

DISSERTATION

DEVELOPMENT OF THE HUMAN-AI COLLABORATION MATURITY MODEL
(HAIC-MM) FOR SMALL AND MEDIUM-SIZED ENTERPRISES

Submitted by

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ABSTRACT

DEVELOPMENT OF THE HUMAN-AI COLLABORATION MATURITY MODEL (HAIC-MM) FOR SMALL AND MEDIUM-SIZED ENTERPRISES

Most AI adoption guidance assumes an organization has a dedicated data science team, a seven-figure technology budget, and the capacity to sustain a multi-year transformation program. However, that describes a Fortune 500 company; it does not describe the 33.2 million small and medium-sized enterprises (SMEs) that make up 99% of U.S. businesses. SMEs face a different reality: limited budgets, employees performing multiple roles, and no clear roadmap for turning AI tools into business value. As generative and agentic AI lower the barrier to capable tools, the challenge has shifted from accessing technology to effectively integrating it into human workflows that produce real business results.

Existing maturity frameworks fall short. An analysis of thirty popular models found that most models simply average human and AI capability scores together, concealing the imbalances that determine whether collaboration succeeds or fails. They also ignore the sequential nature of capability development and measure whether organizations possess AI tools rather than whether people use them effectively.

This dissertation introduces the Human-AI Collaboration Maturity Model (HAIC-MM), a systems engineering framework built for SMEs. HAIC-MM assesses collaboration across seven dimensions and 32 capabilities, with each capability evaluated through questions that separately measure human readiness, AI capability, and the quality of interaction between the two. Its central innovation is a Balance Factor that rewards organizations developing both sides in tandem and

penalizes lopsided investment, producing scores that reflect collaboration reality rather than a misleading composite. A dependency system reinforces this by reducing scores when prerequisite capabilities are underdeveloped.

HAIC-MM was developed by synthesizing thirty existing frameworks and then refined and validated in three stages: a survey with 100 professionals confirming dimension and capability relevance; five focus group sessions with ten practitioners that revised 28 capabilities and added four new ones; and a pilot deployment in which ten SME practitioners completed the full 160-question assessment through the haicmm.com platform. Nine out of ten participants confirmed that the framework captures the collaboration challenges they face, the reports provide guidance they can act on, and the Balance Factor reflects how collaboration actually works in their organizations.

This research contributes a framework that treats human-AI collaboration as a system-level property, a replicable methodology for building maturity models from diverse domains, and a self-service platform that delivers maturity reports without consultant support. The findings are published in two peer-reviewed journal articles and are available through a free assessment at haicmm.com.

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My deepest gratitude goes to my advisor, Dr. Erika Gallegos. Her mentorship shaped this dissertation and my growth as a researcher in ways I did not fully anticipate when this journey began.

Dr. Gallegos brought a rare combination of scholarly rigor and genuine care to her role. She held my work to a high standard while making it clear that she believed I could meet it. When a section needed restructuring or an argument lacked precision, she engaged with the problem at an exceptionally detailed level, working alongside me until we arrived at something stronger. That level of commitment from an advisor is not something a student should take for granted, and I certainly do not.

Her analytical thinking strengthened every part of this research. She has a remarkable ability to see beneath the surface of an argument and ensure that every claim rests on sound evidence. Whether the issue involved the structure of the framework, the logic behind the HAIC-MM scoring methodology, or the coherence of the model, her guidance through the most demanding parts of this dissertation was decisive.

What I value most is that her support extended beyond the academic requirements of the role. Completing a doctoral program at this stage in life, while carrying full-time professional responsibilities, demanded a different kind of mentorship, and she understood that from the start. When progress slowed and the work felt distant, her steady encouragement kept me moving.

I am deeply grateful for her patience, generosity, and lasting influence on how I approach research. This dissertation would not exist in its current form without her.

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Chapter 1. Introduction

1.1. Motivation and Problem Statement

Most artificial intelligence (AI) adoption guidance was written for organizations that have dedicated data science teams, seven-figure technology budgets, and the luxury of running multi-year transformation programs. While that describes a Fortune 500 company, it does not describe the 33.2 million small and medium-sized enterprises (SMEs) that account for 99% of all U.S. businesses and employ nearly half the private workforce (US Small Business Administration, 2022). SMEs operate under a different set of constraints, including limited technical expertise, workforce capacity, resource planning capabilities, and financial resources.

The gap between what SMEs need and what existing guidance provides has grown wider as AI itself evolves. Large language models and agentic systems have lowered the entry barrier, giving smaller organizations access to capabilities that previously required significant infrastructure investment. More recently, the emergence of agentic AI, where autonomous agents can reason, plan, and execute multi-step tasks with minimal human oversight, has accelerated this shift further (Gunning & Aha, 2019; Masterman et al., 2024). SMEs can now access remarkably capable tools. What they lack is a structured framework for evaluating how well their workforce and AI systems collaborate, identifying where the gaps are, and building a realistic path forward. That is the problem this dissertation addresses.

The returns from AI depend less on what technology an organization acquires and more on how effectively its workforce and AI systems operate together. Organizations that deliberately design human-AI collaboration workflows report productivity gains of up to 40% (Vaccaro et al., 2024), and as AI agents grow more capable of independent action, the need for structured collaboration grows with them (Xu et al., 2025; Kapoor et al., 2024).

Existing frameworks do not adequately provide this structure and fail to align practically with the unique operational constraints of SMEs. A comparative analysis of thirty frameworks across AI maturity, digital transformation, and human-machine teaming identified recurring limitations (Ortolano & Gallegos, 2025). Most treat human capability and AI capability as independent components and then average the scores together, which conceals the very imbalances that determine whether collaboration actually works. They also tend to ignore the sequential nature of capability development; an organization cannot achieve AI-driven innovation if it has not yet established basic data quality management or employee AI literacy. Finally, they measure whether organizations possess AI tools rather than whether those tools are effectively used in partnership with human judgment.

This dissertation introduces the Human-AI Collaboration Maturity Model (HAIC-MM) to address these gaps. HAIC-MM is a systems engineering framework that assesses human-AI collaboration across seven dimensions and 32 capabilities using a balance-based scoring approach. Rather than averaging across capability areas, it measures collaboration quality directly, rewarding organizations that develop human readiness and AI capability in tandem while penalizing lopsided investment. The maturity progression spans from early AI exploration to symbiotic partnership, where staff orchestrate AI agents autonomously and the organization demonstrates full agentic readiness. This approach applies systems engineering principles to what is fundamentally a sociotechnical problem, consistent with the Systems Engineering Research Center's (SERC) SE4AI roadmap and its vision of human-machine co-learning (McDermott et al., 2020). HAIC-MM was developed through the synthesis of 30 existing models, refined through empirical validation with 100 survey participants and five practitioner focus groups, and validated through pilot deployment with ten SME professionals.

1.2. Research Aims and Research Questions

1.2.1. Research Aim 1: Development of HAIC-MM

The objective of the first research aim was to build a maturity model grounded in existing research. Thirty existing frameworks (ten AI maturity models, ten digital transformation frameworks, and ten human-machine teaming assessments) were synthesized using Becker et al.'s (2009) established methodology for maturity model development. The resulting output from this first research aim was an initial HAIC-MM framework that served as the foundation for subsequent refinement and validation. Two research questions guided this aim:

- **RQ1.1:** What frameworks exist for developing new maturity models?
- **RQ1.2:** How do the strengths and limitations of existing maturity models guide the development of the HAIC-MM?

1.2.2. Research Aim 2: Refinement of HAIC-MM

Building the initial model was only the first step. The second aim was to test whether the framework resonated with practitioners and to refine it based on their feedback. An online survey with 100 professionals was conducted to confirm the relevance of the framework's dimensions and capabilities, followed by five focus group sessions with ten industry practitioners who refined maturity descriptions and assessment questions to better reflect SME realities. This aim also produced the complete scoring methodology, a mathematical framework that converts assessment responses into actionable maturity scores and includes the balance factor that distinguishes HAIC-MM from traditional averaging approaches. Two research questions guided this aim:

- **RQ2.1:** How do stakeholder survey responses inform the refinement of the HAIC-MM's capabilities?

- **RQ2.2:** How do insights from practitioner focus groups contribute to improving the clarity, relevance, and practical applicability of HAIC-MM dimensions and assessment questions?

1.2.3. Research Aim 3: Validation of HAIC-MM

A framework is only useful if practitioners can complete it, understand the results, and act on them. The third aim was to pilot test the deployable HAIC-MM, delivered through the haicmm.com web platform, with ten SME practitioners from diverse industries to determine whether it works in practice. Participants completed the full 160-question assessment and provided structured feedback on three evaluation dimensions: (1) usability of the assessment process, (2) usefulness of the generated maturity insights and success factor outputs, and (3) applicability to SME operational realities. Three research questions guided this aim:

- **RQ3.1:** How effectively can SME practitioners complete and interpret the HAIC-MM assessment?
- **RQ3.2:** How does the HAIC-MM output support SMEs in identifying priorities and guiding organizational improvement?
- **RQ3.3:** How well does the HAIC-MM align with the operational realities and constraints typical of SMEs?

Chapter 2. Background

2.1. Introduction

This chapter reviews the research that informed the development of the Human-AI Collaboration Maturity Model (HAIC-MM). The review covers four areas: the principles and emerging practices of human-AI collaboration, the history and structure of capability maturity models, a detailed analysis of 30 existing frameworks across three domains, and the specific challenges that SMEs face when adopting AI. The chapter concludes with a synthesis of the gaps these frameworks leave unaddressed, gaps that directly motivated the design of HAIC-MM.

2.2. Human-AI Collaboration and Human-Machine Teaming

The relationship between humans and AI in organizational settings has moved well beyond simple automation. Where earlier technology waves replaced manual tasks with machines, AI introduces a qualitatively different capability. It does not simply automate what humans already do. It augments how they evaluate information, make decisions, and respond to operational conditions (Daugherty & Wilson, 2018). AI systems can identify patterns in data that manual analysis would not detect, recommend actions based on historical outcomes, incorporate corrections from human operators, and adapt to changing conditions in real time. Daugherty and Wilson (2018) describe this as the "missing middle," a set of collaborative activities where humans and machines each contribute capabilities that neither possesses alone. This creates a working dynamic between people and technology that previous generations of automation never required. A conventional software tool executes the same logic regardless of who uses it or what changes around it. An AI system that recommends which customer complaints to escalate, or which production line to inspect next, produces better outcomes when it receives adequate feedback from

the staff who work with it. For SMEs, this shift means that the quality of interaction between the workforce and AI systems becomes a direct determinant of the value those systems produce. For example, AI can help a 50-person company operate with the analytical capacity of a much larger organization, but only if the people and the technology are adequately designed to work together.

2.2.1. Foundations of Human-Machine Teaming

Human-machine collaboration has evolved significantly over the past several decades, expanding from simple control systems to complex collaborative partnerships between humans and intelligent technologies. Early conceptual foundations can be traced to Norbert Wiener's (1961) pioneering work on cybernetics, which established the principle of feedback loops between humans and machines to regulate complex systems (Wiener, 1961). These early ideas introduced the notion that machines could operate not only as tools, but also as components of adaptive systems guided by human input. Human systems integration aligns with this framework by emphasizing the importance of designing machines and systems around human needs, capabilities, and limitations so that technology improves, rather than disrupts, human performance (Ahmed & Miller, 2023).

During the late twentieth century, advances in computing expanded these concepts through the development of computer-aided design (CAD) and computer-aided manufacturing (CAM) systems. These technologies allowed humans and machines to collaborate in increasingly sophisticated ways, supporting design, engineering and manufacturing processes. This period also saw the emergence of the field of human-computer interaction (HCI), which focused on designing systems that allow humans to interact effectively with computational technologies (Zhang et al., 2002; Shneiderman, 1983; Botyarov & Gallegos, 2025; Miller & Boyle, 2017). These developments laid the groundwork for modern approaches to human-machine teaming.

The rapid advancement of AI and machine learning in the twenty-first century further expanded the potential for human-machine collaborations (Alipour & Gallegos 2026; Alipour et al., 2026). Technologies such as natural language processing, image recognition, predictive analytics, and robotics have enabled machines to perform tasks that previously required human cognitive (Goodfellow et al., 2016; Alipour et al., 2024). Autonomous systems now perform increasingly complex operations while still requiring human oversight and decision-making (Thrun et al., 2006). As a result, researchers increasingly describe modern human-machine interaction as a form of collaborative partnership rather than simple tool use.

More recently, generative AI systems have further transformed the scope of human-machine teaming. Foundation models, including large language models (e.g., GPT-5.4, Claude Sonnet 3.7, Gemini 3.1) are capable of generating human-like text, images, audio, and software code while interacting conversationally with human users (Alipour & Gallegos, 2025). These capabilities extend earlier versions of collaborative intelligence, in which human and machine agents combine complementary strengths to solve complex problems (Brown et al., 2020). The emergence of these technologies has intensified interest in understanding how humans and AI systems can function effectively as collaborative partners within organizational environments.

2.2.2. Human-AI Collaboration in Organizational Contexts

The increasing sophistication of AI technologies has shifted organizational perspectives from viewing AI as a tool for automation to recognizing its potential as a collaborative partner. Rather than simply replacing human labor, AI systems can augment human capabilities, support decision-making, and enable organizations to operate more effectively in data-intensive environments. This shift is particularly relevant for small and medium-sized enterprises (SMEs),

where AI can expand analytical capacity and operational efficiency despite limited organizational resources.

