul

“I need it to hit a specific problem because I need to articulate and measure value. And I need to do it on a 2-year payback period. I talk about the value proposition with each phase and each step. And I think that's important with AI, because, you know, it's expensive. It's new to us. We don't have digital adopters. I could easily spend a lot of money and have a bunch of people who don't have the skill set to use it” – Gloria

For AI initiatives driving measurable outcomes, metrics and KPIs can help track them for internal reporting and leadership showcase. Lila and Paul shared few examples:

“What we do is we try to understand, if we do this, what is going to be the ROI. If we do it for a 5-year period, what would be the return we would get, and what value or impact it will create on our P&L. We also build metrics that will help us monitor the progress of those metrics.” – Smith

“I'm starting with value.” – Lila

Even though some firms are able to track value for their AI programs in a standalone manner, there is a larger need to track and showcase how AI is transformative to deliver business goals.

“I think the capabilities are improving, but in terms of value realization, it's still not clear, because some of it is nebulous and the biggest issue I have is that people are still spending money on capabilities, but really not seeing scale on them end” – Andy

“How are you measuring the value of AI initiatives over time? Part of the task of the steering committee is to develop a template or something that can help to measure the business value from any use cases. Can you add value and increase the price? Or can you produce it cheaper? Or can you increase the sales volume? How does it affect the top line and the bottom line?” – Peter

6.c. AI Explainability and Usability

Explainability emerged as a core governance concern, particularly as participants linked it to building trust. Leaders pointed out it is important to have a way to cross-check the accuracy of any AI-driven decisions. If end-customers become privy to any

incorrect decision taken by AI, the resulting loss of trust could be irreparable. As Andy and Mia noted below:

“So, you need to have guardrails in all of these things, so that you understand. You need to be able to double-check. You need to make sure that the progress can be tested. And that you know each step of the way, you are being careful in terms of how the model is evolving. It makes it even more difficult when you cannot explain the reasons. So, like everything else, I mean, we are being careful in how to identify data sources and what we are putting into the training models.” - Andy

“At the end of the day it is a large language model, and nobody is checking it or reviewing it from a human perspective, and if the answer is not inaccurate, we fear that they (end-customer) will lose trust in the capability, and it would be harder to roll out. So, we want to make sure that all checks and balances are done, and we have tested it enough that it is providing the most accurate information to the grower” – Mia

In order to enable managers to implement strategic AI with direct impact on a firm's business goals, insisting on AI explainability is crucial as it can help them gain confidence in this applied technology.

“If I want to embrace the technology, do I trust this specific solution for me to drive day to day operations which means is, is it precise, is it understandable, is the user experience friendly enough for me to engage. The precision of the outcome builds upon the fact that you need to have the right data. I'm going to be a little bit wavy in technically and engaging with your recommendation, because I don't know if it's precise enough, because the data is wrong – Paul”

6.d. Responsible & Sustainable AI

Participants pointed to the importance of ensuring that AI is responsible and sustainable, extending governance beyond compliance into questions of ethics and long-term impact.

There are overlapping observations about the human factors about AI, which can be addressed by ensuring Responsible AI. Our data indicates that AI governance frameworks need to carefully embed responsible AI, so that it does not get lost in the race towards AI advancements. As Reema pointed out:

“We should be able to set more audacious goals than past years for functions where there's evidence and broad studies on where AI works really well. And so, setting those goals in a way that still allows teams to innovate on the how and to do it responsibly, ensuring that there are also values like trust, compliance, ethics, you know, ensuring that there's enough rigor, and how experimentation happens – Reema

Our data indicated that organizations are also thinking about implementing sustainable AI.

Roy and Lila talked about how they are thinking through this, while acknowledging that there are no defined solutions out there, but these are areas that need attention.

“One thing that I did not anticipate was people's concern about the environmental impact of AI. There are more data centers coming every day. And you need more powerful systems to run these AI solutions. And those data centers are causing environmental impact. We still don't know how we're going to generate the amount of electricity these data centers will need eventually to run these AI systems. The concern is real. It's there. But it's going to take some time for that innovation to happen around that.” - Roy

“We retain and archive 7 years of all data, including copies, staging data, all attributes and all variations. We are only 3 years into this journey, so we've not yet

gotten to the point where this is going to break our back. That will quickly get to a point where it becomes a problem. So, defining what is good adherence, practice and storage practice is important when we said our principles around ethical use and environment consciousness. So, we can't burn energy on data process or have consumed a significant amount of data storage in line with our policy.” – Lila

These findings underline that responsible AI is multidimensional—covering ethics, legality, fairness, privacy, and environmental sustainability—and is increasingly expected by both internal and external stakeholders.

In conclusion, our research suggests that organizational AI Governance impacts a firm's AI Orientation, supporting proposition #6. Our analysis suggested four interconnected dimensions of AI Governance, which include AI Operating Model and governance Structure, AI Value Capture, AI Explainability and usability, and Responsible and sustainable AI.

To complement the manual qualitative coding approach and provide greater transparency regarding the frequency of each theme in our interview data, we calculated the proportion of interview participants supporting each of the six propositions and then estimated the corresponding 95% Wilson confidence interval. This approach provides a more accurate interval estimate than a normal approximation for smaller sizes (Wilson, 1927). Our study is a qualitative study and not meant for statistical generalization. However, we believe reporting the frequency and Wilson's confidence intervals will provide readers a more transparent view of how strongly each proposition is supported by each participant. Table below summarizes the Wilson confidence interval for the six propositions in this study.

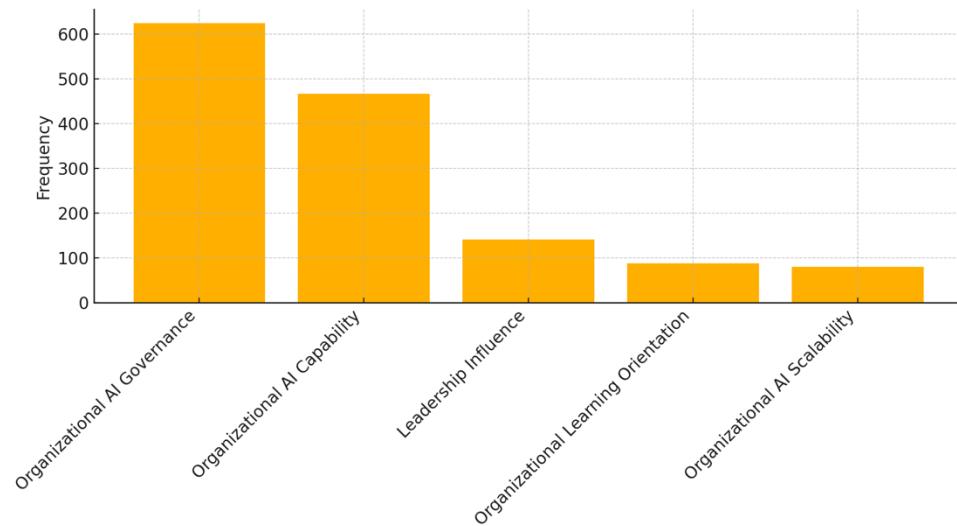
Theme	Interviews with support (x)	Total interviews (n)	Proportion supported (x/n)	Wilson Lower 95%	Wilson Upper 95%	Strength label	Sample sentence
Leadership Influence	20	20	1	0.839	1.000	almost all	Almost All (100%) of respondents (20/20) mentioned Leadership Influence; 95% CI 84%–100%.
Organizational AI Capability (merged)	20	20	1	0.839	1.000	almost all	Almost All (100%) of respondents (20/20) mentioned Organizational AI Capability (merged); 95% CI 84%–100%.
Enterprise Alignment	13	20	0.65	0.433	0.819	a majority	A Majority (65%) of respondents (13/20) mentioned Enterprise Alignment; 95% CI 43%–82%.
Organizational AI Scalability	19	20	0.95	0.764	0.991	almost all	Almost All (95%) of respondents (19/20) mentioned Organizational AI Scalability; 95% CI 76%–99%.
Organizational Learning Orientation	19	20	0.95	0.764	0.991	almost all	Almost All (95%) of respondents (19/20) mentioned Organizational Learning Orientation; 95% CI 76%–99%.
Organizational AI Governance	20	20	1	0.839	1.000	almost all	Almost All (100%) of respondents (20/20) mentioned Organizational AI Governance; 95% CI 84%–100%.

Findings from Method 2 – AI-assisted coding using QualiGPT as a research tool

As the motivation for this research stemmed from the power of AI in today's world, this study was motivated to investigate the use of AI as a complementary tool in qualitative inquiry, aiming to understand how it might enhance analytical depth and rigor. After the primary analysis leveraging Quirkos, we then went on to perform our second proposed analysis using QualiGPT as a support researcher. We used QualiGPT to analyze the same set of 20 interview datasets. The prompts we used to work with QualiGPT are provided in Appendix D for reference.

We first asked QualiGPT to do deductive reasoning based on the a priori codebook. QualiGPT confirmed that Organizational AI Governance, Organizational AI Capability, Leadership Influence, Organizational Learning Orientation, Organizational AI Scalability impact AI Orientation. The responses from QualiGPT that while Enterprise Alignment also impacts AI Orientation, the frequency is lower than other factors. This

also indicated that Enterprise Alignment is overlapping more with Execution capability and may not be treated as a standalone factor. The frequency of deductive codes from QualiGPT is represented below:



We then prompted QualiGPT to perform inductive coding based on human-AI thematic exploration. We wanted the tool to go through the interview data more qualitatively and summarize potential latent themes that potentially go beyond just word frequency or clustering – closer to how a human would interpret the meaning, emotions, tension etc. We then asked the tool to suggest potential emerging themes or additional determinants for AI Orientation based on this analysis. The emergent themes listed by QualiGPT via human-AI thematic exploration are given below:

#	Emergent Theme	Description
1	AI Operating Model Fractures	Leaders often describe fragmented efforts, unclear ownership and inconsistent execution, suggesting a lack of cohesive operating frameworks.