Daugherty and Wilson (2018) describe this transformation as the emergence of the era of human-AI collaboration, in which humans and intelligent machines work together to generate value. Their framework identifies six principles that characterize this collaborative relationship (Daugherty & Wilson, 2018):

1. *Reimagining Processes*: AI enables businesses to rethink operations entirely, not just automate existing workflows. For SMEs, this means AI can help them innovate and compete with larger enterprises by transforming traditional processes into more efficient ones.
2. *Human-AI Symbiosis*: AI handles tasks that are repetitive, data-intensive, or beyond human processing capacity, while humans focus on creativity, emotional intelligence, and complex decision-making. This division of effort is particularly valuable for SMEs, where it helps overcome resource limitations by redirecting human effort toward higher-value activities.
3. *AI as a Co-Worker*: Rather than viewing AI as a tool that replaces jobs, this principle positions AI as a collaborator that augments human work. AI provides insights, automates routine tasks, and enhances productivity, while fostering a culture of continuous learning and adaptation. For SMEs in particular, treating AI as a collaborative partner allows small teams to expand their capabilities without increasing headcount.
4. *AI-Driven Innovation*: AI generates deeper insights and enables more informed decision-making, leading to new products, services, and business models. SMEs that

adopt this approach can develop unique market offerings and improve customer experiences.

5. *Workforce Reskilling*: Effective human-AI collaboration requires continuous education and training programs that equip employees with the skills to work alongside AI. For SMEs, this investment is essential for the workforce to use AI capabilities fully.
6. *Ethical Considerations*: AI deployment raises issues of bias, transparency, and accountability that must be addressed to build trust with stakeholders and ensure responsible use (Floridi et al., 2018). For SMEs, establishing responsible AI practices can also strengthen customer trust and support sustainable adoption despite limited governance resources.

Daugherty and Wilson (2018) conceptualize human-AI collaboration as a continuum of work activities: some tasks suit humans, others machines, and many a collaborative interaction (see Figure 1). Humans retain primary responsibility for leadership, empathy, creativity, and ethical judgment, while machines excel at processing large data volumes, conducting transactions, and generating predictive insights. The greatest organizational value emerges in the hybrid space, where humans and AI collaborate by training algorithms, interpreting outputs, and enhancing decision making.

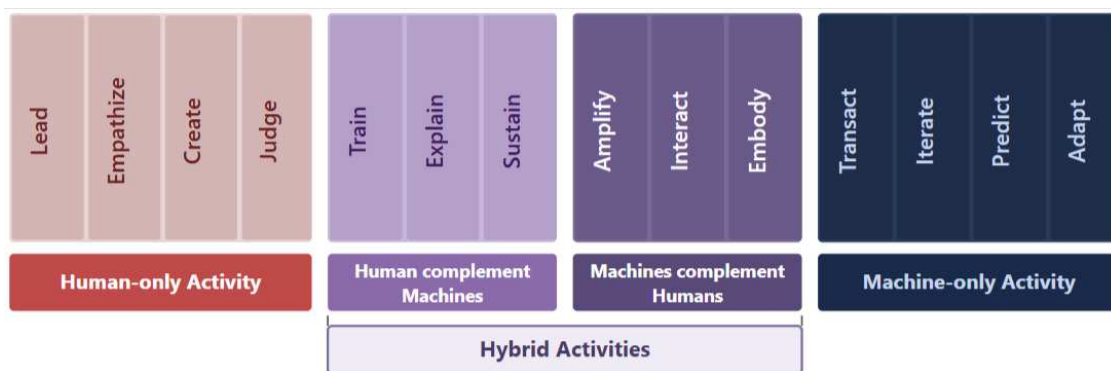


Figure 1: Human-AI Task Continuum (Daugherty & Wilson, 2018)

This continuum and breakdown of activities is further described in Table 1, which breaks down these three activity types (i.e., human-only, hybrid, machine-only) with their specific activities and what each means in practice. In this chart, the “activities” listed for the “hybrid roles” (e.g., train, explain, etc.) represent the collaborative space where human-AI partnerships generate the most organizational value (Daugherty & Wilson, 2018; Rahilly et al., 2024).

Table 1: Human, Hybrid, & Machine Roles, Adapted from Daugherty & Wilson (2018)

Activity Type	Activities	Description
Human-Only	Lead, Empathize, Create, Judge	Roles requiring strategic thinking, emotional intelligence, creativity, and ethical judgment. These remain irreplaceable by AI.
Hybrid: Humans Complement Machines	Train, Explain, Sustain	Humans training AI to perform tasks, interpreting AI outputs for others, and maintaining AI systems over time.
Hybrid: Machines Complement Humans	Amplify, Interact, Embody	AI enhancing human memory and processing capacity, enabling seamless interaction, and taking physical form through robotics to work alongside people.
Machine-Only	Transact, Iterate, Predict, Adapt	Routine transactions, repetitive processes at scale, forecasting based on large datasets, and continuous learning without human intervention.

For example, in a customer service context an AI system may handle routine inquiries and routes requests efficiently (i.e., transact, iterate), while human agents manage complex cases that require empathy and contextual reasoning (i.e., empathize, judge). When integrated effectively, the AI system can surface relevant customer data to support human decision making, enabling faster and more effective problem resolution (i.e., amplify, interact). This collaborative approach is key to enhancing the agility and resilience of SMEs in an increasingly digital and AI-driven business landscape. By adopting AI applications that strengthen sensing, seizing, and transforming

capabilities, SMEs can respond more effectively to uncertainty, improve efficiency, and reduce business risks (Drydakis, 2022, Philbin et al., 2022).

2.2.3. Complementary Capabilities of Humans and AI

Effective human-AI collaboration depends on leveraging the complementary strengths that each brings. Machines excel at computing, analyzing large volumes of data, and producing consistent outputs at high speed (Brynjolfsson & McAfee, 2014). In contrast, humans excel at decision-making, intuitive reasoning, emotional intelligence, and ethical judgment (Daugherty & Wilson, 2018). However, human performance is also sensitive to contextual and environmental factors such as workload, uncertainty, and stress, which can influence decision quality (Miller & Boyle, 2013; Miller, 2013). This reinforces the importance of designing human-AI systems that account for variability in human cognitive states. Rather than forcing either to perform tasks they are not suited for, organizations benefit from deploying AI for routine, data-intensive work while directing human effort toward complex and creative activities (Kaplan & Haenlein, 2019).

McKinsey Global Institute estimated that AI and automation technologies could affect as many as 375 million workers globally by 2030, requiring substantial changes in workforce skills and organizational structures (Manyika et al., 2017). Cognitive technologies such as computer vision, natural language processing, and robotics are already transforming work environments across industries (Schatsky et al., 2014).

For organizations seeking to harness these technologies effectively, the challenge lies not simply in deploying AI systems but in designing environments that enable humans and machines to collaborate productively. This perspective shifts attention from automation alone to the broader concept of human-AI teaming, where performance improvements emerge through the integration of complementary capabilities.

2.2.4. Theoretical Foundations of Human-AI Team Effectiveness

Research on team effectiveness provides a useful theoretical foundation for understanding human-AI collaboration. One influential framework is Wageman, Hackman, and Lehman's (2005) model of the "*Five Conditions for Team Effectiveness*", which identifies structural and contextual factors that enable teams to perform successfully. Although originally developed for human teams, these conditions can also be applied to teams composed of both human and artificial agents.

1. *Real Team*: In human-AI collaboration, this means clearly defining the roles and responsibilities between human and AI team members. Just as in human-only teams, there must be a shared understanding of each entity's tasks, skills, and decision-making authority (Brynjolfsson & McAfee, 2014; Wilson & Daugherty, 2018).
2. *Compelling Direction*: Human-AI teams need clear, measurable objectives that both partners can work toward. Clear goals align AI applications with strategic organizational outcomes and drive engagement (McDermott et al., 2020).
3. *Enabling Structure*: Organizational infrastructure, including data governance, technology integration, and workflow optimization, must be designed to enable smooth human-AI collaboration. Effective data management systems enable AI to access and process relevant information quickly, supporting human decision-making (Gartner, 2023).
4. *Supportive Context*: Both human and AI team members need the right resources, training, and support to contribute effectively. Continuous learning opportunities help organizations keep pace with the evolving AI landscape (McKinsey, 2023; Deloitte, 2022).

5. *Expert Coaching*: The integration of AI systems requires expert oversight and guidance, including coaching human team members on using AI capabilities effectively and fine-tuning AI systems to align with the team's evolving needs (Wilson & Daugherty, 2018; PwC, 2022).

Viewing human-AI collaboration through the lens of team design highlights an important insight, that effective collaboration depends not only on technological capabilities but also on the organizational structures that enable humans and AI systems to function as coordinated partners. These conditions suggest that organizations can improve problem-solving, productivity, and responsiveness to market changes by treating the human-AI relationship as a team design problem rather than a technology deployment problem (Jarrahi, 2018). For SMEs, where teams are smaller and roles less specialized, this perspective is especially relevant.

2.2.5. Human-Machine Teaming Capabilities

While team effectiveness theory provides a conceptual foundation for collaboration, research on human-machine teaming offers a more detailed understanding of the capabilities required for effective interaction between humans and AI systems. Human-machine teaming research emphasizes that intelligent systems should be designed not merely as tools but as collaborative team members capable of supporting shared goals and adapting to human needs (Johnson & Vera, 2019). This perspective also requires evaluating humans as embedded within a broader ecosystem of interconnected technologies, where human roles, decisions, and interactions shape how the system functions as a whole (Coronado & Gallegos, 2025).

Early conceptualizations compared AI systems to human co-pilots that assist human operators in complex decision environments (Urlings & Jain, 2002). Building on this idea, subsequent research has identified a set of capabilities necessary for effective human-machine

collaboration. These capabilities include the ability for humans to direct and control AI behavior, understand the reasoning behind AI decisions, maintain shared situational awareness, and participate in shared decision making processes. Additional capabilities include transparency-related features such as observability, explainability, common ground, and interoperability, as well as authority-balance features such as cognitive load balance and directability, and secure-interaction features such as reliability and security. The full list of these capabilities, as well as associated publications and definitions were compiled by Herrmann and Huang (2020), which are provided in Table 2.

Table 2: Synthesized HAIC Capabilities by Herrmann and Huang (2020)

Capability	Key Authors	Definition
Directability, Controllability, Accountability	Urlings & Jain (2002); McDermott et al. (2017); Johnson & Vera (2019); Smith (2019)	Humans can control the system, allocate authority between human and machines, intervene in ongoing processes, redirect resources, and modify workflow parameters
Explanation	Smith (2019); Cruz et al. (2019); Xu (2019)	Machine learning must be interpretable by design; humans recognize when and why AI takes action; users understand the algorithms and parameters used
Observability, Directing Attention, Predictability	Urlings & Jian (2002); McDermott et al. (2017); Smith (2019)	System provides information about states and parameters; humans can verify what AI is doing and why; team members can recognize future intentions and anticipate changes
Ethical, Honest	Smith (2019); Xu (2019)	Humans can recognize they are interacting with AI; information is presented to support simplicity and understandability
Learning	McDermott et al. (2017); Smith (2019)	Human-machine teams can adapt seamlessly to unexpected situations; machines improve regularly to meet human needs and technical standards
Shared Decision Making	McDermott et al. (2017); Johnson & Vera (2019)	Shared decision-making eliminates human oversight slips and reduces human error; partners can use multiple views and solutions to jointly understand the problem space

Transparency	Johnson & Vera (2019); Cruz et al. (2019)	Awareness of errors and biases from machine learning models with ability to correct them; evidence for decisions is presented for humans
Shared Knowledge of State	McDermott et al. (2017); Johnson & Vera (2019)	Humans stay apprised of information the machine uses; relevant beliefs and assumptions are shared; team members maintain a constantly updated shared picture
Cognitive Load Balance	Johnson & Vera (2019)	Manageable human workload achieved by balancing distribution between human and machine with changing contexts
Interoperability	Johnson & Vera (2019)	Ability to connect the human-machine team into broader systems
Security	Smith (2019)	AI system provides understandable security methods and is reliable; protects HMT processes, data, and services from unauthorized access

These capabilities define the operational characteristics that enable human-AI teams to function effectively. They ensure that humans maintain appropriate oversight while allowing AI systems to contribute computational power and analytical insights. For resource-constrained organizations like SMEs, the adaptability of these capabilities is particularly relevant because it allows task allocation to adjust as team needs and contexts change (Amershi et al., 2019).

2.2.6. Learning and Adaptation in Human-AI Teams

Human-AI collaboration is not static; rather, it evolves through continuous learning and adaptation. Humans improve AI systems by providing training data, feedback, and performance evaluations, while AI systems assist humans by identifying patterns within complex datasets and generating decision-support insights. This reciprocal learning cycle is a central mechanism through which collaborative performance improves over time (Xu et al., 2023; Dellermann et al., 2019; Te'eni et al., 2023).

Several mechanisms support this reciprocal learning. Adaptive leadership allows human and AI partners to assume leadership roles depending on the requirements of a given situation,

enabling teams to leverage the strengths of each participant (Johnson et al., 2014). Transparency also plays a critical role, as AI systems that clearly explain their reasoning help build trust and allow humans to rely more effectively on AI contributions (Gunning & Aha, 2019; Johnson et al., 2022). User feedback further strengthens the cycle because human input through training data, performance evaluations, and corrective feedback drives the iterative improvement of machine learning systems (Shneiderman, 2020). Simulation-based training can also support collaboration by using realistic scenarios that help humans and AI develop shared mental models and team fluency, enabling more effective coordination (Xu et al., 2023). Ethical alignment is equally important because guiding AI development with human ethical considerations helps ensure that technological advances remain consistent with beneficial outcomes and human-centered values (Jobin et al., 2019).

2.2.7. Building Trust in AI Systems

Trust represents one of the most critical factors influencing the successful implementation of human-AI collaboration (Stewart & Gallegos, 2025; Miller & Boyle, 2019). While large organizations may have the resources to absorb failures during AI adoption, SMEs often face greater operational risks when deploying new technologies. If employees do not trust an AI system, they may either disregard its recommendations (reducing the value of the technology) or rely on it without appropriate oversight, increasing the risk of costly errors.

Explainability plays a central role in building this trust. Decision makers are more likely to rely on AI-generated recommendations when they understand the factors influencing those outputs. For example, an operations manager reviewing AI-generated demand forecasts may wish to understand which variables influenced the prediction and why certain data points were weighted

more heavily than others. Explainable AI techniques help address this need by making algorithmic reasoning accessible to non-technical users (Gunning & Aha, 2019).

Reliability and transparency further reinforce trust. Consistent performance builds confidence in an AI system's capabilities, while transparency allows users to understand how the system processes information and produces recommendations (Hoff & Bashir, 2015; Arnold et al., 2019). Continuous human oversight also remains necessary because AI systems trained on historical data may lose accuracy as conditions change (Brynjolfsson & Mitchell, 2017).

Organizations often develop trust gradually by introducing AI systems in stages. For instance, an organization might initially use AI to provide decision support for inventory management before gradually expanding its authority to automate routine purchasing decisions. This incremental approach allows employees to observe system performance and develop confidence in its capabilities before granting greater autonomy (Madni & Madni, 2018).

2.3. Capability Maturity Models

Before an organization can improve its capabilities, it must first understand its current level of development. Capability maturity models provide a structured way to assess this position by defining progressive stages of capability growth and offering a framework for evaluating organizational readiness. For SME leaders evaluating AI adoption, understanding how maturity models function, and why they are relevant, provides essential context for the HAIC-MM framework developed in this research.

2.3.1. Definition and Historical Background

Capability Maturity Models (CMMs) originated in the late 1980s within the field of software engineering. The Software Engineering Institute (SEI) at Carnegie Mellon University

introduced the Capability Maturity Model for Software (CMM-SW) in 1991 as a framework for improving software development processes (Paulk et al., 1993). The model later evolved into the Capability Maturity Model Integration (CMMI), which unified several maturity frameworks into a comprehensive structure now widely used as a benchmark for developing maturity models across disciplines (Chrissis et al., 2011).

Since their introduction, maturity models have expanded beyond software engineering into a wide range of domains including business process improvement, technological implementation, and organizational strategy (Röglinger et al., 2012). These models provide a standardized language and methodology for assessing process capability and identifying areas for improvement (Becker et al., 2009; Röglinger et al., 2012; Wendler, 2012).

The concept of “maturity” refers to the degree of evolution a process or organizational capability has achieved, typically progressing from informal and ad hoc practices to structured and optimized approaches (Wendler, 2012). A “model”, in this context, is a structured framework designed to support systematic analysis and improvement of organizational processes (Becker et al., 2009). When combined, maturity models help organizations evaluate operational readiness, identify gaps in processes or infrastructure, detect skill deficiencies, and plan strategic improvements.

Most maturity models share a similar architecture composed of several key constructs:

1. *Dimensions or Domains*: Broad categories representing the model's main areas of assessment (Paulk et al., 1993).
2. *Capabilities or Process Areas*: Specific activities or competencies within each dimension, arranged in stages that reflect increasing effectiveness (Becker et al., 2009).

3. *Performance Indicators or Assessment Criteria*: Measurable factors used to evaluate capability performance at each level (Kaplan & Norton, 1996).
4. *Maturity Levels*: Evolutionary stages representing capability development, often ranging from Level 1 (Initial) to Level 5 (Optimizing), (Crosby, 1979; de Bruin et al., 2005).

These constructs do not function in isolation. They form an interconnected architecture where each element supports and informs the others. The maturity model defines the overall scope and objectives of the assessment. Dimensions segment that scope into broad evaluation areas, each containing specific capabilities that organizations must develop. Those capabilities are measured through assessment criteria tied to defined metrics, and each capability maps to a maturity level that indicates the organization's current stage of development. Improvement actions provide the bridge between assessment and advancement, specifying the strategic steps needed to move from one maturity level to the next.

Figure 2 presents an entity relationship diagram that illustrates how these constructs relate to each other, showing the structural foundation that underlies most maturity models in the literature and that informed the architecture of HAIC-MM. This chart was made using the Mermaid online diagraming tool.

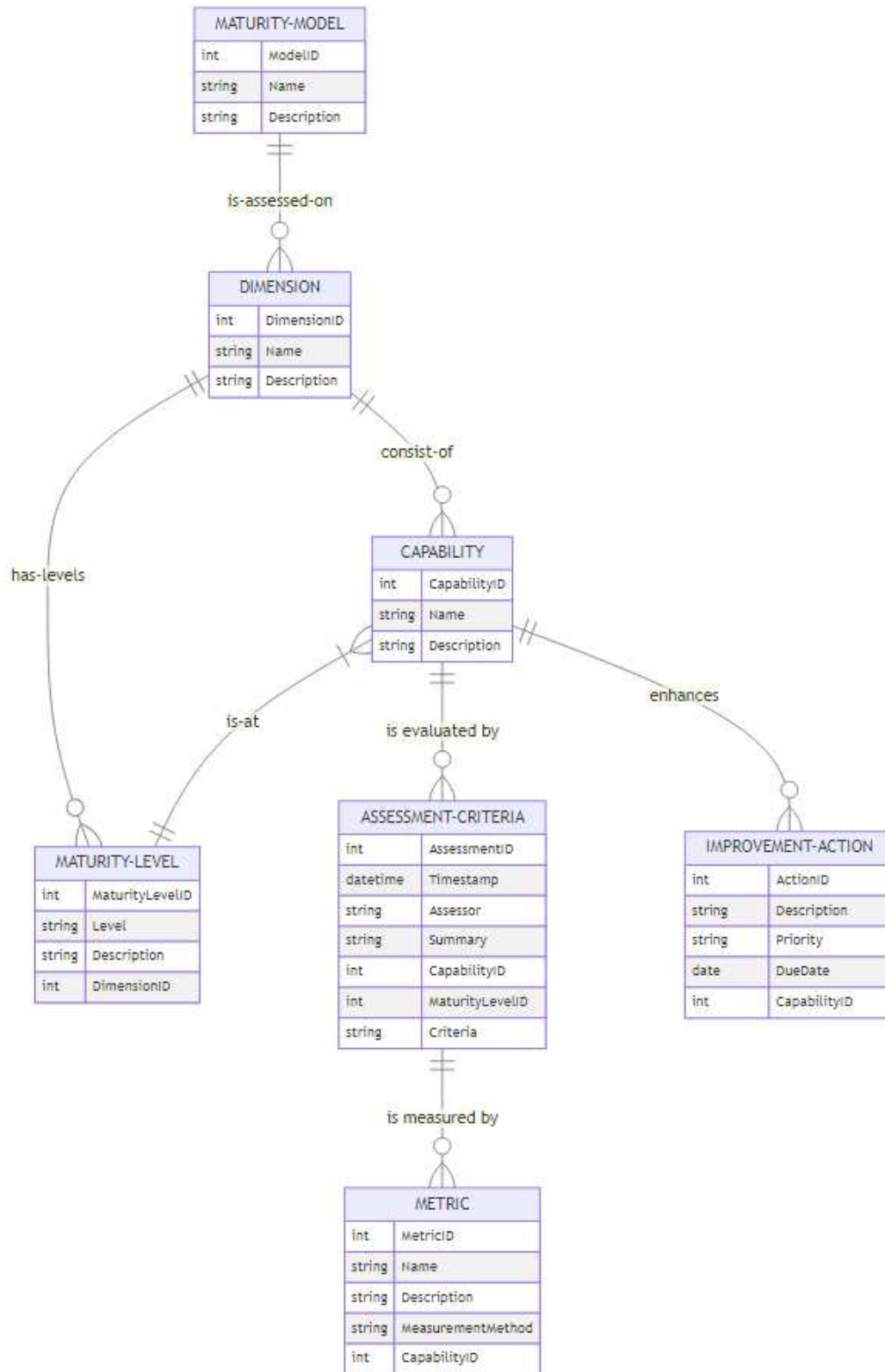


Figure 2: Entity Relationship Diagram of a Basic Maturity Model Structure

2.3.2. Maturity Models Across Industries

Maturity models have been adapted across a wide range of industries, demonstrating their versatility as strategic assessment tools. Table 3 presents examples of maturity models used in diverse domains including healthcare, manufacturing, cybersecurity, and public administration.

Table 3: Maturity Models Across Industries

Model	Industry	Purpose	Citation
Organizational Project Management Maturity Model (OPM3)	Project Management	Assesses project, program, and portfolio management maturity	PMI (2013)
Electronic Medical Record Adoption Model (EMRAM)	Healthcare	Measures IT adoption progress across healthcare systems	HIMSS Analytics (2022)
Manufacturing Maturity Model (M4)	Manufacturing	Guides lean manufacturing implementation	Sajjad et al. (2023)
Systems Engineering Maturity Model (SEMM)	Aerospace/Defense	Evaluates systems engineering process maturity	INCOSE (2015); (Madni & Sievers (2018)
PCI DSS Maturity Model	Financial Services	Assesses payment card security compliance	PCI Security Standards Council (2016)
BIM Maturity Model	Construction	Guides building information modeling adoption	Succar (2009); Giel & Issa (2013)
Smart Grid Maturity Model (SGMM)	Energy/Utilities	Assesses smart grid technology implementation	Paulk (2009) SGMM Team (2011)
Open Government Maturity Model (OGMM)	Public Sector	Evaluates government digital service maturity	Lee & Kwak (2012)
Cybersecurity Capability Maturity Model (C2M2)	Cybersecurity	Assesses cybersecurity risk management capabilities	U.S. Department of Energy (2014)
McKinsey Digital Quotient (DQ)	Cross-industry	Measures digital readiness across organizational dimensions	Catlin et al. (2015)

This cross-industry adoption highlights the flexibility of maturity models. Although they originated in software engineering, the underlying pattern of staged capability development has proven applicable to many organizational contexts. Whether assessing cybersecurity readiness, digital transformation progress, or manufacturing modernization, maturity models provide a structured method for evaluating current capability and defining a roadmap for improvement.

2.3.3. Relevance for SME Leaders

For SMEs, where resources must be carefully managed, maturity models provide structured guidance that supports strategic decision-making. Research across multiple industries suggests that their value extends beyond process improvement into several operational areas.

Decision Making and Resource Allocation. Maturity assessments help leaders identify where investment will have the greatest impact. For example, when a 75-person manufacturer applied ISO/IEC 15504, the assessment revealed that the organization was over-investing in already-mature quality control processes while neglecting supply chain capabilities that constrained growth (Aguilera-Caracuel & Ortiz-de-Mandojana, 2013). Similarly, applications of the Business Process Maturity Model (BPMM) in service-sector SMEs provided leaders with data-driven insight for budget allocation decisions that had previously relied largely on intuition (Röglinger et al., 2012).

Culture and Employee Engagement. Maturity models can also promote a culture of continuous improvement by making progress measurable and visible across teams. The Integrated Manufacturing Maturity and Sustainability Model (IMMSM) demonstrated this effect in small manufacturing organizations by enabling employees to track capability development over time (Salah & Rahim, 2019). Implementations of the ITIL Maturity Model have also shown positive

effects on organizational performance by providing staff with clearer service management responsibilities and development pathways (Marrone & Kolbe, 2011).

Stakeholder Alignment. Maturity models often provide a shared framework that helps align stakeholders across organizational functions. The Requirements Engineering Maturity Model (REMM), for example, has been used by software SMEs to coordinate cross-functional teams and improve project delivery outcomes (Niazi et al., 2005). Similarly, the Malcolm Baldrige National Quality Award framework has helped organizations across sectors build consensus among diverse stakeholders by providing a common language for performance excellence (Baldrige Performance Excellence Program, 2021).

Risk Mitigation and Compliance. Organizations operating in regulated environments frequently use maturity models to assess risk management and regulatory compliance. The Cybersecurity Capability Maturity Model (C2M2) has helped SMEs in the energy sector identify cyber vulnerabilities and strengthen security practices (U.S. Department of Energy, 2014). Studies have highlighted the critical role of human-AI collaboration in enhancing cybersecurity risk detection, decision making, and compliance monitoring (Lanigan et al., 2025; Aliebrahimi & Miller, 2023). Likewise, the General Data Protection Regulation (GDPR) Maturity Model has supported healthcare SMEs in improving data privacy practices and reducing legal and reputational risk (Tikkinen-Piri et al., 2018).

Talent Management and Development. Maturity models can also help organizations identify skill gaps and prioritize workforce development initiatives. The Pharmaceutical Supply Chain Maturity Model has been used to identify workforce capabilities that most strongly influence operational performance (Mehralian et al., 2016), while Lean Six Sigma maturity assessments have revealed training needs not captured by generalized development programs (Garousi et al., 2020).

These studies demonstrate that maturity models function as more than simple assessment tools. They provide strategic frameworks that help organizations identify improvement priorities, coordinate stakeholders, and guide resource allocation. For SMEs, where operational resources are limited and strategic decisions must be carefully prioritized, maturity models offer a disciplined approach to capability development and long-term growth (Kazanjian et al., 2002; Rosemann & de Bruin, 2005).