2	Strategic Symbolism Vs Execution Reality	Many firms appear to embrace AI rhetorically (branding, announcements) but struggle to operationalize or align initiatives with measurable impact
3	Leadership Vulnerability and Emotional Labor	Executives reverse personal strain, confusion or role stress as they navigate unfamiliar technological domains, which affects confidence and momentum
4	Value Skepticism from Operational Leaders	On-the-ground leaders demand concrete ROI rather than conceptual pitches, showing a friction between strategic vision and daily realities.
5	Cultural discontinuity across generations	Younger engineers embrace AI rapidly, while senior leadership hesitates - indicating a readiness gap rooted in organizational culture.
6	Learning Overwhelm and Capability Anxiety	Firms feel underprepared to upskill at pace, often “building the plane while flying it”, pointing to systemic learning constraints

Emergent Themes from QualiGPT (Human-AI Thematic Exploration)

We then asked QualiGPT to suggest proposed determinants based on the deductive and inductive coding. The below table summarizes the key themes highlighted by QualiGPT:

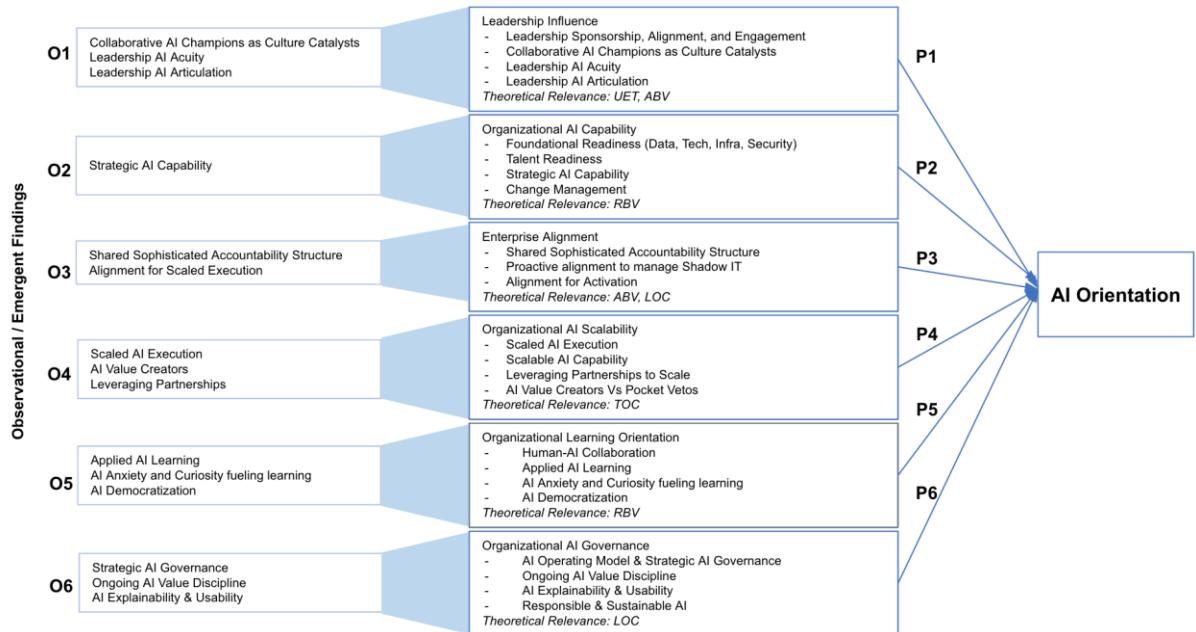
#	Proposed Determinant	Emergent Theme	Actionable Levers for Practitioners

1	AI Operating Model Maturity	AI Operating Model Fractures	Design clear roles, decision rights, integration structures for AI governance
2	Execution - Alignment Capability	Strategic Symbolism Vs Execution Reality	Establish KPIs, performance tracking, and change accountability for AI plans
3	Leadership AI Resilience	Leadership Vulnerability and Emotional Labor	Provide support, upskilling and peer learning for executive-level AI fluency
4	Operational AI Value Discipline	Value Skepticism from Operational Leaders	Embed ROI logic into project design, link AI to core process improvements
5	Cultural AI Readiness	Cultural discontinuity across generations	Bridge generational learning styles, encourage bidirectional mentorships
6	Learning Agility Infrastructure	Learning Overwhelm and Capability Anxiety	Build modular, just-in-time learning systems, assign AI literacy ownership

Updated Research Informed Model

We integrated insights from both Analysis 1 (manual coding leveraging Quirkos) and Analysis 2 (AI-assisted coding with QualiGPT) to strengthen the robustness of our analysis and deepen our understanding of AI Orientation. Study 1 provided researcher-driven interpretation grounded in established qualitative research methodologies, ensuring rigor, transparency, and contextual richness. Study 2 offered AI-enabled coding and thematic extraction, which enhanced emerging themes and helped with additional triangulation.

Combining our findings from both the studies, we were able to validate the six core propositions, refine their associated sub-themes, and identify additional observational findings. This combined view provides a more comprehensive picture of the determinants of AI Orientation, balancing traditional human qualitative analysis rigor, combined with an AI-assisted analysis approach.



Chapter 5: Discussion

We make three key interrelated contributions through this qualitative research study.

Theoretical Contribution: Revised Research Model for AI Orientation

First, our theoretical contribution lies in developing a revised research model of AI Orientation, integrating perspectives from RBV, UET, ABC, TOC and LOC. We refined the six determinants and associated sub-themes of AI Orientation, thereby capturing a nuanced understanding of how organizations can embed AI strategically. The refined research model positions AI Orientation as a multi-dimensional construct shaped by governance, capability, leadership, scalability, alignment, and learning. While prior research has conceptualized AI Orientation at a higher level (Li et al., 2021; Yao et al., 2025), our findings based on qualitative experiences provide granular insights into each determinant, thereby extending the theoretical depth of the construct.

For example, within Leadership Influence, the data revealed distinct sub-themes like Leadership AI Articulation, Leadership AI Acuity and Collaborative AI Champions. This moves the discussion beyond traditional leadership sponsorship towards a more nuanced understanding of actionable steps leaders can take to advance strategic AI Orientation. Effective leadership in the AI era requires articulating a clear and compelling AI vision (aligned to Simon's Belief Systems), demonstrating AI acuity through informed decision-making and technological literacy, and leaders or AI Champions who adopt a collaborative and participatory style are better able to accelerate their firm's AI journey by inspiring commitment, aligning cross-functional teams, and engaging both internal and external stakeholders in the pursuit of shared AI-driven goals.

While organizational AI capability has been extensively studied in existing research, strategic AI capability has not been studied as a key theme for advancing AI journey. Our findings indicated that believe this is an important dimension of AI Orientation that can help organizations orient their AI capabilities towards value creation through operational excellence, customer intimacy, or product innovation. Organizations need to build the capability to map AI initiatives to business processes aligned to their strategic goals, if they want to apply AI strategically, and not just technical AI capabilities.

We refined Organizational AI Governance based on sub-themes around AI operating model, ongoing value capture, and explainability. Our findings indicated that effective AI governance is an important dimension of AI Orientation when it extends beyond compliance and ensures that AI initiatives are aligned with strategic objectives and that value captured from AI applications is monitored on an ongoing basis. Our observational findings around AI scalability highlighted why execution excellence is important to scaling AI initiatives, and how AI value creators play a key role in doing that. The role of external ecosystem partners in advancing AI Orientation was an important finding, as it was not highlighted in existing research. We observed that enterprise alignment for AI initiatives played an important role in execution excellence. Additionally, our findings around learning orientation enabled us to think broadly about human-AI collaboration, and how leaders need to deliberately address AI anxiety to encourage more learning and democratization of AI technologies across the firm.

Our theoretical refinement of AI Orientation extends prior conceptualizations of AI Orientation, which often emphasize either technical resources or leadership vision in

isolation (Li et al., 2021; Yao et al., 2025). Our findings suggest that AI Orientation is to be treated as an integrated strategic posture aligned to organizational goals that emerges when scalable capabilities, leadership influence, governance mechanisms, and organizational learning are aligned. By offering this integrative model, the study contributes to theory-building in information systems and strategic management, laying the groundwork for future empirical testing and cross-industry comparison.

Methodological Contribution: AI-assisted Qualitative Research

The second major contribution of this study lies in the methodological exploration of AI-assisted qualitative research. While our primary analysis was through the traditional approach of manual coding using Quirkos, we also employed an AI-enabled tool called QualiGPT as a collaborative research tool. The use of QualiGPT alongside traditional manual coding leveraging Quirkos illustrates how generative AI technologies can act as support research tool, enhancing triangulation and expanding analytical breadth and depth. This hybrid approach serves as a pathway for human-AI collaboration in qualitative research process, opening new possibilities for analysis large volumes of data responsible, while maintaining human ingenuity and involvement.

Both methods provided rich insights from data through deductive and inductive analysis approaches. Our manual coding approach supported all six propositions, as more than half of all interview participants supported all six propositions. It also allowed us to have deeper engagement and intimacy with participants' words, tone, and specific organizational context. This helped us arrive at informed sub-themes based on their experiential nuances to enhance the research model. QualiGPT, by contrast provided

rapid pattern-based recognition and frequency-based deductive summaries. We observed that QualiGPT included five of the six propositions in their deductive frequency reports and dropped enterprise alignment. This could be because while most participants mentioned it, some tied it immediately with execution and scalability. In manual coding, the human researcher could analyze it in the specific organizational context and conclude that enterprise alignment as a proposition is still supported and added specific experiential nuances for a richer model.

We observed that QualiGPT was able to provide excellent cross-interview thematic suggestions. For example, through pattern recognition, QualiGPT highlighted value skepticism as a key issue, and suggested to embed ROI logic into project design and link AI to core process improvements, thereby suggesting an Ongoing AI Value Discipline. While we identified AI Value Capture as a sub-theme through our manual coding process, this provided a deeper nuance and called it as ongoing value discipline.

Manual coding requires substantial time and cognitive effort, but it fosters data intimacy which is critical for analysis rigor. QualiGPT accelerates synthesis, and identifies patterns across multiple participants, and this algorithmic business thinking can help identify actionable pathways a manual researcher may not notice. While manual coding may introduce human researcher bias, QualiGPT introduces concerns around algorithmic bias and lack of transparency in certain cases.

We summarized the comparison of Quirkos-based manual coding and QualiGPT-based AI-assisted coding in the table below:

Analysis Dimension	Quirkos-based manual coding	QualiGPT based AI-assisted coding

Context awareness	Captured contextual nuances due to several rounds of data analysis	Provided context per QualiGPT guidelines. Not transparent about context awareness
Accuracy & Completeness	Supported all six propositions and detailed sub-themes.	Supported five out of six propositions in the frequency summary table
Bias	Risk of human subjectivity and bias	Risk of algorithmic bias
Transparency	Coding decisions are explicit and traceable	Lack of transparency and groupings not always explainable
Cognitive Load & Data Intimacy	High data intimacy due to repeated cycles of manual data analysis. Time sensitive and high cognitive demand,	Reduces cognitive load. Accelerated data synthesis and pattern recognition. Researcher may not get a chance to get intimate with data
Triangulation Value	Foundational primary analysis with rigor	Offers ways for cross-validation, and highlights potential patterns and better actionable reports and visuals of insights

In summary, we do not suggest QualiGPT was more accurate than manual coding. However, we suggest that AI-assisted qualitative research has huge potential as the tools evolve in that space, as it provides complementary value. Manual coding ensured analysis rigor and researcher data intimacy, whereas AI-assisted coding provided better efficiency, triangulation and pattern identification. This experience highlights the future potential of a more evolved hybrid human-AI approach in qualitative research, where generative AI

technologies can augment qualitative analysis of large datasets responsibly, while retaining human in the loop.

Managerial Contribution: Implications for Practice

Finally, our study makes an important managerial contribution by offering executives and managers a structured framework for advancing AI Orientation in their firms. These insights are particularly important where organizations are noticing that their AI adoption is often fragmented, technology-driven and not aligned to strategic goals. Leaders can use the determinants and their sub-themes as a diagnostic framework to assess readiness, identify gaps and guide AI-related investments. The study underscores the importance of why AI cannot be looked at as a standalone context, instead its potential should be explored in the context of organizational strategic goals. It encourages practitioners to approach AI not as a set of siloed projects or experimentation, instead as a core element of strategic orientation.

Additionally, we provide two supplementary analyses for the benefit of practitioners in Appendix E and F. First supplementary analysis shares our findings from the manufacturing industry and the critical factors that influence AI Orientation in the manufacturing industry. Second supplementary analysis introduces a Theory of Constraints tool called Strategy & Tactics Tree that practitioners can use to apply the proposed AI Orientation framework in their organizational context. Leaders can use the tool to align AI Orientation framework to their internal organizational constraints and can be expanded further to create an actionable roadmap to reach their goal.

Limitations & Future Directions

This study is based on twenty semi-structured interviews with senior AI leaders, offering rich insights into how organizations navigate the challenges of advancing their AI Orientation. Our findings represent the lived experiences of leaders in specific organizational contexts. While our qualitative research offers rich insights from managerial experiences around AI Orientation, the findings should not be interpreted as generalizable across all industries. Furthermore, our participants were concentrated in specific industries, which may constrain the transferability of the results across industrial sectors. Since we had 12 out of 20 participants from the Manufacturing industry, we did a supplementary analysis focused on the Manufacturing industry to share industry-relevant insights from our interview participants. Future research could extend this inquiry by conducting industry-specific studies thereby testing whether the determinants identified here hold consistently across firms that share similar industrial, operational, technological, and regulatory environments.

Since AI Orientation is still an emerging construct with evolving definitions and measurement approaches, this study contributes by identifying its determinants through qualitative exploration. Future research could build on this by conducting a quantitative study with a larger and more diverse set of firms, employing a survey design to measure the relative influence of each determinant. In addition, this study captures leader perspectives at a single point in time; a longitudinal design, revisiting the same leaders after one year or more, could provide valuable insights into how AI Orientation evolves as organizations mature in their adoption journey.

Our research findings highlight several underexplored domains related to strategic AI Orientation. Leadership emerged as a critical determinant, underscoring the need to better conceptualize leadership traits needed for the AI era. Constructs such as Leadership AI Acuity and Leadership AI Articulation could provide valuable future research avenues to understand if certain leadership styles (charismatic, transformational or hybrid) are more effective in driving AI Orientation. Other areas deserving scholarly attention include AI explainability, particularly how it influences senior leaders' confidence in decision-making. Given the importance of cognitive and affective trust of AI by employees and leaders in shaping AI Orientation in a firm, extended research is needed on human – AI collaboration.

Organizational AI Governance is another area where additional research is needed for embedded ongoing AI value discipline frameworks that help firms continuously demonstrate and report business impact of applied AI. While this research informs how organizations can pursue high AI Orientation by providing insights about the determinants, more research is required to build a capability maturity model for AI activation in firms. Our findings indicate that these maturity models should be developed with greater focus on strategic AI, rather than only technical readiness.

Our methodological approach also offers future directions for research. Our study explored the use of AI-assisted qualitative research using QualiGPT as a complementary tool for our primary analysis. While this helped us with better triangulation and pattern recognition, further studies should systematically compare the accuracy and applicability of AI-enabled tools for qualitative research. This would help in understanding the role of AI in qualitative research and inform best practices in human-AI collaboration in research

One interesting finding from our study was that Sustainable AI is acknowledged as an underexplored area. We had anecdotal references from our participants about the concerns around the long-term impact of AI models on sustainability. This is highly underexplored in research and needs further exploration from a research angle and practitioner angle.

Finally, while our study focused on the determinants of AI Orientation, more research is needed to examine its firm-level consequences. Recent research has explored how AI Orientation impacts technological innovation (Eicke et.al.,2025) and operational efficiency (Yao et.al, 2025). However, many critical questions remain – Does AI Orientation influence organizational performance and value creation? Does an effective AI Orientation translate into improved employee outcomes or customer experience? As more enterprises are exploring the transformative potential of AI, answering these questions would not only validate AI Orientation as a strategic construct but also establish its broader organizational implications. Collectively, these research directions would help strengthen both the theoretical foundation and the practical utility of AI Orientation. This stream of inquiry can connect the determinants, dimensions and outcomes of AI Orientation.

REFERENCES

Amabile, T. M. (2020). Creativity, artificial intelligence, and a world of surprises. *Academy of Management Discoveries*, 6(3), 351-354.

Accenture. (2024). *Reinventing enterprise operations with Gen AI* (Report). <https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Reinventing-Enterprise-Operations-FA-9-25-24.pdf>

Akhtar, Z. B. (1990). *Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions*. *Metaverse*. 2024; 5 (2): 2731. Computers in Industry.

Åström, J., Reim, W., & Parida, V. (2022). Value creation and value capture for AI business model innovation: a three-phase process framework. *Review of Managerial Science*, 16(7), 2111-2133.

Baker, W. E., & Sinkula, J. M. (1999). The synergistic effect of market orientation and learning orientation on organizational performance. *Journal of the academy of marketing science*, 27(4), 411-427.

Banker, R. D., Feng, C., & Pavlou, P. A. (2022). Businessperson or technologist: stock market reaction to the alignment between CIO background and firm strategy. *Journal of management information systems*, 39(4), 1006-1036.

Baird, A., & Maruping, L. M. (2021). The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *MIS quarterly*, 45(1).

Barmer, H., Dzombak, R., Gaston, M., Palat, V., Redner, F., Smith, T., & Wohlbier, J. (2021). Scalable ai.

Barnard, A. (2010). What is theory of constraints (TOC). *Goldratt Group*, 44(8), 479-489.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.

Barney, J. B., & Clark, D. N. (2007). *Resource-based theory creating and sustaining competitive advantage*. Oxford University Press.

Benbya, H., Leidner, D. E., & Preston, D. (2019). MIS quarterly research curation on information systems alignment. *MIS Quarterly*, 1-19.

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). *Special issue editorial: Artificial intelligence in organizations: Implications for information systems research*. *Journal of the Association for Information Systems*, 22(2), Article 10.

Bousetouane, F. (2025). *Physical AI agents: Integrating cognitive intelligence with real-world action*. arXiv. <https://arxiv.org/abs/2501.08944>

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

Braga, A., & Logan, R. K. (2017). The emperor of strong AI has no clothes: limits to artificial intelligence. *Information*, 8(4), 156.

Brock, J. K.-U., & Von Wangenheim, F. (2019). Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. *California management review*, 61(4), 110-134.

Brynjolfsson, E., & McAfee, A. N. D. R. E. W. (2017). Artificial intelligence, for real. *Harvard business review*, 1(1), 1-31.

Carpenter, M. A., Geletkanycz, M. A., & Sanders, W. G. (2004). Upper echelons research revisited: Antecedents, elements, and consequences of top management team composition. *Journal of management*, 30(6), 749-778.

Carter, M., Grover, V., & Thatcher, J. B. (2011). The emerging CIO role of business technology strategist. *MIS Quarterly Executive*, 10(1).

Cetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B., & Knight, S. (2022). Explicating AI literacy of employees at digital workplaces. *IEEE transactions on engineering management*, 0,1-14.

Chan, R. Y. K., Huff, S. L., Barclay, D. W., & Copeland, D. G. (1997). Business strategic orientation, information systems strategic orientation, and strategic alignment. *Information Systems Research*, 8(2), 125–150.

Chau, D. C., Ngai, E. W., Gerow, J. E., & Thatcher, J. B. (2020). THE EFFECTS OF BUSINESS-IT STRATEGIC ALIGNMENT AND IT GOVERNANCE ON FIRM PERFORMANCE: A MODERATED POLYNOMIAL REGRESSION ANALYSIS. *MIS quarterly*, 44(4).

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48, 24-42.

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

Dettmer, H. W. (1997). *Goldratt's theory of constraints: A systems approach to continuous improvement*. ASQ Quality Press.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organizations. *International Journal of Production Economics*, 226, 107599.

Eicke, A. K., [other authors]. (2025). Strategic AI Orientation and technological innovation. *Journal of Product Innovation Management*. Advance online publication.

Enns, H., & McDonagh, J. (2008). The Impact of CIO Influence Attempts on the Relational Side of ICT-Business Alignment.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and organization*, 28(1), 62-70.

Floridi, L. (2008). The method of levels of abstraction. *Minds and machines*, 18(3), 303-329.

Gao, R. X., Krüger, J., Merklein, M., Möhring, H. C., & Váncza, J. (2024). Artificial Intelligence in manufacturing: State of the art, perspectives, and future directions. *CIRP Annals*, 73(2), 723-749.

Gartner. (n.d.). *Leadership driving AI revolution in the boardroom*. Gartner Research. <https://www.gartner.com/en/articles/leadership-driving-ai-revolution-in-the-boardroom>

Gatignon, H., & Xuereb, J. M. (1997). Strategic orientation of the firm and new product performance. *Journal of Marketing Research*, 34(1), 77-90.

Gerow, J. E., Thatcher, J. B., & Grover, V. (2015). Six types of IT-business strategic alignment: an investigation of the constructs and their measurement. *European Journal of Information Systems*, 24(5), 465-491.

Goldratt, E. M. (1986). *The goal: A process of ongoing improvement*. North River Press.

Goldratt, E. M. (1990). *What is this thing called theory of constraints and how should it be implemented?* North River Press.

Goldratt, E. M., Goldratt, R., & Abramov, E. (2002). Strategy and tactics. *Goldratt Consulting*, 33.

Goryunova, E., & Yawson, R. M. (2025). “Nested Complexity” Framework for Human-Centered AI-Augmented Leadership. *Journal of Leadership Studies*, 19(2), e70016.

Gross, D., & Korolov, M. (2025, January 27). *Agentic AI: Promising use cases for business*. CIO. <https://www.cio.com/article/3603856/agentic-ai-promising-use-cases-for-business.html>

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of management review*, 9(2), 193-206.

Hammond K (2024). *Exploring the Power of Generative AI: What the future may hold* [Conference Presentation] SIM TechExec 2024.

Hang, H., & Chen, Z. (2022). How to realize the full potentials of artificial intelligence (AI) in digital economy? A literature review. *Journal of Digital Economy*, 1(3), 180-191.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of management review*, 32(4), 1199-1228.

Hartikainen, M., Väänänen, K., & Olsson, T. (2023, April). Towards a human-centred artificial intelligence maturity model. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1-7).

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.

Heyder, T., & Posegga, O. (2021). Extending the foundations of AI literacy. In *ICIS* (Vol. 9, pp. 1-9).

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business horizons*, 65(3), 329-339.

Howell, J. M. (2005). The right stuff: Identifying and developing effective champions of innovation. *Academy of Management Perspectives*, 19(2), 108-119.

Howell, J. M., & Higgins, C. A. (1990). Champions of change: Identifying, understanding, and supporting champions of technological innovations. *Organizational dynamics*, 19(1), 40-55.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of service research*, 21(2), 155-172.

Huang, C. L., Li, R. K., Chung, Y. C., & Hsu, Y. W. (2013). A study of using critical chain project management method for multi-project management

improvement. *International Journal of Academic Research in Economics and Management Sciences*, 2(3), 55.

Huang, Y., Sun, X., & Fan, Q. (2025). AI Orientation, global value chain collaboration, and the international performance of entrepreneurial firms: a technology affordance theory perspective. *Chinese Management Studies*.

Jeyaraj, A., Rottman, J. W., & Lacity, M. C. (2006). A review of the predictors, linkages, and biases in IT innovation adoption research. *Journal of Information Technology*, 21(1), 1–23.