2.3.4. Systems Engineering and Strategic Value

Within systems engineering, maturity models serve several strategic functions that make them particularly valuable for organizations adopting emerging technologies such as AI. First, maturity models enable standardized assessment and benchmarking by providing a common language for evaluating systems engineering capabilities across organizations and projects (Madni & Sievers, 2018; Paulk, 2009). Second, they support road mapping and capability enhancement by outlining sequential stages of improvement that guide organizations in developing capabilities over time (Huldt & Stenius, 2019; Teunissen, 2021). This structured progression is especially important in systems engineering contexts where organizations must balance established development processes with the flexibility needed to adopt new methods, tools, and technologies (Gracias & Gallegos, 2025; Gracias & Gallegos, 2024). Third, maturity models facilitate resource prioritization, helping organizations identify where investment will generate the greatest impact (Madni & Sievers, 2018; Garousi et al., 2020). Fourth, they promote alignment with industry standards and regulatory requirements, including frameworks such as ISO/IEC/IEEE 15288 for systems engineering processes (ISO/IEC/IEEE, 2015; Kossiakoff et al., 2018). Finally, maturity models support continuous improvement, enabling organizations to refine their capabilities as

technologies and operational environments evolve (Ross & Rhodes, 2015; Ramasesh & Browning, 2014; INCOSE, 2015).

For SMEs exploring AI adoption, these functions translate into practical value. Maturity models provide a structured method for assessing current organizational capabilities, identifying development priorities, and directing limited resources toward the area's most likely to improve performance.

2.4. Review of Existing Maturity Model Frameworks

To build HAIC-MM on a solid foundation, a comprehensive review of 30 existing frameworks was conducted across three domains: ten human-machine teaming (HMT) frameworks, ten AI maturity models, and ten digital transformation (DT) maturity models. This section describes the research strategy used to identify and select these frameworks. It then summarizes the findings within each domain and concludes with a synthesis of the themes and limitations that emerged across all 30 frameworks.

2.4.1. Research Strategy and Framework Selection

The literature search drew from six academic and industry databases: Scopus, ResearchGate, ACM Digital Library, Web of Science, Google Scholar, and IEEE Xplore. The sources were supplemented by the Colorado State University Library and the Journal of Artificial Intelligence Research (Van de Ven, 2007; Adams et al., 2014). Search terms included combinations of "capability maturity models," "human-machine teaming," "artificial intelligence maturity," "digital transformation maturity," "digital maturity," and "contemporary digital technologies." The initial search yielded over 400 publications, which were narrowed to 30 frameworks (ten per domain) using the selection criteria described below.

Frameworks were selected using a thematic saturation approach: models were iteratively reviewed within each category until additional frameworks provided diminishing returns in novel insights (Becker et al., 2009). All 30 frameworks were then evaluated against four established standards:

- *Maturity Model Standards*: General criteria for well-designed maturity models (Proenca & Borbinha, 2016)
- *Systems Engineering Principles*: ISO/IEC/IEEE 15288 and INCOSE standards (ISO/IEC/IEEE, 2015)
- *Human-Computer Interaction Principles*: User-centered design, usability, and accessibility (Shneiderman, 1983)
- *MITRE's HMT Guidelines*: The Human-Machine Teaming Systems Engineering Guide (McDermott et al., 2018)

Domain-specific selection criteria were also applied. For HMT frameworks, selection was guided by ten themes from MITRE's guide: observability, predictability, directing attention, exploring solution space, adaptability, directability, calibrated trust, common ground, information presentation, and design process (McDermott et al., 2018). For AI maturity models, criteria included data management and governance, technology integration, AI strategy, use case applicability, modular deployment feasibility, and organizational culture (Chui et al., 2018). For DT models, criteria included customer experience, data and analytics, digital strategy, technology architecture, organizational alignment, flexibility and customization, and staff development (Mithas et al., 2013).

2.4.2. Human-Machine Teaming (HMT) Frameworks

Ten HMT frameworks were analyzed for their coverage of MITRE's key HMT requirements and their relevance to SME contexts. Table 4 summarizes the frameworks and their alignment with core HMT criteria.

Table 4: Analysis of Human-Machine Teaming Frameworks

Framework	Authors	Key HMT Criteria Addressed	Primary Application
Collaborative Intelligence Quotient (CIQ)	Johnson et al. (2014)	Common ground; observability; directing attention; design process	Team dynamics
Machines as Teammates (MaT)	Seeber et al. (2020)	Calibrated trust; directability; adaptability; design process	Team collaboration design
Team Situation Awareness and Conflict (TSAC)	McNeese et al. (2021)	Common ground; observability; calibrated trust; adaptability	Situational awareness
Human-Autonomy Teaming Review (HAT)	O'Neill et al. (2020)	Common ground; observability; directability; calibrated trust; adaptability	Autonomy integration
Human Modeling for Human-Robot Collaboration (HMHR)	Hiatt et al. (2017)	Directing attention; exploring solution space; adaptability; calibrated trust	Robot collaboration
Framework for Exploring Adaptive HMT (FAHMT)	Madni & Madni (2018)	Adaptability; exploring solution space; common ground; observability	Adaptive teaming
Teaming With a Synthetic Teammate (TST)	McNeese et al. (2018)	Common ground; directing attention; calibrated trust; adaptability	Synthetic teammates
Utility of Explainable AI in Ad Hoc HMT	Paleja et al. (2021)	Calibrated trust; adaptability; common ground; information presentation	Mutual understanding via XAI
MAHMT Framework	Madni & Madni (2018)	Adaptability; directability; exploring solution space; calibrated trust	Model-based HMT
Resilience in Human-Machine Teams (R-HMT)	Keller & IJtsma (2021)	Adaptability; common ground; information presentation; observability; calibrated trust	Resilient teaming

Across these ten frameworks, several themes emerged consistently. Common ground, calibrated trust, and adaptability appeared as requirements in nearly every framework, confirming their centrality to effective human-machine collaboration. Observability and directability (i.e., the ability to understand what AI is doing and to redirect it when necessary) were also widely recognized as essential capabilities. The analysis identified eight critical gaps in the HMT literature:

1. *Lack of SME-Centric Approaches*: Frameworks are predominantly designed for larger enterprises and do not address the resource constraints and organizational structures typical of SMEs (Acs & Audretsch, 2013; European Commission, 2019).
2. *Limited Operational Guidance*: Most frameworks provide high-level insights without actionable steps for practical implementation (Brynjolfsson et al., 2017; Davenport et al., 2020).
3. *Insufficient Adaptability to AI Evolution*: Frameworks are not dynamic enough to accommodate rapid changes in AI technology (Korinek & Stiglitz, 2019; Smith & Anderson, 2014).
4. *No Effectiveness Metrics for Human-AI Work*: Specific metrics for evaluating the productivity and quality of human-AI collaboration are largely absent (Whittlestone et al., 2019).
5. *Narrow Focus Rather than Comprehensive Coverage*: Many frameworks concentrate on singular aspects such as trust or situational awareness without addressing the full range of collaboration requirements (Seeber et al., 2020; McNeese et al., 2021).

6. *Adoption Barriers Overlooked:* Cost, talent availability, legacy systems, and organizational culture, the factors that determine whether SMEs can actually implement these frameworks, are often not addressed (Ransbotham et al., 2017).
7. *Minimal Empirical Validation:* Few frameworks provide quantitative evidence of their real-world impact on team performance, particularly in SME settings (Dwivedi et al., 2019).
8. *Limited Interdisciplinary Integration:* Limited interdisciplinary integration: Emerging fields like explainable AI (XAI) and the integration of insights from cognitive psychology, data science, and organizational behavior are underrepresented (Paleja et al., 2021; McDermott et al., 2018).

2.4.3. AI Maturity Models

Ten AI maturity models were analyzed across seven evaluation criteria: recognition in academic and industry circles, data management practicality, AI implementation feasibility, technology compatibility, AI strategic planning, real-world business case relevance, and organizational culture readiness (Chui et al., 2018). Table 5 summarizes the models and their key characteristics.

Table 5: Analysis of AI Maturity Models

Model	Citation	Industry Focus	SME Relevance	Maturity Levels	Key Strengths
IBM AI Digital	Vaish et al. (2020)	General	High	3	Strong ethics and trust focus
AIMI (AI Innovation Maturity Index)	Yams et al. (2020)	General	Medium	5	Innovation management

Microsoft AI	Vorvoreanu et al. (2023)	Tech	High	5	Business-tech alignment, accessible
Element AI	Element AI (2020)	Tech	Low	5	Human-centric approach
StatWorx AI	STATWORX (2020)	General	High	5	Simple, actionable for SMEs
Gartner AI	Jafarzadeh et al. (2025); Krijger et al. (2023)	General	Medium	5	Growth-oriented strategy
OVUM AI	Pringle & Zoller (2018); Ellefsen et al. (2019)	Tech	Low	4	Sharp operational focus
Alsheibani AIMM	Alsheibani et al. (2019)	General	Low	5	Innovation emphasis
Applied AI	Hartmann et al. (n.d.)	General	High	4	Operational excellence
Accenture AI	Accenture (2022)	General	High	5	Comprehensive analysis

The AI maturity models varied substantially in their construct counts and structural complexity. Dimensions ranged from four (i.e., Alsheibani, Accenture) to nine (i.e., Applied AI), capabilities from eight (i.e., Alsheibani) to 23 (i.e., AIMI), and maturity levels from three (i.e., IBM) to five (e.g., most models). This variability reflects different assumptions about what AI maturity means and how to measure it.

The central limitation of AI maturity models is that most are designed for large-scale enterprises, with limited attention to SME demands (De Bruin et al., 2005; Schallmo & Williams, 2018). The four specific deficiencies emerged during the analysis:

1. *Disparate Focus Areas*: Models vary widely in what they emphasize (ethics vs. technology vs. innovation vs. operational excellence), with no single model addressing all areas comprehensively (Schallmo & Williams, 2018; Wendler, 2012).

2. *Lack of SME Specificity*: Scalability, resource constraints, and organizational agility, the defining characteristics of SME operations, are not adequately addressed (Minh & Thanh, 2022).
3. *No Graduated Progression*: Models do not accommodate the graduated steps that SMEs must navigate through maturity levels, often assuming resource availability and organizational sophistication that SMEs lack (Teunissen, 2021).
4. *Technology-Centric Focus*: AI maturity models focus on technical readiness, data governance, and automation but often overlook collaborative human-AI interactions, employee upskilling, and fostering staff trust in AI outputs (Ortolano & Gallegos, 2025).

2.4.4. Digital Transformation (DT) Maturity Models

Ten DT maturity models were analyzed across eight evaluation criteria: scholarly and industry recognition, flexibility and customization, staff development and reskilling, data and analytics, customer focus, digital strategy, technology architecture, and organizational alignment (Mithas et al., 2013). Table 6 summarizes the models and their key characteristics.

Table 6: Analysis of Digital Transformation Maturity Models

Model	Citation	Industry Focus	SME Relevance	Maturity Levels	Primary Focus
PwC Digital Enterprise	Schallmo & Williams (2018)	General	Medium	4	Value chain digitization
IMPULS Industry 4.0 Readiness	Lichtblau et al. (2015)	Manuf.	Medium	6	Smart operations
VTT Digitalization	Matt et al. (2015)	General	Low	5	Strategy integration
CapGemini Digital Mastery	Vial (2019)	General	Medium	4	Customer experience

BCG Digital Acceleration Index	Westerman et al. (2014)	General	Low	4	Leadership commitment
Forrester Digital Maturity 4.0	Sebastian et al. (2017), Gill & VanBoskirk (2016)	Tech	Medium	4	Cultural transformation
McKinsey Digital Quotient	De Bruin et al. (2005)	General	Medium	3	Strategic alignment
Deloitte Digital	Minh & Thanh (2022)	General	Medium	5	Customer-centricity
Acatech Digital Maturity Index	Teunissen (2021), (Schuh et al., 2020)	Manuf.	Medium	6	Smart solutions
KPMG DT Assessment	Wendler (2012)	General	Medium	5	Digital readiness

Like the AI maturity models, DT models varied in structural complexity. Dimensions ranged from four (i.e., CapGemini, Forrester, McKinsey) to eight (i.e., KPMG), while capabilities ranged from 15 (i.e., CapGemini, Forrester) to 40 (i.e., KPMG). Most models were rated "Medium" for SME relevance, meaning they are adaptable to SMEs but not specifically designed for them. No model was rated "High" for SME tailoring. Two critical limitations emerged:

1. *Lack of Human-AI Emphasis:* DT models cover infrastructure, customer experience, and organizational culture but fail to address how human employees can effectively work alongside AI-powered technologies to drive transformation. This is especially concerning given AI's growing role in SME operations (Chui et al., 2018; Ghobakhloo & Iranmanesh, 2021).
2. *No Comprehensive Collaboration Framework:* None of the reviewed DT models provide guidance for integrating AI while simultaneously respecting and enhancing human worker roles. What is needed is not just a model addressing the technological aspects of AI adoption, but a roadmap for the cultural and organizational changes

necessary for meaningful human-AI collaboration (Sycara & Sukthankar, 2006; Turner & Phillips, 2020).

2.4.5. Cross-Domain Synthesis

Across all 30 frameworks, several patterns emerged that directly informed the design of HAIC-MM, as summarized in Table 7. The recurring pattern across all three domains is that existing frameworks treat human capability, AI capability, and process integration as independent components. Each domain contributes valuable insights (HMT on team dynamics and trust, AI maturity models on technical readiness and data governance, DT models on organizational strategy and culture), but none integrates these perspectives into a unified framework designed for the SME context.