Johnson, V., Torres, R., Maurer, C., Guerra, K., Srivastava, S., & Mohit, H. (2023). The 2022 SIM IT Issues and Trends Study. *MIS Quarterly Executive*, 22(1).

Johnson, Vess; Maurer, Chris; Torres, Russell; Guerra, Katia; Mohit, Hossein; Srivastava, Smriti; and Chatterjee, Sourav (2025) "The 2024 SIM IT Issues and Trends Study," *MIS Quarterly Executive*: Vol. 24: Iss. 1, Article 9.

Jones, M. L., Kaufman, E., & Edenberg, E. (2018). AI and the ethics of automating consent. *IEEE Security & Privacy*, 16(3), 64–72.

Jorzik, M., Frank, L., & Gimpel, H. (2023). *The role of top management in artificial intelligence–enabled business model innovation*. *Electronic Markets*, 33(1), 1–24.

Kappelman, L. A., McLean, E. R., Johnson, V., & Gerhart, N. (2014). The 2014 SIM IT key issues and trends study. *MIS Q. Executive*, 13(4), 7.

Karahanna, E., & Preston, D. S. (2013). The effect of social capital of the relationship between the CIO and top management team on firm performance. *Journal of management information systems*, 30(1), 15–56.

Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetişensoy, O., & Demir Kaya, M. (2024). The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *International Journal of Human–Computer Interaction*, 40(2), 497-514.

Kim, S. W., Kong, J. H., Lee, S. W., & Lee, S. (2022). Recent advances of artificial intelligence in manufacturing industrial sectors: A review. *International Journal of Precision Engineering and Manufacturing*, 23(1), 111-129.

Klein, C., & DeBruine, M. (1995). *The theory of constraints and the thinking processes: A brief introduction. Proceedings of the 1995 International Conference on Systems Thinking in Management*. University of Pennsylvania Press.

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, 44(6), 1425-1452.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>

Li, D., Pan, Z., Wang, D., & Zhang, L. (2023). A study on artificial intelligence orientation and new venture performance. *Asia Pacific Business Review*, 29(4), 967–989.

Li, J., Li, M., Wang, X., & Thatcher, J. B. (2021). Strategic Directions for AI: The Role of CIOs and Boards of Directors. *MIS quarterly* (3).

Liang, H., Wang, N., Xue, Y., & Ge, S. (2017). Unraveling the alignment paradox: how does business—IT alignment shape organizational agility? *Information Systems Research*, 28(4), 863-879.

Liu, D., Zhang, J., Dinh, A.-D., Park, E., Zhang, S., Xu, C., & others. (2025). *Generative physical AI in vision: A survey*. Preprint. arXiv. <https://arxiv.org/abs/2501.10928>

Long, D., & Magerko, B. (2020, April). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems*.

Luftman, J., & Kempaiah, R. (2007). An Update on Business-IT Alignment: "A Line" Has Been Drawn. *MIS Quarterly Executive*, 6(3).

Mäntymäki, M., Minkkinen, M., Birkstedt, T., & Viljanen, M. (2022). Putting AI ethics into practice: The hourglass model of organizational AI governance. *arXiv preprint arXiv:2206.00335*.

Mabin, V. J., & Balderstone, S. J. (2003). The performance of the theory of constraints methodology: analysis and discussion of successful TOC applications. *International Journal of Operations & Production Management*, 23(6), 568-595.

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS quarterly*, 487-505.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434.

MIT NANDA, Challapally, A., Pease, C., Raskar, R., & Chari, P. (2025, July). *State of AI in business 2025: The GenAI divide* (Report). https://www.artificialintelligence-news.com/wp-content/uploads/2025/08/ai_report_2025.pdf

Murugesan, S. (2025). *The rise of agentic AI: Implications, concerns, and the path forward*. *IEEE Intelligent Systems*, 40(2), 8-14.

Myszak, J. M., & Filina-Dawidowicz, L. (2025). Leaders' Competencies and Skills in the Era of Artificial Intelligence: A Scoping Review. *Applied Sciences*, 15(18), 10271.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2019). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*, 43(1), 223–238.

Newell, A., & Simon, H. A. (1958). Elements of a theory of human problem solving. *Psychological Review*, 65(3), 151–166. <https://doi.org/10.1037/h0048495>

Ng, A. Y., & Jordan, M. I. (2001). On discriminative vs. generative classifiers: A comparison of logistic regression and naive Bayes. *Advances in Neural Information Processing Systems*, 14(NIPS 2001), 841–848.

Ocasio, W. (1997). Towards an attention-based view of the firm. *Strategic Management Journal*, 18(S1), 187–206.

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI governance: Identifying best practices and potential barriers and outcomes. *Information Systems Frontiers*, 25(1), 123-141.

Peppard, J. (2010). Clarifying the ambiguous role of the CIO. *MIS Quarterly Executive*, 9(1), 31–44.

Pinski, M., Hofmann, T., & Benlian, A. (2024). *AI literacy for the top management: An upper echelons perspective on corporate AI Orientation and implementation ability*. *Electronic Markets*, 34(1).

Pisano, G. P., & Teece, D. J. (2007). How to capture value from innovation: Shaping intellectual property and industry architecture. *California management review*, 50(1), 278-296.

Queiroz, M., Anand, A., & Baird, A. (2024). Manager appraisal of artificial intelligence investments. *Journal of Management Information Systems*, 41(3), 682-707.

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

Ravichandran, T., & Lertwongsatien, C. (2005). Effect of information systems resources and capabilities on firm performance: A resource-based perspective. *Journal of management information systems*, 21(4), 237-276.

Ruokonen, M., & Ritala, P. (2025). Managing Generative AI for Strategic Advantage. *Research-Technology Management*, 68(4), 11-20.

Sabherwal, R., Sabherwal, S., Havakh, T., & Steelman, Z. (2019). How does strategic alignment affect firm performance? The roles of information technology investment and environmental uncertainty. *MIS quarterly*, 43(2), 453-474.

Sagodi, A., van Giffen, B., Schniertshauer, J., Niehues, K., & vom Brocke, J. (2024). How Audi scales artificial intelligence in manufacturing. *MIS Quarterly Executive*, 23(2), 167–186.

Schneider, J., Meske, C., & Kuss, P. (2024). Foundation models – A new paradigm for artificial intelligence. *Business & Information Systems Engineering*, 66(3), 221–231. <https://doi.org/10.1007/s12599-024-00851-0>

Schneider, J. (2025). *Generative to agentic AI: Survey, conceptualization, and challenges*. arXiv. <https://arxiv.org/abs/2504.18875>

Schneider, J., Abraham, R., Meske, C., & vom Brocke, J. (2023). Artificial intelligence governance for businesses. *Information Systems Management*, 40(3), 229-249.

Schweiger, S. A., Stettler, T. R., Baldauf, A., & Zamudio, C. (2019). The complementarity of strategic orientations: A meta-analytic synthesis and theory extension. *Strategic Management Journal*, 40(11), 1822–1851.

Shoemaker, T. E., & Reid, R. A. (2005). Applying the TOC thinking process: a case study in the government sector. *Human Systems Management*, 24(1), 21-37.

Simons, R. (1994). Levers of control: How managers use innovative control systems to drive strategic renewal. *Harvard Business Press*.

Singh, A., & Hess, T. (2020). How chief digital officers promote the digital transformation of their companies. In *Strategic information management* (pp. 202-220). Routledge.

Sinkula, J. M., Baker, W. E., & Noordewier, T. (1997). A framework for market-based organizational learning: Linking values, knowledge, and behavior. *Journal of the academy of Marketing Science*, 25(4), 305-318.

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, 134, 574-587.

Slater, S. F., & Narver, J. C. (1996). Competitive strategy in the market-focused business. *Journal of market-focused management*, 1(2), 159-174.

Sobel, M. G., & Klein, G. (2009). Relation of CIO background, IT infrastructure, and economic performance. *Information & Management*, 46(5), 271-278.

Stanford Institute for Human-Centered Artificial Intelligence. (2020). AI definitions. <https://hai.stanford.edu/sites/default/files/2020-09/AI-Definitions-HAI.pdf>.

Tiwana, A., Konsynski, B., & Venkatraman, N. (2013). Information technology and organizational governance: The IT governance cube. *Journal of management information systems*, 30(3), 7-12.

Treacy, M., & Wiersema, F. (1993). Customer intimacy and other value disciplines. *Harvard business review*, 71(1), 84-93.

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68, 102588.

Vejseli, S., & Rossmann, A. (2017). The impact of IT governance on firm performance a literature review.

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, 4(4), 404-409.

Wade, M., & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS quarterly*, 107-142.

Wilson, H. J., & Daugherty, P. R. (2018, July 24). *Collaborative intelligence: Humans and AI are joining forces*. *Harvard Business*

Review. <https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces>

Wingate, D., Burns, B. L., & Barney, J. B. (2025). Why AI Will Not Provide Sustainable Competitive Advantage. *MIT Sloan Management Review*, 66(4), 9-11.

Wu, S. P.-J., Straub, D. W., & Liang, T.-P. (2015). How information technology governance mechanisms and strategic alignment influence organizational performance. *MIS quarterly*, 39(2), 497-518.

Yin, R. K. (2009). *Case study research: Design and methods* (Vol. 5). sage.

Yin, R. K. (2018). *Case study research and applications* (Vol. 6). Thousand Oaks, CA: Sage.

Yao, N. C., Bai, J., & Yu, Z. (2025). Does AI Orientation facilitate operational efficiency? A contingent strategic orientation perspective. *Journal of Business Research*, 186, Article 114994.

Yoo, Y. D. (1995). Integration of expert systems with hypermedia. *Proceedings of the International Conference on Intelligent Manufacturing*, 259–270. Society of Photo-Optical Instrumentation Engineers (SPIE).

<https://doi.org/10.1117/12.216626>

Zacharias, N. A., Nijssen, E. J., & Stock, R. M. (2016). Effective configurations of value creation and capture capabilities: Extending Treacy and Wiersema's value disciplines. *Journal of Business Research*, 69(10), 4121–4131.

Zhang, B., Anderljung, M., Kahn, L., Dreksler, N., Horowitz, M. C., & Dafoe, A. (2021). Ethics and governance of artificial intelligence: Evidence from a survey of

machine learning researchers. *Journal of Artificial Intelligence Research*, 71, 591–666-591–666.

Appendix A: IRB Approval

Please see below the IRB Approval Document



January 27, 2025

Principal Investigator: Seelakshmy Geethakumari (UMSL-Student)
Department: Business DBA

Your IRB Application to project entitled Evolution of a new strategic orientation in the AI era: Exploring the Determinants of AI Orientation was reviewed and approved by the UMSL Institutional Review Board according to the terms and conditions described below:

IRB Project Number	2122671
IRB Review Number	444063
Initial Application Approval Date	January 27, 2025
IRB Expiration Date	January 27, 2026
Level of Review	Exempt
Project Status	Active - Exempt
Exempt Categories (Revised Common Rule)	45 CFR 46.104(d)(2)(iii) with limited IRB review
Risk Level	Minimal Risk
	This is the Informed Consent form for participation in research activities.
Approved Documents	This document details the interview script and questions.
	This document describes the recruitment approach and recruitment materials that will be used during this research study.
	This document includes the screenshots of the research website.
	This document shows the active SSL certificate for the research website.

The principal investigator (PI) is responsible for all aspects and conduct of this study. The PI must comply with the following conditions of the approval:

1. Enrollment and study related procedures must remain in compliance with the University of Missouri regulations related to interaction with human participants at https://www.umsystem.edu/ums/rules/collected_rules/research/ch410/410.010_research_involving_humans_in_experiments.
2. No subjects may be involved in any study procedure prior to the IRB approval date or after the expiration date.
3. All changes must be IRB approved prior to implementation utilizing the Exempt Amendment Form.

4. The Annual Exempt Form must be submitted to the IRB for review and approval at least 30 days prior to the project expiration date to keep the study active or to close it.
5. Maintain all research records for a period of seven years from the project completion date.

If you are offering subject payments and would like more information about research participant payments, please click here to view the UM Policy: https://www.umsystem.edu/ums/policies/finance/payments_to_research_study_participants

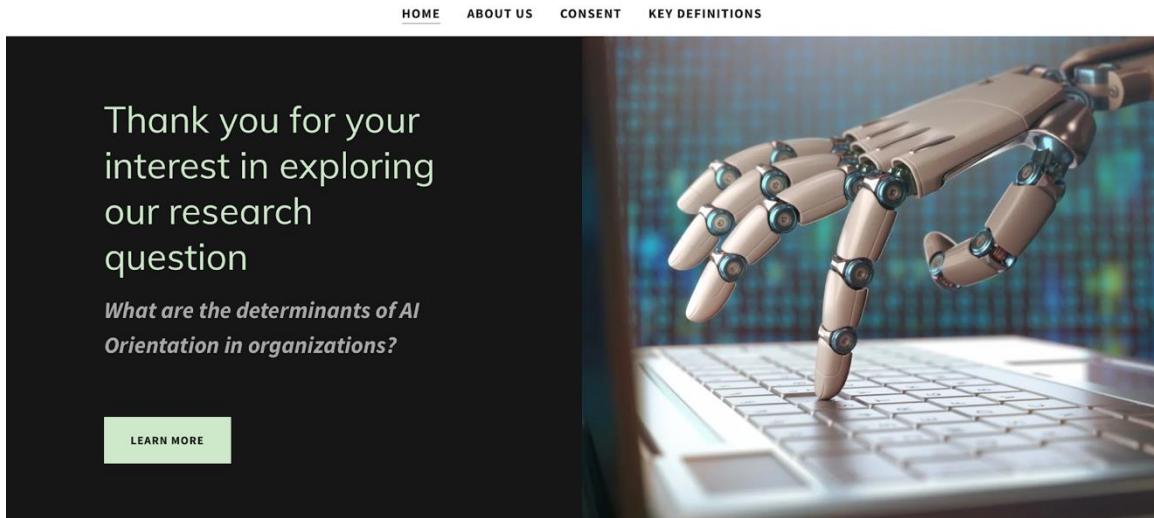
If you have any questions or concerns, please contact the UMSL IRB Office at 314-516-5972 or email to irb@umsl.edu.

Thank you,
UMSL Institutional Review Board

Appendix B: AI Orientation – Website for Recruitment

Please see below for screenshots of each page created for Recruitment Website.

Website home page contains the following:



[HOME](#) [ABOUT US](#) [CONSENT](#) [KEY DEFINITIONS](#)

SEEKING BUSINESS LEADERS TO HELP US EXPLORE AI ORIENTATION

Help us by participating in a 45 min - 1 hour interview to discuss Strategic AI, the determinants of AI, AI governance, AI capability & scalability, as well as Enterprise Alignment and AI Value Capture.

[PARTICIPANT SURVEY & SIGN-UP](#)



What is AI Orientation and Why is it important?

While AI is heralded as one of the most transformative technologies, scholars caution that its strategic impact may still not be fully realized. In a recent MIT Sloan Management Review study, Wingate, Burns, and Barney (2025) argue that AI alone cannot offer a sustainable competitive advantage, as the technology can be a source of homogenization. It is essential to find novel and strategic ways to use AI, leveraging human creativity, as enterprises strive to capture enduring value from AI.

We define *AI Orientation (AO)* as a firm's deliberate application of AI technologies to achieve its strategic goals. Given the strategic importance of AI in firms today, it is essential to consider AI as a strategic orientation (Li et.al., 2021) and understand the determinants in detail. Its relevance has surged in addressing operational challenges, prompting a growing number of firms to weave it into their strategies (Wilson & Daugherty, 2018; Accenture Report, 2024). With increasingly capable AI systems, organizations can analyze data and make autonomous decisions effectively (Davenport et al., 2020).

[HOME](#) [ABOUT US](#) [CONSENT](#) [KEY DEFINITIONS](#)

Our Research Study

The purpose of this research is to explore the determinants of AI Orientation in organizations. We plan to perform a qualitative analysis to conduct this study. Specifically, we aim to examine the experiential nuances firms encounter in their AI journey through in-depth interviews with senior leaders influencing AI-related decisions. These experiences could span across leadership influence, AI capability & scalability, enterprise alignment & AI governance and organizational learning. For a complete list of relevant definitions for this research study, please click below.



[KEY DEFINITIONS](#)



How can you help?

We seek interview participation from senior leaders with direct influence on AI-related decisions within their organizations. We are specifically interested in your experience around the impact of leadership influence, AI capability & scalability, enterprise alignment & AI governance and organizational learning on your firm's AI journey.

To qualify, you must meet the following criteria:

- You are a senior leader in a US-based public or privately held firm with direct influence on AI-related decisions (as strategy, recommendations, technical/value/people suggestions) in your firm.
- You have a minimum of 10 years of work experience in the United States
- Your company has at least 100 employees.

HOME ABOUT US CONSENT KEY DEFINITIONS

Please click the link below, review the information to determine if you are comfortable participating, and complete the form so that the researcher can contact you to get your interview scheduled. If you have any questions or concerns, feel free to reach out to the researcher at sreelakshmy.geethakumari@umsl.edu.

PARTICIPANT SURVEY & SIGN-UP



If a potential participant, clicks on the “Participant Survey and Sign-up” button on the Home Page above, they will be taken to the following page:

Consent Form

Please read and acknowledge consent before advancing to screening form. Please read the information to follow carefully; it will outline what participation in the study will require and potential risks, allowing you to make an informed decision regarding whether to participate in the study.

1. You are invited to participate in a research study. The purpose of this research is to explore the determinants of AI Orientation in a firm. Through qualitative interviews with senior leaders, the study seeks to identify key determinants of AI Orientation in a firm.
2. Your participation will involve a 45-60 minute interview conducted and recorded using Zoom technology. You can either use the video-conferencing feature or the phone-call feature of Zoom. During the interview, we will discuss your experiences influencing your firm's AI initiatives. We will ask you to describe the challenges and best practices that you faced as you have advanced the AI orientation of your firm.
3. There is a loss of confidentiality risk associated with this research. This risk will be minimized by
 - We will keep your name, company name, your supervisor's name, and all other identifying info private. We will replace them with pseudonyms.
 - When we report the results of the study, we will use quotations from your interview, but your identity will not be revealed. We will use pseudonyms only.
 - The recording of interview will be stored on a UMSL-approved, secure, password-protected server. We will keep the recording until the study has been completed and then we will delete the recording.
4. There are no direct benefits for you participating in this study

5. Your participation is voluntary and you may choose not to participate in this research study or withdraw your consent at any time. You will NOT be penalized in any way should you choose not to participate or withdraw.

6. We will do everything we can to protect your privacy. As part of this effort, your identity will not be revealed in any publication that may result from this study. In rare instances, a researcher's study must undergo an audit or program evaluation by an oversight agency (such as the Office for Human Research Protection) that would lead to disclosure of your data as well as any other information collected by the researcher.

7. If you have any questions or concerns regarding this study, or if any problems arise, you may call the Principal Investigator, Sreelakshmy Geethakumari at 657-226-9951 or Faculty Advisor, Dr. Joseph Rottman, at 314-516-6286. You may also ask questions or state concerns regarding your rights as a research participant to the University of Missouri-St. Louis Office of Research Compliance, at 314-516-5972 or irb@umsl.edu.

I AGREE TO THIS CONSENT FORM AND TO PARTICIPATE IN THE RESEARCH STUDY

I DO NOT AGREE TO THIS CONSENT FORM AND DO NOT WISH TO PARTICIPATE IN THIS STUDY.

If a potential participant, clicks on the “I DO NOT AGREE...” button on this page, they will be taken to the following page:

Thank You

We appreciate you for carefully considering participation.

If you have suggestions regarding other potential participants who may fit the criteria for this research study, please reach out to the principal investigator, Sree at sreelakshmy.geethakumari@umsl.edu.



If a potential participant clicks on the “I AGREE...” button on this page, they will be taken to the following page:

Questions Responses 2 Settings

AI Orientation Research - Participant Screening

Please respond to the following questions to confirm your eligibility to participate: _____

This form is automatically collecting emails from all respondents. [Change settings](#)

Your Name *
Short answer text

Your Organization *
Short answer text

Your Current Role / Title (eg: Chief Information Officer, VP - Data & Analytics) *
*Must be serving in a senior leadership position, defined as C-Suite, Senior Vice President/Vice President, Senior Director or comparable
Short answer text

+

⤒

⤔

⤖

⤘

⤙

Questions Responses 2 Settings

Are you a Senior Leader in your firm with direct influence on AI-related decisions (as strategy, recommendations, technical/value/people suggestions) in your firm?

Yes

No

Do you have a minimum of 10 years of work experience in the United States? *

Yes

No

How many employees does your organization employ within the United States? *

1. Less than 100

2. 101 - 500

3. 501 - 1000

4. More than 1000

Questions Responses 2 Settings

Gender Identity

1. Female
2. Male
3. Non-Binary
4. Prefer not to answer

Race or Ethnicity

- White or Caucasian
- Asian
- Black or African American
- Hispanic, Latino or Spanish Origin
- Middle Eastern or North African
- Native Hawaiian or Other Pacific Islander
- Multiracial (Select all of the above that apply.)
- Prefer not to answer
- Other...

In the text box below, please provide your preferences (i.e. preferred day of week, preferred time of day, etc.) for the interview. *

Short answer text

How do you prefer to be contacted to schedule an interview? *

1. Email
2. Phone call
3. Text

Please provide applicable contact information in regard to question above (i.e. email or phone number) *

Short answer text

If a potential participant clicks on the “About US tab, they will be taken to the following page:

About the Researchers

Sreelakshmy Geethakumari (Principal Investigator)

Sree is currently a Consulting Partner (Managing Director) at Accenture, with over 20 years of technology experience. She specializes in enabling clients to harness the power of artificial intelligence, data analytics, and cloud computing to drive growth and efficiency. At Accenture, she is responsible for technology growth and digital innovation within the Auto & Mobility portfolio across North America. She is an engineer by training and holds an MBA from the Indian Institute of Management, Lucknow, India. She has also studied Algorithmic Business Thinking at MIT and is currently a doctoral candidate at the University of Missouri-St. Louis. Her doctoral research focuses on the intersection of information systems and strategic management. She is a strong proponent of industry-academia collaboration and a life-long learner. She proudly serves on the board for Women in Cloud, and is a passionate advocate to encourage more women in technology.