Table 7: Cross-Domain Gap Analysis

Gap Theme	HMT Frameworks	AI Maturity Models	DT Models
Lack of SME-centric design	Frameworks target large enterprises	Designed for large-scale organizations	No model rated “High” for SME tailoring
No human-AI collaboration focus	Partial: some address trust and awareness, but narrowly	Focus is on AI capability, not human-AI synergy	Significant omission
Limited practical guidance	High-level insights without actionable steps	Some provide roadmaps, but not SME-specific	Consulting models too complex for SME adoption
No collaboration effectiveness metrics	Significant gap	Not addressed	Not addressed
Insufficient empirical validation	Minimal quantitative evidence	Not explicitly validated for SMEs	Not explicitly validated for SMEs
Limited adaptability to AI evolution	Frameworks not dynamic enough	Graduated progression steps missing	Maturity stages exist but lack AI integration

Adoption barriers ignored	Cost, talent, legacy systems, culture overlooked	Resource constraints acknowledged but not addressed	Implicit in discussions but not operationalized
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2.5. SME-Specific AI Adoption Challenges

SMEs face a distinct set of challenges when adopting AI that generic enterprise frameworks were not designed to address. Understanding these challenges is essential for developing a maturity model that reflects SME operational reality.

Resource Constraints. SMEs typically operate with limited budgets, IT infrastructure, and specialized talent. Unlike large enterprises that can dedicate teams to AI strategy and implementation, SMEs often require employees to manage AI initiatives alongside their existing responsibilities (Bughin et al., 2021; Pelletier & Cloutier, 2019). Any maturity model for SMEs must provide modular, adaptable pathways that account for these limitations.

Technical Expertise Gaps. The shortage of AI-skilled professionals affects SMEs disproportionately. While large enterprises can recruit from a competitive talent pool and offer premium compensation, SMEs must often develop AI capabilities through existing staff or external partnerships (Ransbotham et al., 2017). IDC's AI Strategies View (2022) identified lack of skilled staff as the most frequently cited reason for AI project failures.

Complexity of Integration. Integrating AI into existing business processes requires changes to workflows, data management practices, and organizational structures. For SMEs with less formalized processes, this integration can be particularly disruptive (Canhoto & Clear, 2020). The absence of dedicated IT departments also means that integration responsibilities often fall to employees who already carry significant operational workloads.

Trust and Acceptance Barriers. Employees may resist AI adoption due to concerns about job displacement, lack of understanding of AI capabilities, or negative experiences with prior technology implementations. Building trust requires transparency, gradual introduction, and evidence of AI's positive impact on work quality (Gunning & Aha, 2019; Hoff & Bashir, 2015). Similar patterns have been observed in human-systems integration studies of technology adoption in resource-constrained environments, where user perceptions and contextual factors significantly influence adoption outcomes (Ahmed & Miller, 2022).

Ethical and Governance Challenges. AI introduces concerns related to data privacy, algorithmic bias, transparency, and accountability that require governance frameworks SMEs may not have the expertise or resources to develop independently (Floridi et al., 2018; Jobin et al., 2019). Without guidance, SMEs risk either ignoring these issues or becoming paralyzed by their complexity.

Generic Framework Misfit. Perhaps the most significant challenge is that most available frameworks assume organizational structures, resources, and data capabilities more typical of large enterprises. The “one-size-fits-all” approach of many existing models overlooks the resource constraints, flexibility requirements, and dynamic nature of SME environments, potentially leading to implementation challenges and suboptimal outcomes. Similar limitations have been observed in engineering domains such as obsolescence management, where traditional models often fail to account for supply chain uncertainty, evolving system requirements, and constrained organizational resources, necessitating more flexible and context-aware approaches (Chellin & Gallegos, 2024; Chellin & Miller, 2023).

These challenges do not exist in isolation. Instead, they form a reinforcing cycle in which each barrier compounds the others, making it progressively more difficult for SMEs to adopt AI

effectively. Resource constraints limit the ability to hire or develop AI expertise, which in turn limits the organization's capacity to design and execute adequate integration plans. Poor integration then produces disappointing results, eroding employee trust and leadership confidence in AI initiatives.

As trust declines, organizational support for further AI investment often weakens, resulting in budget reductions, shelved projects, and talent attrition, all of which reinforce the original resource constraints. At the same time, the generic framework misfit operates alongside this cycle. Since most available guidance assumes enterprise-scale resources and data capabilities, SMEs seeking external support frequently encounter roadmaps that are not realistic for their circumstances. This mismatch often pushes organizations back toward reduced investment and stalled progress. Figure 3 illustrates this cycle, which was made using an HTML editor.

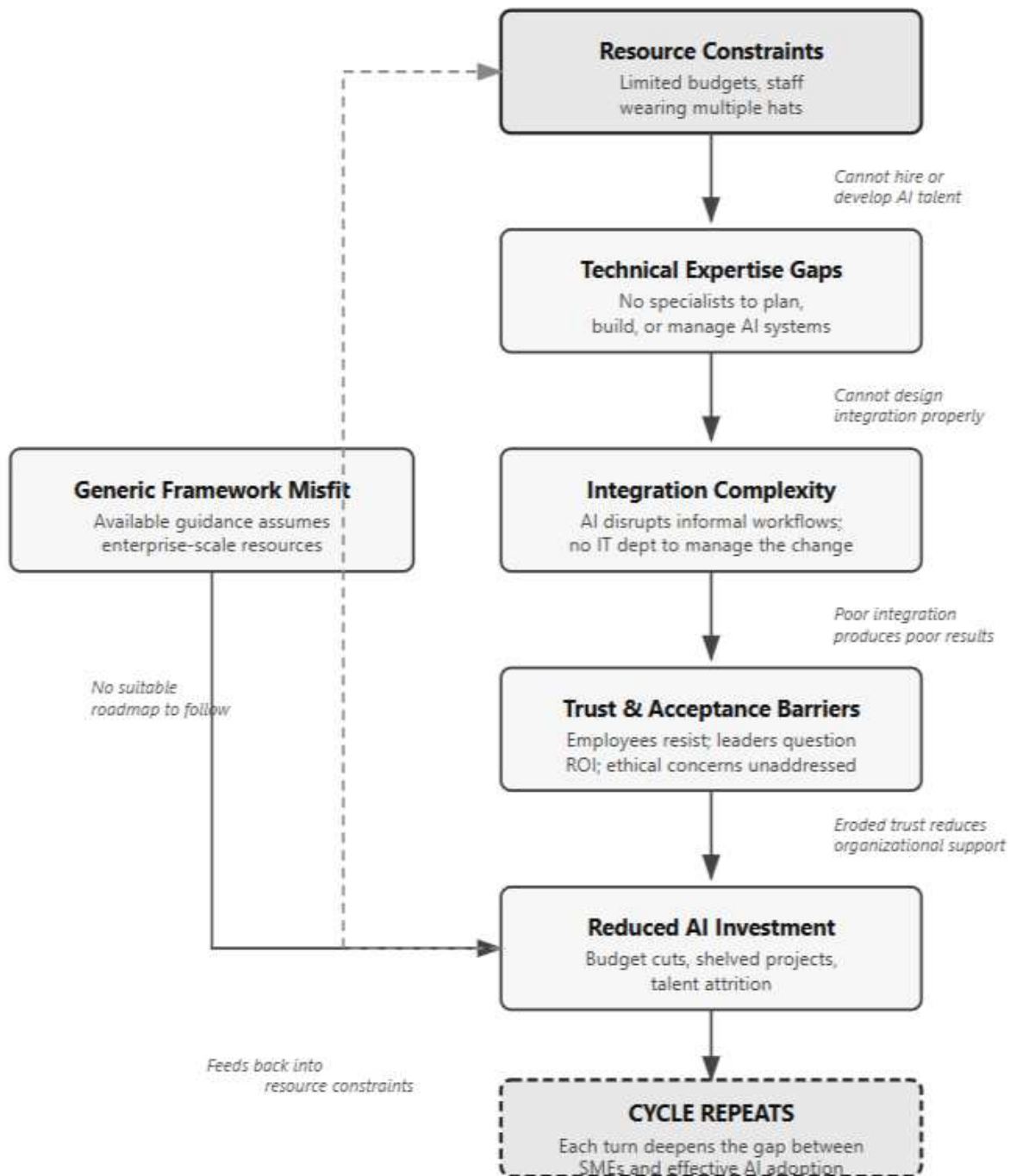


Figure 3: SME AI Adoption Challenge Cycle

Each turn through this cycle widens the gap between SMEs and effective AI adoption. Without a maturity model that accounts for these interdependencies and provides staged, realistic

guidance at each point in the cycle, SMEs risk remaining trapped in a pattern where limited resources produce limited results, which in turn justify further resource limitations. Breaking this cycle requires a framework that is designed specifically for the SME context, one that provides actionable steps at each maturity stage rather than assuming that organizations already have the capacity to execute complex transformation programs.

2.6. Gaps in Literature

The analysis of 30 frameworks across three domains reveals five critical gaps that directly motivated the development of HAIC-MM. Each gap represents a limitation that prevents existing frameworks from serving SMEs effectively. The key gaps are summarized in Figure 4 and detailed further in the corresponding sections.

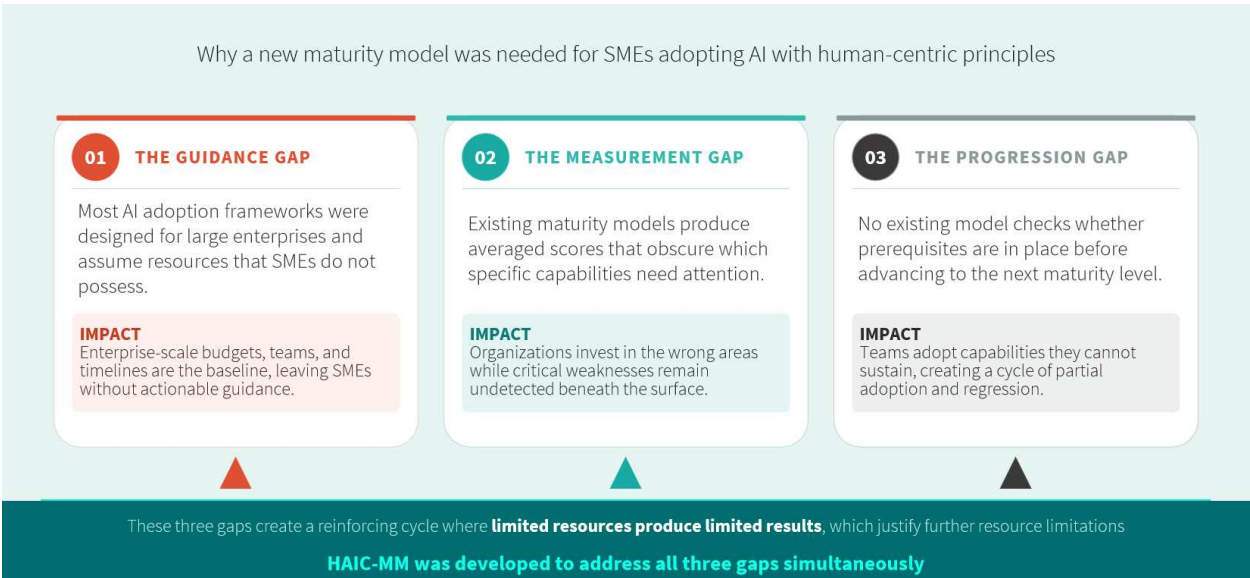


Figure 4: Key Gaps HAIC-MM Addresses

Collectively, these gaps highlight why SMEs have lacked an adequate framework for guiding human-AI collaboration. Existing frameworks provide valuable insights individually but

offer only partial perspectives when organizations require comprehensive guidance tailored to their specific constraints and opportunities. The HAIC-MM framework was therefore developed to address these limitations by integrating insights from all three domains into a unified model with a scoring methodology that captures collaboration quality, enforces realistic progression, and provides actionable guidance tailored to SME operational realities.

2.6.1. HMT Frameworks Treat AI as a Tool Rather than a Collaborative Partner

While HMT frameworks emphasize team dynamics, they typically treat AI as a tool that executes tasks assigned by humans rather than as an evolving, learning entity that works alongside human workers. The Collaborative Teaming Framework (Sycara & Sukthankar, 2006), for example, outlines important factors such as trust, communication, and task allocation, but does not envision AI contributing to problem-solving and decision-making in its own right. This limited view overlooks the potential for AI systems that actively augment human intelligence and adapt over time.

HAIC-MM addresses this limitation by defining five maturity levels that trace the progression from AI as an experimental tool (L1: AI Exploration) to AI as a fully integrated collaborative partner (L5: Symbiotic Partnership). The model explicitly assesses the quality of collaboration rather than simply whether AI tools are present.

2.6.2. AI Maturity Models Oversimplify SME Needs

Existing AI maturity models chart paths for technology integration but fail to account for the resource constraints, flexibility requirements, and organizational realities that define SME operations. The “one-size-fits-all” approach assumes levels of investment, infrastructure, and

specialized talent that most SMEs cannot match (Chui et al., 2018; Schallmo & Williams, 2018; Minh & Thanh, 2022).

HAIC-MM addresses this limitation through organization size adjustments (different scoring factors for small, medium, and large organizations), dependency-based capability progression that enforces realistic sequencing, and assessment content calibrated to SME operational contexts.

2.6.3. DT Models Ignore Human-AI Collaborative Dynamics

DT models typically cover technology infrastructure, customer experience, and organizational culture but rarely address how human workers and AI systems can effectively collaborate. This omission is particularly concerning for SMEs, where every employee's ability to work effectively with AI directly impacts organizational performance (Westerman et al., 2014; Ghobakhloo & Iranmanesh, 2021).

HAIC-MM therefore places human-AI collaboration at the center of its assessment structure. Five of its seven dimensions directly evaluate collaboration quality, from leadership's AI literacy to employee experience with AI tools and the effectiveness of human-AI task allocation.

2.6.4. No Existing Model Integrates HMT, AI Maturity, and DT Perspectives

The 30 frameworks reviewed each contribute valuable insights from their respective domains: HMT frameworks focus on team dynamics and trust, AI maturity models emphasize technical readiness and data governance, and DT models address organizational strategy and cultural transformation. However, no existing model synthesizes these perspectives into a unified framework.

SMEs require a model that simultaneously evaluates technological capability, human readiness, and collaboration quality, because a deficiency in any one area undermines the other two. HAIC-MM was therefore developed through the explicit synthesis of all three domains. Its seven dimensions and 32 capabilities incorporate HMT principles (trust, observability, adaptability), AI maturity concepts (data governance, technology integration, strategy alignment), and DT requirements (organizational culture, process harmonization, continuous learning). The three HAIC pillars (i.e., Human-Centric, AI-Centric, and Collaborative) ensure that each domain is represented in every assessment.

2.6.5. Existing Models Treat Capabilities Independently and Conceal Imbalances

Traditional maturity models typically produce composite scores by averaging across different capability areas. This approach can conceal critical imbalances. For example, an organization with strong human expertise but weak AI infrastructure may receive the same score as one with balanced but moderate capabilities, despite vastly different operational realities and improvement needs.

No existing model explicitly penalizes imbalanced development or rewards balanced capability progression. HAIC-MM addresses this limitation through its balance factor. Rather than averaging scores across human-centric, AI-centric, and collaborative capabilities, the balance factor measures the quality of collaboration by rewarding balanced development and penalizing uneven investment. As a result, two organizations with identical raw scores but different collaboration balances receive different maturity assessments, reflecting the practical reality that balanced capabilities produce better outcomes.

Chapter 3. Aim 1 - Development of HAIC-MM

3.1. Introduction

Chapter 2 established that existing frameworks across three domains (i.e., human-machine teaming, AI maturity, and digital transformation) each provide valuable but incomplete guidance for SMEs seeking to build effective human-AI collaboration. No existing model integrates all three perspectives, and none addresses the specific resource constraints, collaboration dynamics, and staged progression needs of smaller organizations. This chapter presents the development of HAIC-MM, describing the process of taking those 30 frameworks apart, identifying what works and what is missing, and building a unified model designed for SMEs. The product of this research aim was the initial HAIC-MM framework for subsequent refinement (Research Aim 2) and validation (Research Aim 3).

This chapter addresses Research Aim 1: to draw on existing human and AI maturity models, integrate their insights, and develop a novel Human-AI Collaboration Maturity Model using a validated methodological approach. Two research questions guided this work:

- **RQ1.1:** What frameworks exist for developing new maturity models?
- **RQ1.2:** How do the strengths and limitations of existing maturity models guide the development of the HAIC-MM?

3.2. Methods

3.2.1. Selecting a Development Methodology

Building a maturity model requires a structured process, one that ensures the resulting framework is grounded in evidence rather than assumptions. Seven prominent procedural models

for maturity model development were evaluated to identify the most suitable approach for HAIC-MM. Table 8 summarizes the candidate methods and their key characteristics.

Table 8: Comparison of Seven Procedural Development Methodologies

Methodology	Key Characteristics	Strengths	Limitations
De Bruin et al. (2005)	Six-phase iterative strategy with continuous validation feedback	Strong iterative validation	Extensive revision cycles may be impractical for large models
Becker et al. (2009)	Eight-step methodology grounded in scientific principles	Highest rigor; prioritizes validation and stakeholder input	Resource-intensive
Mettler & Rohner (2009)	Flexible designs adaptable to emerging needs	Rapid iteration capability	Risk of scope creep
Salviano et al. (2009)	Incorporates multidisciplinary stakeholder inputs	Aids adoption through diverse perspectives	Risk of incoherence across disciplines
Maier et al. (2012)	Grounded in extensive case study data	Strong real-world applicability	Requires rigorous case vetting
Van Steenbergen et al. (2010)	Uses internal team domain expertise early	Quick initial development	Risk of blind spots from narrow perspectives
Von Wangenheim et al. (2010)	DESRIST methodology balancing academic and industry priorities	Balanced academic-practitioner view	May overlook organizational factors

Each methodology was rated across six evaluation criteria: validation rigor, multidisciplinary inputs, adaptability, accessibility, balanced perspectives, and integration of people, processes, and technology. Methodologies were evaluated as High, Moderate, or Low for each criteria to identify which aspects of the development process each approach addresses effectively and where limitations remain, as summarized in Table 9. The resulting pattern shows that no single methodology scores High across all six criteria. De Bruin et al. (2005) and Becker et al. (2009) demonstrate the strongest validation rigor but offer limited adaptability. Mettler &

Rohner (2009) and Maier et al. (2005) provide the greatest accessibility but exhibit weaker validation foundations. Salviano et al. (2009) stands out for its emphasis on multidisciplinary participation.

Table 9: Qualitative Assessment of Development Methodologies

Method	Validation	Multidisciplinary Input	Adaptability	Accessibility	Balanced View	People / Process / Technology
De Bruin et al. (2005)	High	Low	Low	Moderate	Moderate	Low
Becker et al. (2009)	High	Low	Low	Moderate	Moderate	Low
Mettler & Rohner (2009)	Moderate	High	Moderate	Low	Low	Low
Salviano et al. (2009)	Low	Low	High	High	Low	Low
Maier et al. (2005)	Moderate	Low	Moderate	High	Low	Low
Van Steenberg et al. (2010)	Low	Low	Low	Low	High	Low
Von Wangenheim et al. (2018)	Moderate	Low	Moderate	Moderate	Low	High

This distribution indicates that relying on a single methodology would leave important gaps. To address this limitation, a hybrid approach was adopted that combines Becker et al.'s (2009) structured maturity model development methodology with Hevner et al.'s (2004) design science research (DSR) principles. Becker et al. (2009) provides a step-by-step process optimized for constructing maturity models from existing frameworks, which aligns closely with the requirements for developing HAIC-MM. Hevner et al.'s (2004) DSR principles complement this structure by grounding the development process in practical, real-world problems and ensuring

that the resulting artifact (i.e., the maturity model) addresses genuine organizational needs rather than purely theoretical considerations.

This combination offers several key advantages. First, Becker et al.'s (2009) methodology provides a clear and systematic blueprint for each development phase, from problem identification through model construction and validation. Second, the DSR framework (Hevner et al., 2004) ensures that design decisions remain anchored in real SME challenges rather than being driven solely by academic objectives. Third, both approaches emphasize collaboration with practitioners, enabling the model to reflect operational realities and practitioner experience. Finally, the combined approach incorporates validation throughout multiple stages of development, reducing the risk of producing models that appear conceptually sound but prove ineffective in practice.

3.2.2. *Classifying the Model Type*

Maturity models serve different purposes depending on their design intent. Three types are recognized in the literature:

- *Descriptive Models*: Assess the current state of capabilities, providing diagnostic snapshots that reveal where an organization stands and where gaps exist (De Bruin et al., 2005; Wendler, 2012).
- *Prescriptive Models*: Define a target state and provide specific recommendations for moving from one maturity level to the next (Maier et al., 2012; Lasrado et al., 2015).
- *Comparative Models*: Enable benchmarking against peers or industry standards (Mettler & Rohner, 2009; Wendler, 2012).

HAIC-MM was designed as a descriptive model, serving as an analytical tool that establishes a baseline assessment of an organization's human-AI collaboration capabilities. This choice reflects the SME context, where organizations need to understand their current position

before planning future development. A descriptive approach provides flexibility by focusing on current-state evaluation and avoiding the prescriptive complexity that could make the model impractical for resource-constrained organizations (Ghobakhloo & Iranmanesh, 2021; Teunissen, 2021).

3.2.3. Theoretical Integration

HAIC-MM integrates three theoretical domains to address the complexity of human-AI collaboration in SMEs. The first domain draws on systems engineering principles. Guided by ISO/IEC/IEEE 15288 and INCOSE standards, this perspective anchors HAIC-MM in systems thinking by viewing AI integration as a combination of people, processes, and technology with emergent properties rather than as a standalone technology deployment. Human-systems integration (HSI) further extends this perspective by ensuring that human requirements are explicitly incorporated into system design processes, rather than treated as secondary considerations (Corl & Gallegos, 2024). Systems engineering also contributes lifecycle management, ensuring iterative development from initial assessment through continuous improvement, as well as requirements engineering that aligns AI capabilities with SME constraints and needs (ISO/IEC/IEEE, 2015).

The second domain is human-computer interaction theory, which emphasizes the usability and interpretability of AI systems. Consider an SME employee encountering an AI recommendation they do not understand. Without user understanding, the system's output goes unused; without ease of use, the employee works around the tool rather than with it; without trust, they override it entirely. HCI principles (Shneiderman, 1983) address these risks by ensuring that AI systems prioritize usability, accessibility, and effectiveness. The result is AI that employees are more likely to adopt rather than resist.

The third domain incorporates organizational behavior theory, which addresses the human and cultural dimensions of AI integration. Change readiness prepares leadership and employees for transformation, while knowledge integration combines human expertise with AI capabilities through structured learning and communication. An adaptive culture supports organizational agility through continuous learning and experimentation. Whereas HCI focuses primarily on the individual user’s experience, organizational behavior theory examines the collective dimension of adoption, including how teams, departments, and leadership structures absorb and sustain AI-driven change.

The intersection of these three domains, illustrated in Figure 5, represents the unified approach taken by HAIC-MM. By integrating systems engineering rigor, human-centered design principles, and organizational adaptability, the model provides a comprehensive foundation for assessing and guiding human-AI collaboration in SMEs.

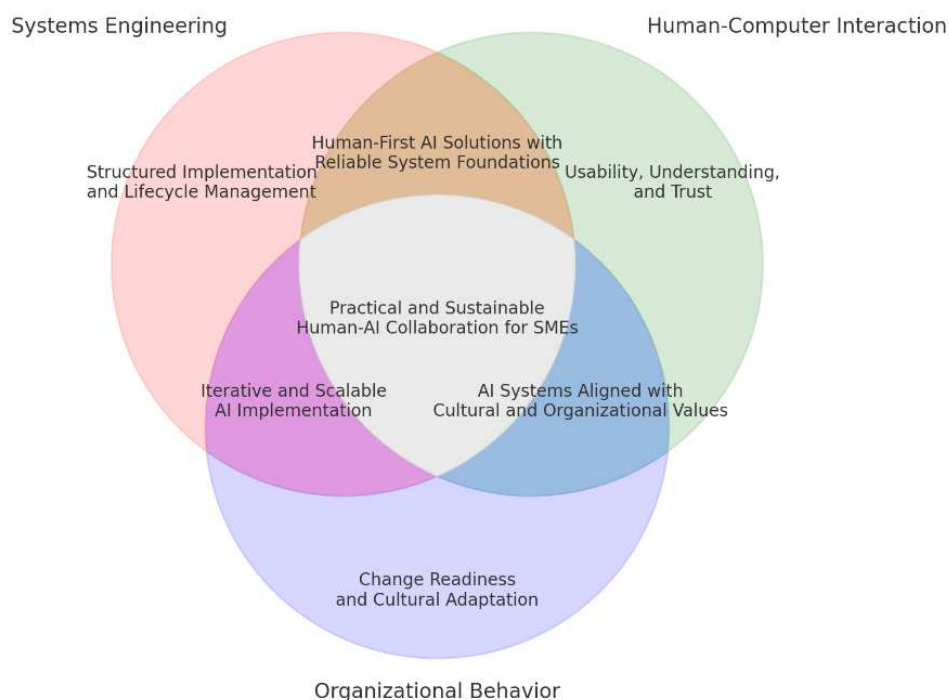


Figure 5: Synergy of Theoretical Foundations in HAIC-MM

3.2.4. Development Process

The development of HAIC-MM followed Becker et al.'s (2009) six-stage process, with design science research principles applied throughout the process, as illustrated in Figure 6. Table 10 maps each stage to its activities, inputs, and outputs.