Dr. Joseph Rottman (Dissertation Chair & Advisor)

Joseph Rottman, D.Sc. is the Director of the International Business Institute, Chair of the CoBA Strategic Planning & Innovation Committee, and Professor of Information Systems at the University of Missouri-St. Louis. He is also a past Research Fellow in the Chinese Academy of Social Sciences and the Center for International Studies. He earned his Doctor of Science in Information Management from Washington University in St. Louis. He has conducted research and spoken internationally on global sourcing, innovation diffusion and public-sector IT. He has conducted case studies in over 40 firms and has been engaged by Fortune 500 firms to analyze and improve their offshore strategies. He has published three books and over 25 articles and book chapters. His publications have appeared in *Sloan Management Review*, *MIS Quarterly Executive*, *Information Systems Frontiers*, *Strategic Outsourcing: An International Journal*, *IEEE Computer*, the *Journal of Information Technology*, the *American Review of Public Administration and Information and Management* and leading practitioner outlets such as CIO Insight and the Cutter Consortium. He was the 2006 recipient of the Anheuser-Busch Excellence in Teaching award, and is on the editorial board of *MIS Quarterly Executive*.



Dr. Michael Seals (Dissertation Committee Member)

Michael J. Seals is Vice President and Chief Information Officer for Hussmann Corporation, a subsidiary of Panasonic, and is responsible for the company's global IT activities. Hussmann was founded in St. Louis in 1906 and is the market leader of refrigeration equipment for food retailers. Seals was appointed as the company's CIO in 2016. He joined Hussmann in 2012 as the Director, Strategy and Business Development. In that capacity, he helped develop and lead the company's digital platform strategy. Prior to joining Hussmann, Seals spent most of his career at two multi-national beverage companies, PepsiCo and Anheuser-Busch, in roles which spanned information technology, strategic planning and corporate development. He earned his master's in business administration from St. Louis University and Doctorate in Business Administration from University of Missouri, St. Louis.



Dr. John Meriac (Dissertation Committee Member)

Dr. John P. Meriac is an Associate Professor in the Department of Global Leadership and Management. His research interests are in the areas of individual differences, personnel selection issues, and performance management. He has published over 30 journal articles and book chapters, including top outlets such as *Journal of Management*, *Journal of Applied Psychology*, and *Personnel Psychology*. In addition, he has given over 60 conference presentations at national and international meetings. He received his Ph.D. in Industrial and Organizational Psychology from the University of Tennessee. Dr. Meriac teaches courses in Advanced Quantitative Methods, Human Resource Management, Leadership, and Organizational Behavior topics at the graduate and undergraduate levels. He is an Associate Editor of the journal *Human Performance* and serves on the editorial boards of *Journal of Organizational Behavior*, *Journal of Business and Psychology* and *Personnel Assessment and Decisions*.



If a potential participant clicks on the “Key Definition button on the home page, or Key Definitions page in the top bar, they will be taken to the following page:

Key Definitions

Artificial Intelligence (AI)

Artificial Intelligence systems can be broadly defined as systems designed to perform actions that, if performed by humans, would be considered intelligent (Hammond, 2024). AI includes "a broad collection of computer-assisted systems for task performance, leveraging machine learning, automated knowledge repositories, image recognition, natural language processing, and large language models" (Von Krogh, 2018).

AI Literacy / AI Fluency

A human's holistic proficiency concerning AI that enables critical usage and evaluation of AI as well as effective communication and collaboration with AI is referred to as AI Literacy or AI Fluency. The collective AI Literacy of the Top Management Team (TMT) is referred to as TMT AI Literacy / Fluency.

Types of AI by application

- AI for automation - that creates business value through substitution of human capabilities to improve efficiency and create cost advantages.
- AI for augmentation - that creates business value by complementation of human cognitive capabilities to improve decision making and drive innovation.

AI Capability & Scalability

AI capability is the ability of a firm to select, orchestrate, and leverage its AI-specific resources. Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands. The core of sustainable AI-based value generation is a scalable AI system

AI Orientation

AI Orientation is defined as a firm's overall strategic direction and goals associated with introducing and applying AI technology (Li et al, 2021). Firms need a strategic orientation on AI to navigate the complexities of AI deployment. When companies develop AI as a strategic orientation for them, it becomes a valuable capability for them difficult to imitate, hence providing sustained competitive advantage.

AI Value Capture

Value capture is defined as the mechanisms that ensure an economic return from value creation and that profits are shared throughout the value creation network. It is important to understand how AI creates value and the firm needs to ensure that complementary products, technologies, and services are available within the value-creation network.

as effective communication and collaboration with AI is referred to as AI Literacy or AI Fluency. The collective AI Literacy of the Top Management Team (TMT) is referred to as TMT AI Literacy / Fluency.

Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands. The core of sustainable AI-based value generation is a scalable AI system

and that profits are shared throughout the value creation network. It is important to understand how AI creates value and the firm needs to ensure that complementary products, technologies, and services are available within the value-creation network.

AI Governance

AI governance is a system of rules, practices, processes, and technological tools employed to ensure an organization's use of AI technologies aligns with its strategies, objectives, and values, fulfills legal requirements, and meets the principles of ethical AI followed by the organization.

Learning Orientation

Learning orientation is an organizational characteristic that affects a firm's propensity to value generative and double-loop learning. Firms that have enhanced learning orientations are more willing to question long-held assumptions about their fundamental operating philosophies

*A full list of academic references related to these key definitions has been included in the principal investigator's dissertation report. Not all are included here to improve readability.

Appendix C: Semi-structured Interview Questions

1. Organizational Context

- a. What are your company's key business priorities?
- b. Does your company have a defined AI vision?
 - i. If yes, will you be open to share that?
- c. Please briefly describe how AI has evolved in your company over the years.
- d. Please talk about your experience in your career as it relates to AI initiatives.

2. Leadership Influence

- a. What is the role of C-suite and Top Management Team in defining and implementing a company's AI vision?
 - i. Should top management teams have specific characteristics to support a successful AI journey in your firm? (For, e.g., their educational background, gender, previous experience, familiarity with AI etc)
 - ii. How different is the influence of Top Management Teams and Board on AI Initiatives compared to other enterprise IT initiatives?

3. Organizational AI Capability

- a. How did you establish AI capability in your firm? Elaborate on the journey your firm went through while establishing the AI capability.
 - i. What are the foundational building blocks of AI Capability in your firm?

1. Depending on the response, explore more about data and talent challenges
- ii. What challenges did you face in establishing AI capability in your firm?

4. Organizational AI Governance

- a. Can you share the AI governance practices you implemented in your firm?
 - i. Who is responsible for the success of AI initiatives in your firm?
 - ii. How are you measuring the value from AI initiatives over time?
 - iii. How does your firm view the risks associated with the utilization of AI?
 - iv. Do you follow any best practices for Responsible AI? If yes, how?
 - v. How important is human involvement in AI-driven decision making?

5. Enterprise Alignment

- a. What alignment challenges do you see across your enterprise while implementing AI Projects?
 - i. What proactive measures are taken by your internal departments to align on AI objectives?
 - ii. How does your firm collectively assess AI's ability to create a sustained competitive advantage?

6. Organizational AI Scalability

- a. What are the challenges and best practices that you see as you attempt to scale AI in your firm?

- i. Are you invested in scalable data infrastructures?
- ii. Who is in charge of the data management?
- iii. What are the procedures or processes for managing your data (for AI purposes)?

7. Organizational Learning Orientation

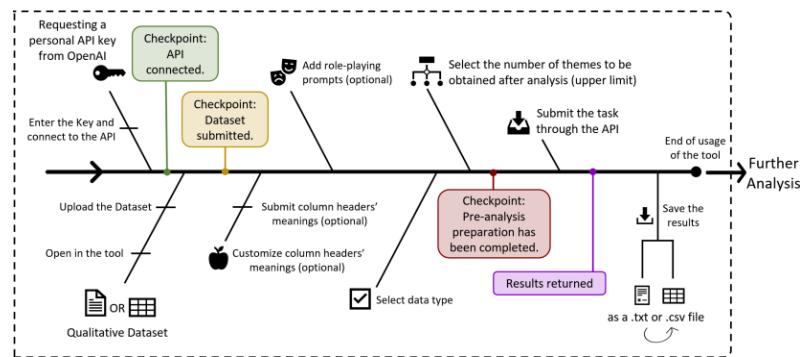
- a. How do you encourage open-mindedness to learn for your employees at various levels?
 - i. What learning practices are you following in your firm?
- b. How are your employees responding to various AI initiatives?
 - i. Do you observe any differences in responses from employees across levels?

8. Closing

- a. Are there any changes in your firm brought by AI that you did not anticipate?
- b. Anything else you would like to share with us?

Appendix D: QualiGPT Analysis Approach Screengrabs

An overview of the usage and flow of QualiGPT is presented below as a reference (Zhang, 2025).



We prompted QualiGPT providing the required context as suggested per QualiGPT guidelines.

You are now an excellent qualitative data analyst and qualitative research expert.

Great! I'm now set up as your expert qualitative researcher and analyst, ready to apply either inductive or deductive coding based on your project needs.

To begin, could you please provide the following information depending on your chosen approach:

 **For Inductive Coding (no codebook needed):**

1. **Study Background:** What's the purpose of your study and any conceptual frameworks you're using?
2. **Goal:** Are you aiming to explore new themes or generate a theory?
3. **Data Collection Method:** How was the data collected (e.g., interviews, focus groups, surveys)?
4. **Input Format:** Will you upload a CSV, Excel, or provide plain text?
5. **Output Format:** Would you like a thematic summary, a table with themes and quotes, or a detailed code list?

 **For Deductive Coding (requires a codebook):**

1. **Study Background:** What's the purpose of your study and the guiding conceptual framework?
2. **Goal:** Are you validating an existing theory or applying a known framework?
3. **Data Collection Method:** What kind of data and how was it collected?
4. **Codebook Format:** Please upload the codebook (CSV/Excel or type it directly).
5. **Input Format:** Will your qualitative data be in CSV, Excel, or text?
6. **Output Format:** Do you want a thematic summary, a table with applied codes and quotes, or raw coded data?

Let me know which path you'd like to follow and share the relevant details or files—then I'll get started right away!

QualiGPT 4.0 

Will you use this data for training the LLM model?

No, your data will **not** be used to train or retrain the language model.

All data you share is handled in accordance with OpenAI's [data usage policy](#). Specifically:

- **Your data stays private** and is **not used for training**.
- **No human reviewers** can see your content unless you explicitly request support and grant permission.
- I process your data **only within this session** to assist with your request.

So you can confidently proceed with sharing your study details, codebook, and data.

We started with **Deductive Coding**, providing the codebook

1. Study Background: The purpose of this research is to explore the determinants and dimensions of AI Orientation in organizations. We are specifically interested in learning about the experiences of senior leaders as their firms navigate the AI journey.

2. Goal: We want to validate the existing literature based on a codebook and look for other emerging themes. We are also interested in any manufacturing industry-specific observations.