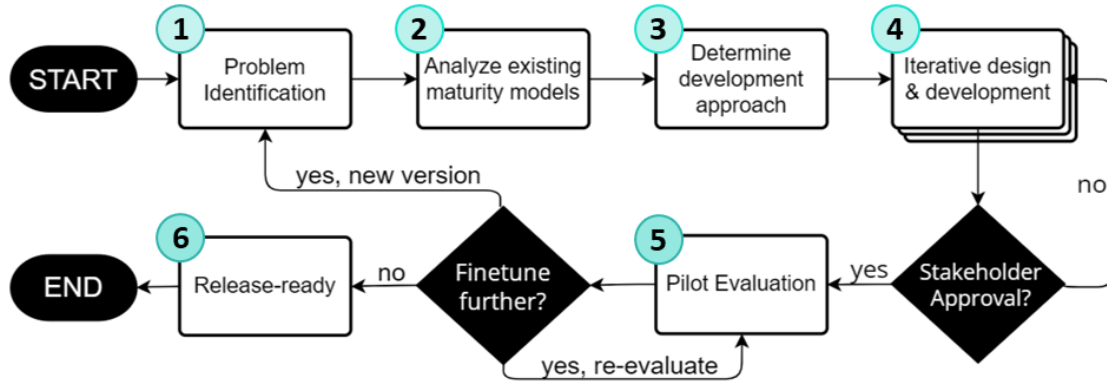


Figure 6: HAIC-MM Development Lifecycle Adapted from Becker et al. (2009)

Table 10: HAIC-MM Development Stages per Becker et al. (2009)

Stage	Activity	Inputs	Outputs
1. Problem Identification	Identified SME-specific challenges in AI adoption through literature review	Publications on SME AI adoption barriers	Seven specific SME challenges documented
2. Analysis	Comprehensive review of 30 frameworks (10 AI, 10 DT, 10 HMT)	Academic databases; industry publications	Strengths, limitations, and gaps of existing models
3. Development Approach	Selected synthesis approach over extension or creation	Evaluation of three strategies per Becker et al. (2009)	Decision to combine elements from all three domains
4. Iterative Design	Decomposed 30 models, built metamodels and pivot models, synthesized into unified structure	Metamodels; Concept matrix; Pivot models	Preliminary HAIC-MM with dimensions and capabilities
5. Validation	Mixed-methods validation with survey (N = 100) and focus groups (N = 10)	Preliminary model; Survey instrument; Focus group protocol	Empirical confirmation and refinement data
6. Refinement	Iterative adjustments based on empirical feedback	Validation results; Practitioner input	Final HAIC-MM structure

3.2.4.1. Stage 1: Problem Identification

The literature review identified seven specific challenges that SMEs commonly face when adopting AI. These challenges defined the problem space addressed by HAIC-MM and are summarized in Table 11.

Table 11: SME Challenges Driving HAIC-MM Development

Challenge	Description	Citation
Resource Constraints	Limited financial and technical resources for AI initiatives	Wang & Ramiller (2009)
Expertise Gaps	Lack of specialized AI knowledge and skills in the workforce	Davenport & Ronanki (2018)
Complexity of Integration	Difficulties integrating AI with existing human workflows	Brock & von Wangenheim (2019)
Trust and Acceptance	Need to build trust and acceptance of AI among employees	Jarrahi (2018)
Ethical and Governance Issues	Ensuring ethical AI use and establishing governance structures	Floridi et al. (2018)
Inconsistent Planning	Misalignment between AI initiatives and business strategy	Kane et al. (2015)
Fragmented Technology Governance	Fragmented oversight leading to security vulnerabilities	Ransbotham et al. (2017)

3.2.4.2. Stage 2: Analysis

The 30 frameworks were identified through a systematic search across six databases, including Scopus, ResearchGate, ACM Digital Library, Web of Science, Google Scholar, IEEE Xplore. The search followed a thematic saturation approach. Each framework was evaluated against maturity model standards (Proença & Borbinha, 2016), systems engineering principles (ISO/IEC/IEEE, 2015), HCI principles (Shneiderman, 1983), and MITRE's HMT guidelines (McDermott et al., 2018).

3.2.4.3. Stage 3: Development Approach

Becker et al. (2009) identify three strategies for developing a new maturity model. One approach is extension, which expands an existing model by adding new constructs, dimensions, or capabilities. A second approach is synthesis, which combines elements from multiple models to create a comprehensive framework. A third approach is creation, which develops a model entirely from the ground up.

Each strategy has advantages. However, the synthesis approach was selected because it enables the integration of multiple perspectives while remaining flexible enough to address SME constraints. The synthesis approach combines the technological capabilities emphasized in AI maturity models with the strategic and operational dimensions found in digital transformation models and the collaboration principles present in human machine teaming frameworks. This approach also allows adaptation for the SME context because elements can be selected and adjusted rather than adopting an existing model without modification. The resulting framework benefits from the flexibility of integrating elements from multiple domains (Madni & Madni, 2018; Dwivedi et al., 2019).

3.2.4.4. Stage 4: Iterative Design and Development

This stage represented the most intensive phase of development and involved systematic decomposition and synthesis of all 30 frameworks. Three analytical techniques guided the process, including metamodels, a concept matrix, and pivot models.

Metamodels were constructed for both the AI and DT model groups by identifying key components and recurring themes from each model's structure (Defize, 2020). The AI metamodel integrated strategic, technical, and human elements across all ten AI maturity models. The DT metamodel performed the same role for the digital transformation models. Different models often

described similar concepts using different terminology. For example, IBM (Vaish et al., 2020) described ethics and accountability, Gartner (2020) referred to leadership and governance, and AIMI (Alsheiabni et al., 2019) emphasized innovation and partnerships. Although labeled differently, each addressed the broader concept of strategic AI oversight. The metamodel consolidated these overlapping concepts into unified clusters and revealed the common building blocks required in a comprehensive model, including strategy, infrastructure, data, skills, process, culture. These metamodels provide a clear taxonomy of what needs to be included in the HAIC-MM, ensuring that we leverage the best practices and insights from existing frameworks while addressing their limitations. These metamodels ensured that the development of HAIC-MM leveraged insights from existing frameworks while also addressing their limitations.

The metamodels also supported two important objectives. First, they enabled the identification of key dimensions and capabilities by breaking the AI and digital transformation models into granular components. This allowed the most relevant elements to be extracted and aligned with SME challenges. Second, the metamodels ensured comprehensive coverage by combining elements across multiple models so that strategic, operational, technological, and human considerations were represented.

A *concept matrix* was then developed for the human machine teaming frameworks. Following the methodology proposed by Webster and Watson (2002), each framework was mapped against ten principles from MITRE's human machine teaming guide. These principles included common ground, observability, predictability, directability, directing attention, exploration of solution space, adaptability, calibrated trust, information presentation, and design process. This comparison enabled identification of the most relevant collaboration principles across the frameworks and revealed areas where existing approaches lacked coverage.

The concept matrix supported two goals. It enabled identification of best practices that could be incorporated into HAIC-MM and it exposed gaps in the existing frameworks that needed to be addressed in the new model. This ensured that the resulting framework incorporated established knowledge while strengthening areas where prior models were incomplete.

The metamodels and concept matrix were then integrated into pivot models. Pivot models represent comprehensive supersets that organize the extracted components into unified structures. The AI pivot model produced five dimensions with 11 capabilities, while the digital transformation pivot model produced seven dimensions. These pivot models were then integrated with the human machine teaming concept matrix to generate the final HAIC-MM structure.

Figure 7 illustrates this synthesis process by showing how models from each domain were decomposed into intermediate analytical structures and then recombined into the unified HAIC-MM framework.

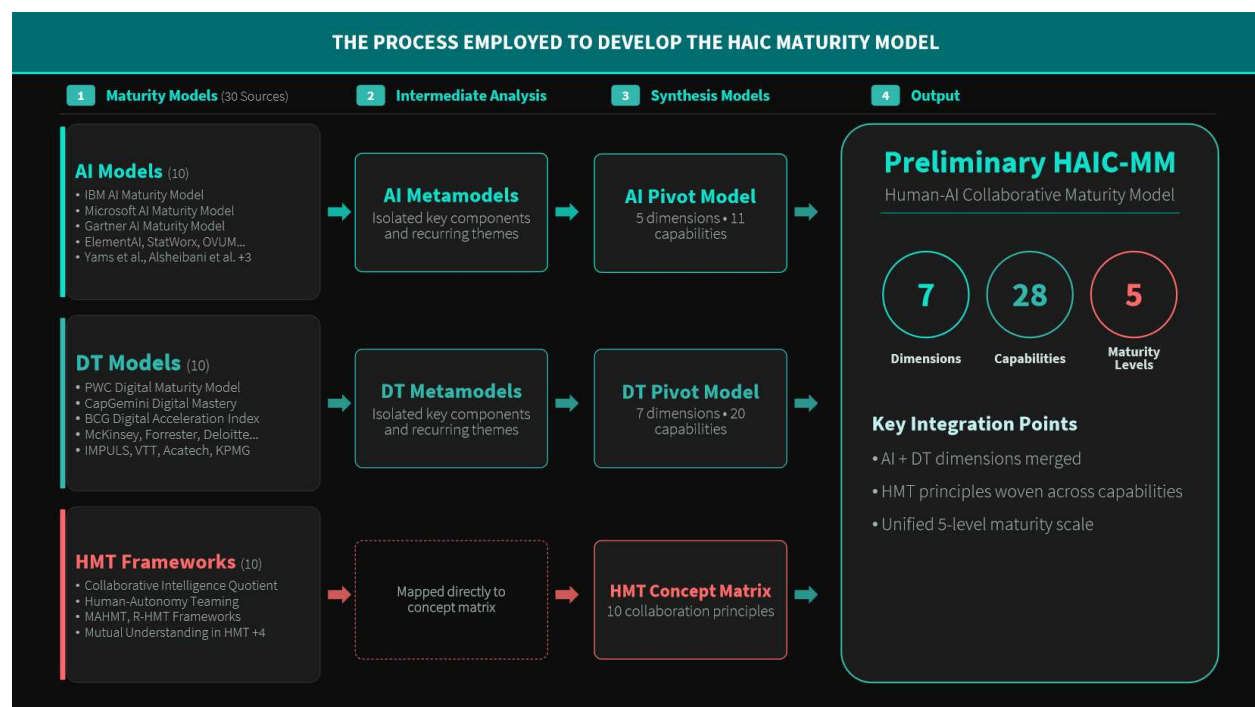


Figure 7: HAIC-MM Development Process Flow

Each domain contributed distinct themes to the synthesis. AI maturity models emphasized strategy, infrastructure, process, and skills. Digital transformation models emphasized digital strategy, technology, operations, and culture. Human machine teaming frameworks contributed collaboration principles including common ground, observability, directability, and adaptability. These domain specific contributions served as the basis for constructing the pivot models, which merged overlapping concepts into a unified seven-dimension structure.

The synthesis process involved five analytical steps. Common dimensions were first identified across all source models. Capabilities were then mapped to each dimension by comparing how the source models measured similar constructs. Terminology was standardized to address differences in naming conventions across models. For example, concepts labeled business impact, vision, and business strategy were standardized under the dimension AI strategy alignment. Maturity levels were then synthesized by identifying common progression patterns across the models. Finally, the pivot models were merged with the concept matrix by integrating the AI and digital transformation pivot models with the human machine teaming principles.

Both inductive and deductive reasoning guided this synthesis. Inductive reasoning identified broader dimensions from recurring patterns observed across the models, while deductive reasoning applied these themes to define specific capabilities. This combination produced a structure that balances comprehensive coverage with practical usability for SMEs.

The selection of seven dimensions and 28 capabilities (later expanded to 32 through practitioner feedback) was intentional. The model needed to be comprehensive enough to cover the full range of human-AI collaboration factors, from strategy and governance through technology integration, process design, customer experience, ethics, and continuous learning, while remaining manageable for SMEs with limited assessment capacity. Seven dimensions provide adequate

breadth without overwhelming organizations with too many categories. The 28 capabilities, distributed at four per dimension, provide the specificity needed for actionable assessment without requiring the kind of resource-intensive evaluation that only large enterprises can sustain.

3.2.4.5. Stage 5: Validation and Stage 6: Refinement

The results of these stages are presented in subsequent chapters. While Becker et al. (2009) specifies validation followed by refinement, HAIC-MM used a multi-stage approach of validation, followed by refinement, followed by validation. Therefore, Research Aim 2 most closely aligns with “Stage 6: Refinement” and Research Aim 3 aligns with “Stage 5: Validation”.

3.3. Results

The synthesis produced a preliminary version of HAIC-MM consisting of seven dimensions and 28 capabilities, with four capabilities assigned to each dimension, and five maturity levels. At this stage, the dimension and capability names reflected the terminology that emerged from the synthesis of existing frameworks rather than language grounded in practitioner usage. The maturity levels were also labeled using generic terminology. This preliminary structure served as the starting point for the first validation and refinement process described under Research Aim 2.

During the refinement phase the model underwent several revisions. These included expanding the structure from 28 to 32 capabilities, revising the terminology used for the dimensions, capabilities, and maturity levels, and refining the 160 current state descriptions to better reflect SME operational realities. Since these revisions were iterative and occurred across multiple stages of validation, presenting the intermediate versions of the model would introduce

redundancy and unnecessary detail. For clarity and coherence, the complete and finalized HAIC-MM after refinement and validation is presented in Chapter 4.

3.4. Discussion

3.4.1. Insights from Development Process

The systematic decomposition and synthesis of the 30 frameworks confirmed and sharpened the five gaps identified in Chapter 2. Each gap translated into a specific design decision in HAIC-MM. Table 12 summarizes these translations.