3. Data Collection Method: We follow a qualitative research method through semi-structured interviews with 20 senior leaders. Zoom interview transcript has been redacted and cleaned to create the required input for qualigpt. 4. Codebook Format: Uploaded along with this.

5. Input Format: Excel with three columns - index, participant pseudonym, interview response content. This is the text that the interview participant told in the interviews. Questions have been removed to avoid confusion.

6. Output Format: I want a table downloaded report with applied codes and quotes, a frequency table for codes, and a separate list of manufacturing-specific codes.

Perfect—thank you for the clear details and for uploading your dataset. I now have the following:

- **Study Objective:** Exploring determinants of AI Orientation through senior leaders' experiences.
- **Goal:** Validate an existing codebook while remaining open to emergent and manufacturing-specific themes.
- **Methodology:** 20 semi-structured interviews (cleaned Zoom transcripts).
- **Input Format:** Excel with index, pseudonym, and cleaned responses.
- **Codebook:** Present in the uploaded file.
- **Desired Outputs:**
 1. A downloadable table with applied codes and quotes.
 2. A frequency table for codes.
 3. A list of manufacturing-specific themes.

I'll now review the uploaded Excel file and begin the deductive coding.

Analyzed ^

```
python          Always show details   Copy
import pandas as pd

# Load the uploaded Excel file to inspect its structure
file_path = "/mnt/data/Consolidated_↓\liGPT_Input.xlsx"
excel_data = pd.ExcelFile(file_path)
```

Codebook.docx
Document

Here is the codebook

Thanks for sharing the codebook. It includes six predefined categories, each associated with a rich set of keywords for deductive coding:

1. Leadership Influence
2. Organizational AI Capability
3. Enterprise Alignment
4. Organizational AI Scalability
5. Organizational Learning Orientation
6. Organizational AI Governance

I will now apply these codes to the interview responses and also:

- Identify any **manufacturing-specific themes** (as emergent observations).
- Create:
 1. A **coded dataset** linking excerpts to the applied codes.
 2. A **frequency table** showing how often each code appears.
 3. A **separate list** of entries specific to the manufacturing sector.

Processing begins now.

Analyzed ^

python Always show details | Copy

```
import re

# Define the codebook categories and their associated keywords
codebook = {
    "Leadership Influence": [
        "top management team", "tmt", "executive leadership team", "elt", "l
        "tmt ai fluency", "tmt characteristics", "tmt ai vision", "organizat
        "board effectiveness", "top management", "leadership", "executive",
        "tmt career experience", "tmt education", "strategy", "leader", "lea
        "leader communication", "collaboration"
    ],
    "Organizational AI Capability": [
        "tangible resources", "data", "technology", "business process", "hum
        "technical skills", "business skills", "people", "talent", "intangib
        "organizational change", "ri↓ proclivity", "resources"
    ],
    "Enterprise Alignment": [
        "strategic alignment", "operational efficiency", "customer satisfaction
        "supplier relationships", "internal processes", "innovation", "risk manag
        "globalization", "regulatory compliance", "ethics"
    ],
    "Organizational AI Scalability": [
        "scalability", "adaptability", "flexibility", "modularity", "reuse", "c
        "data integration", "cloud computing", "big data", "AI infrastructure"
    ],
    "Organizational Learning Orientation": [
        "learning culture", "continuous improvement", "knowledge management", "c
        "innovation", "problem solving", "adaptability", "resilience"
    ],
    "Organizational AI Governance": [
        "governance", "ethics", "compliance", "transparency", "accountability", "r
        "stakeholder management", "risk management", "internal controls"
    ]
}
```

Then we prompted QualiGPT to perform inductive coding, based on Human-AI thematic exploration

Now I want you to perform inductive coding on this data to understand other emerging themes from the experiences of these leaders. I want to do Human-AI Thematic Exploration to go through the interviews more "qualitatively" and summarize potential latent themes that go beyond just word frequency or clustering — closer to how a human would interpret meaning, emotion, tension, etc. From the emerging themes, I want you to identify potential determinants of AI Orientation in firms. Make sure that these determinants are actionable for practitioners and theoretically relevant.



Excellent — you've set a rich, dual-focused goal: to use **Human-AI Thematic Exploration** for **inductive analysis** of interview data, then **distill potential determinants** of AI Orientation that are:

- Grounded in leader experiences
- Latent and meaning-rich (not surface keywords)
- Actionable for practitioners
- Theoretically relevant for scholarly work

Methodological Framing:

Role: Qualitative researcher using grounded theory and reflexive thematic analysis.

Task:

1. Perform open and axial coding to uncover **latent emergent themes** from interview data.
↓
2. Translate themes into **actionable, theoretically coherent determinants** for AI Orientation.

Appendix E: Additional Findings from Manufacturing Industry

The manufacturing industry provides a particularly valuable context for examining AI orientation. From factory equipment to finished products and the entire value chain in between, AI Orientation is pivotal to manufacturing,

Manufacturing is one of the largest industry sectors and can be data-intensive with a focus on operational data through methods such as statistical process control (SPC) and technical architectures relying on programmable logic controllers and robotics. This industry generates abundant structured data, has highly repeated processes and a well-defined performance metrics, aligning well with the strengths that AI can bring to its benefit. At the same time, the urgency to harness AI is growing due to external pressures like global supply chain disruption, geopolitical uncertainties and the push for sustainable operations.

Manufacturing industry has historically witnessed some of the most disruptive innovations that powered the journey from the era of manual production to advanced mechanization that freed humans from hard labor, including the creation of steam engines, automobiles, electric motors, industrial robots etc (Kim et.al., 2022). The accumulation of big data via IoT (Internet of Things) and other connected technologies demanded methods to deal with large amounts of data, and this has been the driving force behind advanced innovations in Industrial AI (AI for the particular goals in the manufacturing industry). The shift towards Industrial AI and autonomous production systems is expected to help manufacturers increase throughout, product yield and resource efficiency (Akthar, 2024)

Advent of smart products driven by IoT enables manufacturers to shift from reactive maintenance to predictive and prescriptive service models, thereby extending their value proposition beyond the post-sales services. As Akhtar (2024) emphasizes, AI and IoT together enable “closed-loop intelligence” where field data informs design, maintenance, and innovation cycles. Real-time insights from smart and connected products help manufacturers to anticipate failures and optimize parts logistics, leading to enhanced operational reliability and customer satisfaction.

Manufacturing firms consider quality and efficiency paramount. The increasing product and process complexity, variability in customer preferences, and significant cost pressures and optimization requirements are forcing manufacturing companies to explore leveraging AI effectively. This indicates that AI orientation in manufacturing is heavily operations-grounded and value-driven. As one of our interview participants from a manufacturing company pointed out, “AI really is not really new to us because we're engineering companies. We used AI for doing predictive maintenance and that kind of machine learning type of traditional AI is not new to us. So, we've been doing that for many years”. AI applications in manufacturing are very closely associated with business outcomes, making the stakes for strategic AI adoption especially high.

Customer experience is evolving, even in Manufacturing. While typically not selling to consumers, the B2B customer experience is evolving to be more consumer-like. IoT and AI facilitate continuous engagement between manufacturers and customers through real-time dashboards, predictive analytics and performance monitoring tools (Gao et.al,2024). This empowers manufacturers to provide tailored data-driven insights to their customers to optimize efficiency and sustainability. Kim et.al (2022) highlights how

the AI with engineering and manufacturing sectors can create a foundation for intelligent and adaptive manufacturing systems, thereby enriching manufacturing industry with the power of merging technologies.

However, manufacturers face unique challenges as they continue their AI journey, such as legacy infrastructure, stringent regulatory requirements, and the highest level of quality control, all of which shape how manufacturing can apply AI towards their strategic goals. In our study, twelve of the twenty participants represented firms in the manufacturing sector. This concentration provided us an opportunity to examine sector-specific dynamics. We conducted a supplemental analysis of these interviews, to extract specific findings that are particularly relevant to manufacturing leaders. We believe these findings empower executives and managers in manufacturing industry as they advance their firms' AI orientation.

Key observations from manufacturing industries are listed below:

a. Quality Focus and Explainability:

Manufacturing leaders emphasized that product quality is a key concern for them. For example, Peter noted:

“We're in manufacturing. And you know, we build products to sell right? And a lot of times, you know, our mind is always on the quality of the products. Because whenever you sell a product, you sell at one price. If the product has to be recalled for a quality issue, it's going to cost you way more than that to recall their product” - Peter

“With Generative AI, it's hard to prove a result, right? And that result is reliable. So, like with machine learning, that's consistent. And you have consistent results.

With generative AI becomes much more of a challenge in terms of something that we can put into our operation just from a regulatory standpoint.” – Sam

b. AI Role Clarity & Governance – CIO-CTO Power Structure:

Manufacturing firms have a leadership structure with CTO focused on engineering/manufacturing priorities and CIO focused on internal enterprise IT. The advent of AI initiatives is a pivotal moment where they are forced to work together to implement more cross-functional AI programs towards strategic business goals. For example, Peter and Diana noted:

“Our companies are not set up in a traditional way, where we have a CIO for the whole company. We have the CTOs, they are in charge of the business/product related technology, which is not necessarily IT related.” - Peter

“CTO is more outward and customer-facing, whereas CIO to me is more business infrastructure, and how technologies are internally organized. CTO is the person I would communicate with about AI, for you know more of the commercial. For internal, I would communicate with the CIO” – Diana

AI ownership has not been established at the corporate level in most of these firms. It cannot be pushed down to the plants, and adoption can be a challenge. As Kole noted:

“Things that come down from the central organization, and they will push things down from their central organizations that will have an AI component to them. But again, if it's just pushed down to the plants or pushed down to the sales organizations, it's the end user who needs to use it and understand how they use it for a benefit. So, it won't be successful if that person doesn't use it the right way” - Kole

c. Value Realization (and Skepticism) from Operational Leaders

Traditional manufacturers used to have rule-based and predictive AI in their facilities early on. However, many acknowledged being late entrants to the generative AI journey. Leaders highlighted the need to integrate AI into the core manufacturing journey to realize value and scale across the enterprise.

“I want to improve productivity and equipment effectiveness in our facility.

So, through our models, we are able to predict these metrics and accordingly make changes in our production planning. If there are leaks in any of our process, we can implement either changes to the process or bring people who can be owners to recommend the right changes in those process sets to make those decisions. So that's how we measure value.” – Smith

“We're in the manufacturing space. Our main concern is can we build things cheaper? Can we build things faster or can we somehow sell things at a higher price? And can we sell more of it? Right? Can we sell newer products, more of it. Our concerns are slightly different than maybe a lot of others, because we make physical products.” - Peter

“Now I'm able to see value because I got the car faster to market from a time perspective and from an investment perspective.” - Nancy

d. Manufacturing Firms Are Not “Born Digital”

There are multiple legacy technologies operating in manufacturing industries. There needs to be a cultural shift to leverage AI for core value chain activities. This has created opportunities for technology partners to disintermediate the manufacturer-customer relationship with modern technology. As Gloria pointed out:

“Because we're super analog, only if you're super analytical, will you be able to see that your conversions are slowing down, and that you're losing customers.

Tomorrow, I could have all that at my fingertips. So that's how I see the revolutionary change that we need to incur. I'm in a chemical company. I'm sure we're really low on the learning and digital adoption curve." – Gloria

e. Data Continuity Capability and Readiness

Manufacturing firms have global operations with interdependencies across geographies.

This is an important aspect to consider while scaling AI use cases. While they realize that scaling AI to make a business impact, they find data continuity issues across geographies.

"Right now, data is all localized in different locations, different countries. So how do you even (start scaling)? That's why we need legal help, too. Ideally, you put all the data in some central server. If you don't have data to begin with, how do you scale?"

– Peter

"You have these different (data) silos, and they're not necessarily coming together to create what I call true governance. Because I think the governance around data is really step one so they have true governance around how they're managing their data, how data is cleansed, how it's updated effectively, so that everyone's seeing the same information." - Diana

f. Learning and Upskilling Anxiety

We noted that manufacturing leaders are apprehensive about their engineers turning to AI learning, as it may take away precious engineering time.

"We'll have to build a whole new set of talent for this (AI journey). Ideally, we don't want our best engineers that are good at doing something to jump ship to this AI, we don't even know if it is going to give financial benefits. Whatever we're doing right now is our bread and butter." – Peter

Additional Determinants for Manufacturing Industry

We listed down some of our key observations from the Manufacturing industry above on this appendix. We propose additional determinants specifically for the Manufacturing industry, as industry leaders are trying to fine-tune their S&T Tree.

- **Embedded AI Value Realization** – As manufacturing leaders are keen on scaling initiatives that have direct impact on core manufacturing journey, it is important to mandate AI pilots with direct impact on key metrics like uptime, throughput, defect rates. As digital twins and physical AI evolve further, it will help manufacturing leaders apply AI towards their strategic goals.
- **AI Role Clarity and Governance**- Given the federated nature of manufacturing facilities and corporate offices, it is important to define governance frameworks, responsible AI guidelines and AI implementation standards for advancing AI journey. It also helps to have cross-functional AI councils to socialize the AI success across the organization for better visibility and AI orientation
- **Data Continuity Capability** – The data continuity across geographies and business units needs to be addressed proactively. Internal ownership of data needs to be discussed and decided, so that data readiness does not come in as a constraint as firms attempt to scale AI for value realization.
- **Cross-Tier AI Fluency Development** – While the Manufacturing industry needs a variety of talent, achieving high AI orientation in firms needs a cross-tier AI fluency. There is a dearth of talent at the intersection of engineering, technology and business, who understands the right strategic applications of AI. Firms may have to explore external partnerships as they accelerate their journey initially while continuing to upskill their internal talent.

APPENDIX F: Strategy & Tactics Tree for AI Orientation

Our detailed analysis of interview data indicated that most participants highlighted constraints as they navigate AI journey in their firms. We observed that, irrespective of industry sector, all firms are navigating certain common constraints (leadership influence, operating model etc). At the same time, each organization behaves differently in response to a disruptive technology innovation of this scale. This also implies that each organization may face specific constraints that are internal to their firm. We adopted the Theory of Constraints (TOC) as the theoretical lens for this interpretation and proposed to build a playbook for practitioners as they navigate their journey. This is an illustrative example tool for practitioners as they advance their AI journey.

TOC is a methodology that can be used to guide the implementation of any improvement programs in organizations as they strive to achieve competitive advantage (Mabin & Balderstone, 2000, Shoemaker & Reid, 2005). TOC advocates that every system has at least one constraint (weakest link) that prevents the organization from reaching its goal. TOC suggested a tool called Strategy & Tactics Tree (S&T Tree), which was refined further by Goldratt (Goldratt et.al, 2002) as an effective tool for implementing organizational strategy. Goldratt (2002) argues that if we consider that strategy is to set clear direction, it cannot be just stating the highest objective. Companies need to better specify their strategy by defining more and more specific objectives. We borrow this theoretical lens to study firms pursuing higher AI orientation, as our findings indicate that firms are navigating multiple organizational constraints and need to have a defined, actionable roadmap to advance in their journey.

As an illustrative example, we used S&T tree as a tool to represent the determinants of AI Orientation in an organization, as it effectively communicates the required changes in each level towards a larger organizational goal, navigating the organizational “engines of disharmony” (Barnard, 2010). This tool provides a robust logic-based framework for explaining how firms navigate systemic bottlenecks while advancing their AI transformation journey. Unlike traditional maturity-based models, the S&T Tree articulates the link between strategic objectives (“what to achieve”) and tactical enablers (“how to achieve it”) through a hierarchical cause-and-effect structure. This clarity makes it particularly relevant for organizations seeking to implement AI, where constraints are often multifaceted (Mikalef et al., 2021; Akhtar, 2024). The S&T Tree helps identify critical leverage points that can accelerate AI value realization by decomposing strategic goals into actionable steps while maintaining logical coherence.

Strategy & Tactics (S&T) Tree is a practitioner-oriented tool. At each level of the tree, strategy is the answer to ‘what for’ and the tactic is to answer, ‘how to’. We believe our representation of the determinants of AI Orientation, in an S&T Tree format will enable managers at every level in the organization focus better (Huang et al., 2013) and hold the responsibility and accountability to identify and communicate the strategy and tactic for each proposed change to achieve high AI orientation.

Our proposed S&T Tree outlines the overarching strategies that organizations must pursue to advance AI Orientation. This demonstrates how firms can progress from recognizing constraints to systematically resolving them, thereby advancing AI orientation. The value of this tool is that practitioners can fine-tune strategies and tactics at each level, as relevant to their firms, and also expand further to create an actionable

roadmap. Our research findings indicate various bottlenecks or constraints are organizations are navigating their AI Journey. We propose five interconnected strategic branches for the ultimate goal of achieving high AI Orientation, based on our data. These are (1) Leadership Influence (2) Scalable AI Capability (3) Scaled AI Execution (4) AI Governance (5) Human-AI Collaboration. These strategic branches of AI Orientation collectively represent the pathways for organizations to overcome constraints and achieve the goal.

The Goal: High AI Orientation:

At the top of the S&T Tree is the core goal of this research study – to achieve high AI Orientation. The associated tactic (how) is to apply AI towards strategic goals like customer intimacy, operational excellence, and product development. Our findings emphasized that AI is a strategic orientation only when it is implemented to drive differentiated business outcomes. However, they highlighted various constraints within the organization that may hinder the AI journey as planned. These constraints form the next level of branches in our S&T Tree.

Branch 1: Leadership Influence:

Our interview data emphasize that AI orientation cannot happen without executive sponsorship. Leaders who were able to foster a collaborative culture acted as culture catalysts across the enterprise. Also, leaders are expected to build their AI acuity to understand the current state and make informed strategic decisions. When leaders articulated the value of AI initiatives effectively along with associated guardrails, it empowered and motivated the employees to follow along. In TOC terms in order to have

high leadership influence, all the above factors need to be addressed as the next level of strategy and tactics.

Branch 2: Scalable AI Capability:

The first branch of the tree is Scalable AI Capability. The associated tactic is to establish AI capability in a scalable manner from the beginning. Our findings suggest that subsequent branches for the S&T Tree that can help in achieving scalable AI capability include Foundational Readiness (Data, Technology, Security) and Talent Readiness. Additionally, firms should be capable of mapping AI use cases to business processes in a scalable manner, rather than pursuing technology first.

Branch 3: Scaled AI Execution:

Our results showed that execution in a scaled manner is still a constraint for many firms. In order to scale AI initiatives across the enterprise, our data suggested focusing on enterprise alignment and change management. Our participants also described how empowering “AI value creators” or “Technology Progressives” can drive change management to reduce resistance. External Partnerships were identified as accelerators of execution, though several interviewees warned that external collaborations were only effective with right controls in place in house. In TOC terms, execution becomes the next constraint once capability is in place, and alignment is the key to exploiting it.

Branch 4: AI Governance

Governance surfaced as one of the most frequently cited themes across interviews. Participants noted that having a good AI operating model can enable adoption by addressing bottlenecks around who is responsible and accountable for the success of AI initiatives. Ongoing value capture and showcasing the impact on strategic goals was

highlighted as a key constraint. Conversely, firms that articulated clear governance frameworks, operating models, and explainability mechanisms were better positioned to scale responsibly. Our data also emphasized the importance of sustainable and responsible AI guardrails, framing them as trust-building mechanisms.

Branch 5: Human-AI Collaboration

Several participants called human ingenuity as a key constraint for advancing AI journey. Organizations are acknowledging and addressing this and providing training programs and exploring options to learn applied AI. However, there is AI anxiety among employees due to fear of displacing work, lack of trust for AI-driven decisions etc. Building shared vision, cultivating openness and democratizing AI initiatives across the enterprise can help in reducing human resistance.

S&T Tree for AI Orientation – Developed as an illustrative playbook

Based on the observations above, we applied a theoretical lens of Theory of Constraints in S&T Tree format and created the following playbook that practitioners can use as a starting point. Each firm will have their own constraint, and leaders can develop strategies and tactics to address those specifically and can be built on top of this.

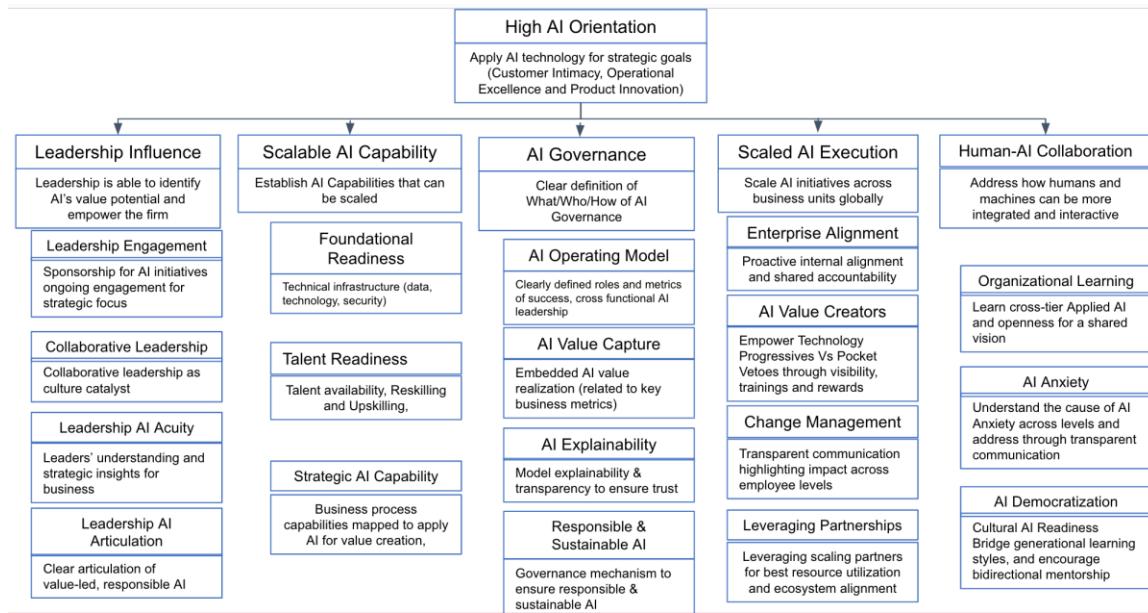


Figure A: Sample S&T Tree for AI Orientation