Table 12: From Literature Gaps to HAIC-MM Design Decisions

Existing Gap	Missing in Existing Frameworks	HAIC-MM Design	Novelty of HAIC-MM
HMT frameworks treat AI as a tool rather than a collaborative partner	AI adoption is measured mainly as technology deployment, not as an evolving human-AI working relationship	Maturity level progression (5 levels) from AI Exploration to Symbiotic Partnership	Measures increasing sophistication in how humans and AI collaborate, not just how much AI is deployed
AI maturity models oversimplify SME needs	Assumes organizations progress similarly regardless of size and constraints	Size-adjusted scoring and dependency-based progression	Reflects real SME constraints, making expectations and scoring more realistic and comparable across company sizes
DT models ignore human-AI collaborative dynamics	Digital transformation maturity often emphasizes culture, process, and tech, but not collaboration dynamics	Collaboration-centered dimensions (5 of 7 dimensions directly assess human-AI collaboration)	Evaluates collaboration outcomes such as leadership AI literacy, employee experience, and human-AI task allocation effectiveness
No existing model integrates HMT, AI maturity, and DT perspectives	Frameworks are typically siloed, assessing AI capability, DT maturity, or HMT principles separately	Three-domain synthesis embedded in every dimension via the three HAIC pillars	Ensures every assessment captures AI capability, DT readiness, and HMT principles (trust, observability, adaptability) in a unified structure

Existing models treat capabilities independently and conceal imbalances	Single averages conceal whether progress is balanced or lopsided across people, tech, and collaboration	Balance factor with pillar-level scoring plus a collaboration bonus / variance penalty	Surfaces misalignment, rewarding balanced growth and penalizing lopsided investment that often causes AI initiatives to fail
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3.4.2. Remaining Development Steps

The development process produced the structural framework of HAIC-MM, including its dimensions, capabilities, maturity levels, and hierarchical architecture. Two critical steps remained. The first was empirical validation to confirm that the model resonates with practitioners and reflects real-world SME challenges, as described in Chapter 5 and Chapter 6. The second was the creation of a scoring methodology that converts assessment responses into actionable maturity scores, along with the development of the user platform that enables HAIC-MM to function as a deployable assessment tool, as described in Chapter 4.

Chapter 4. Final HAIC-MM Framework

4.1. Introduction

Chapter 2 identified five key gaps in existing maturity models, which helped inform the synthesis presented in Chapter 3 that produced the dimensional structure of HAIC-MM. This chapter presents the finalized HAIC-MM framework, incorporating refinements made after the testing described in Chapter 5. The model is presented here to clarify its structure before discussing the validation studies conducted with participants.

The dimensions and capabilities define what HAIC-MM measures (as presented in Chapter 3), but three additional mechanisms were required to address how it measures the quality of collaboration (introduced in this chapter). First, existing models conceal imbalances by averaging across capability areas, so HAIC-MM separates each capability into three measurement streams defined as the HAIC Pillars, which track (1) human readiness, (2) AI capability, and (3) collaboration quality independently. Second, existing models assign the same score to balanced and unbalanced organizations, so the HAIC-MM Balance Factor adjusts capability scores based on pillar alignment. Third, existing models do not verify whether organizations can sustain their assessed maturity, so HAIC-MM's five Success Factors derived from cross-cutting enablers in the source literature serve as a verification layer.

The framework organizes human-AI collaboration into seven strategic dimensions, ranging from leadership and culture to ethics and governance. Each dimension is divided into progressively more specific layers: 32 capabilities, 160 focus areas, and 640 advancement practices. Five maturity levels describe the progression from early-stage AI Exploration (L1) to Symbiotic Partnership (L5). The structure is deliberately layered; broad enough to cover the full scope SMEs face, yet specific enough to generate actionable guidance for gaps identified by the assessment.

Most maturity models tell an organization where it stands. HAIC-MM tells an organization where it stands, why it stands there, and what to do next.

This chapter is organized as follows. Section 4.2 introduces the online platform through which SME leaders interact with the model. Section 4.3 describes the hierarchical structure, explaining the role of each layer and how the five recurring focus-area lenses create a consistent evaluation pattern across all 32 capabilities; it also introduces two diagnostic overlays: the HAIC Pillars and the Success Factors. Section 4.4 presents the scoring methodology, explaining how 160 responses roll up through capabilities and dimensions to produce an overall maturity rating; how the Balance Factor adjusts scores based on whether the human side, the AI side, and their interaction develop at a similar pace; and how dependency checks enforce realistic capability progression. The Balance Factor distinguishes HAIC-MM from conventional models, rather than simply averaging scores, it rewards balanced development and penalizes cases where one side advances faster than the other.

4.2. Online Platform

SME leaders access HAIC-MM through a free web platform at <https://haicmm.com>. They create an account, register an assessment for their organization, and complete 160 questions. Each question targets a specific aspect of human-AI collaboration and asks respondents to rate their organization on a 1-to-5 scale, using response types that range from agreement and satisfaction to frequency and effectiveness.

Once submitted, the platform's scoring engine automatically processes all responses. It calculates scores at every level of the framework hierarchy, computes the Balance Factor for each capability, derives the five Success Factor scores, and breaks down the HAIC Pillar results into Human-Centric, AI-Centric, and Collaborative components. No manual calculation is required.

The system generates ten reports from the results. An Executive Summary provides a high-level overview for senior leadership, while a Gap Analysis identifies weaknesses and their root causes. A Strategic Roadmap sequences improvement initiatives across three planning horizons, and a Tactical Action Plan provides step-by-step implementation guidance for project teams. The remaining six reports include Dimension Deep Dives, Capability Comparisons, Success Factor Analysis, Collaboration Dynamics, Trust and Fairness, and Advancement Practice Status. All scoring, narrative content, and recommendations are generated automatically, ensuring consistent, evidence-based results regardless of who administers the assessment.

4.3. HAIC-MM Framework

HAIC-MM is a layered system. Seven broad strategic dimensions sit at the top, while 640 concrete advancement practices at the bottom guide organizations on how to address identified gaps. Capabilities and focus areas connect these layers, translating strategic direction into specific, measurable assessment questions. The subsections that follow describe each layer, explain how they relate to one another, and introduce the diagnostic overlays that add analytical depth.

4.3.1. HAIC-MM Hierarchical Structure

The model follows a bottom-up scoring architecture. Each assessment response feeds into the level above it, which then feeds into the next, until all 160 answers have contributed to a single overall maturity score. This design produces two results simultaneously: a high-level maturity rating for executive decision-making, and a granular breakdown identifying which capabilities require attention. The hierarchy has four layers. Figure 8 illustrates how each layer translates a broad question into more specific elements, moving from strategic direction at the top to concrete action at the bottom.

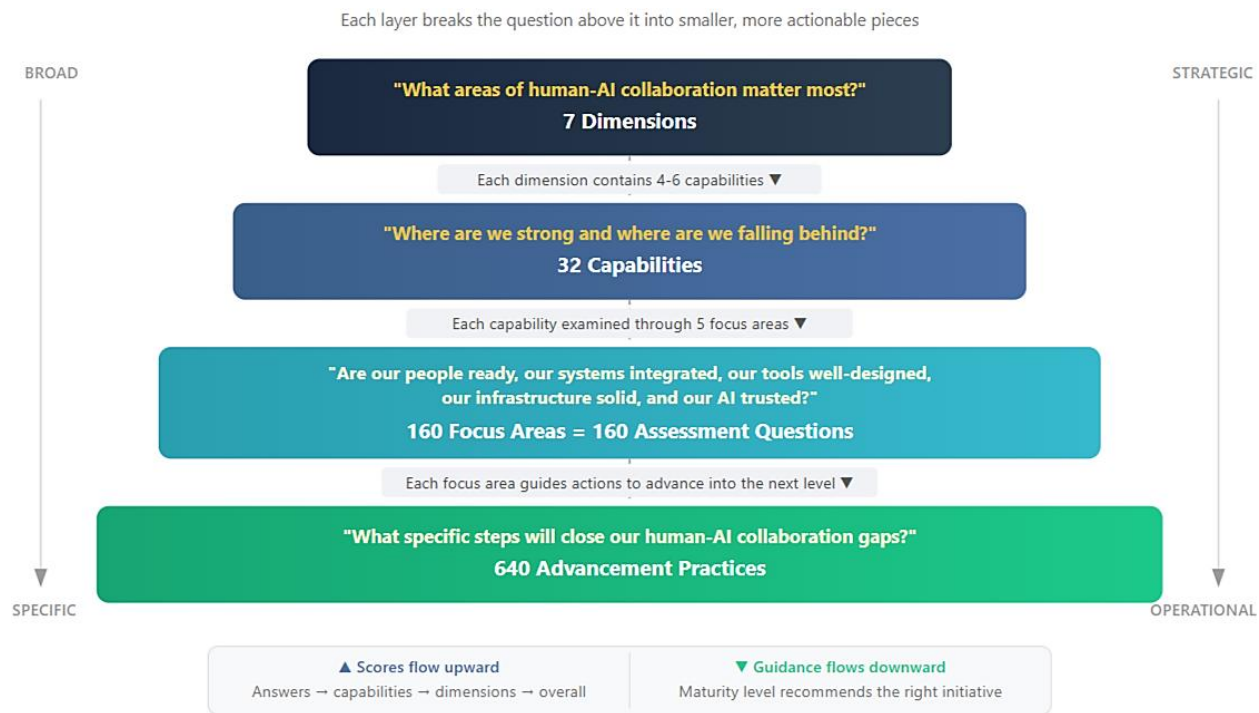


Figure 8: HAIC-MM Hierarchical Structure

Dimensions define the seven broad strategic areas of human-AI collaboration. Dimension results allow leaders to quickly identify which parts of the organization require attention, making this layer the starting point for strategic discussions about human-AI collaboration.

Capabilities translate these broad strategic areas into measurable organizational skills. There are 32 capabilities distributed across the seven dimensions, each weighted according to its strategic importance. This is the layer where individual maturity scores are assigned.

Focus Areas examine each capability from five consistent lenses: Organizational Readiness, Socio-Technical Integration, Human-AI Interaction Design, Systems Engineering Support, and Human-AI Trust Dynamics. These lenses repeat across all 32 capabilities, enabling cross-capability diagnosis. For example, if trust scores are consistently low across many capabilities, the platform identifies this as an organization-wide issue rather than a set of isolated

problems. Each focus area corresponds to one assessment question, producing 160 questions in total (32 capabilities × five focus areas). SME leaders rate each on a 1-to-5 scale.

Advancement Practices are where the model shifts from diagnosis to action. Each focus area contains four practices, producing 640 practices across the framework. These practices provide concrete strategies for improving specific aspects of a capability. The guidance associated with each practice adapts to the organization's maturity level. Each practice includes nine implementation components specifying actions, measurement criteria, review frequency, required resources, and verification methods.

Scores flow upward through the hierarchy, from individual responses to an overall maturity level. Improvement guidance flows downward, from assessed maturity levels to the appropriate advancement practices. The two directions together are what make the model both diagnostic and prescriptive.

The sections that follow examine each layer in greater detail. Two diagnostic overlays are then introduced: the HAIC Pillars, which measure whether workforce, technology, and collaboration are developing at a balanced pace, and the Success Factors, which assess whether the organizational foundation can sustain the assessed maturity level.

4.3.2. Seven Dimensions

Each dimension in the HAIC-MM represents a broad area of organizational activity where human-AI collaboration can succeed or fail. The seven dimensions did not originate from a single framework or a theoretical exercise. Instead, they were developed by synthesizing 30 AI and digital transformation frameworks with human-machine teaming (HMT) principles, as described previously. This synthesis consolidated overlapping concepts from three research domains: AI maturity models, digital transformation frameworks, and cognitive engineering research on

effective humans-machine collaboration. The result is a set of seven dimensions that together capture the range of organizational factors SMEs must address to build productive partnerships between their workforce and AI systems.

Table 13 presents each dimension alongside the consolidated cluster names from the AI, digital transformation, and HMT sources that informed it. The pivot source columns represent cluster names derived from each metamodel rather than individual framework names.

Table 13: HAIC-MM Dimensions with Source Mapping

Dimension	Description	AI Pivot Source	DT Pivot Source	HMT Principles
1. AI-Enhanced Leadership and Strategy	How leadership integrates AI into strategic planning and decision-making	AI Strategy and Governance	Digital Strategy and Governance	Common Ground; Directability
2. Adaptive AI Culture and Empowerment	How the organization's culture embraces and adapts to AI	AI Literacy and Skills	Skills and Culture	Adaptability; Calibrated Trust
3. Harmonizing AI and Human Processes	How well human and AI processes are integrated	Process Efficiency & Interaction	Process and Operations	Exploring Solution Space; Adaptability
4. Human-Centric AI Integration and Experience	How AI is designed with human users in mind	AI Infrastructure & Technology	Technology and Infrastructure	Observability; Adaptability
5. Human-Centered AI Customer Engagement	How AI enhances customer interactions	Customer Experience	Customer Experience	Directing Attention
6. AI Ethics and Human Oversight	How ethical considerations and human oversight are implemented	Data Quality Management	Data Management	Information Presentation; Calibrated Trust
7. Inclusive AI Governance and Learning	How diverse perspectives inform AI governance and continuous learning	AI Literacy and Skills	Skills and Culture	Adaptability; Calibrated Trust

In practice, these dimensions correspond to questions familiar to SME leaders. Dimension 1 examines whether senior leadership can define and communicate a clear AI strategy, without sufficient AI literacy at the leadership level, downstream initiatives struggle. Dimension 2 considers whether organizational culture supports employees experimenting with AI tools or whether resistance slows adoption. Dimension 3 evaluates whether AI technologies are designed with their human users in mind, ensuring they are usable and effective. Dimension 4 focuses on whether workflows allocate tasks appropriately between humans and AI. Dimension 5 extends this analysis to customer-facing operations, examining whether AI enhances or undermines the customer experience. Dimension 6 addresses ethics, oversight, and compliance requirements that can quickly derail AI initiatives if neglected. Dimension 7 considers whether organizations learn continuously, whether governance incorporates diverse perspectives, and whether the workforce continues developing AI-related capabilities over time.

4.3.2.1. Three-Tier Classification

Not all seven dimensions carry the same weight in determining overall maturity. HAIC-MM classifies each dimension into one of three tiers based on its strategic importance, reflected through its assigned weight in the scoring algorithm. Figure 9 shows this classification.

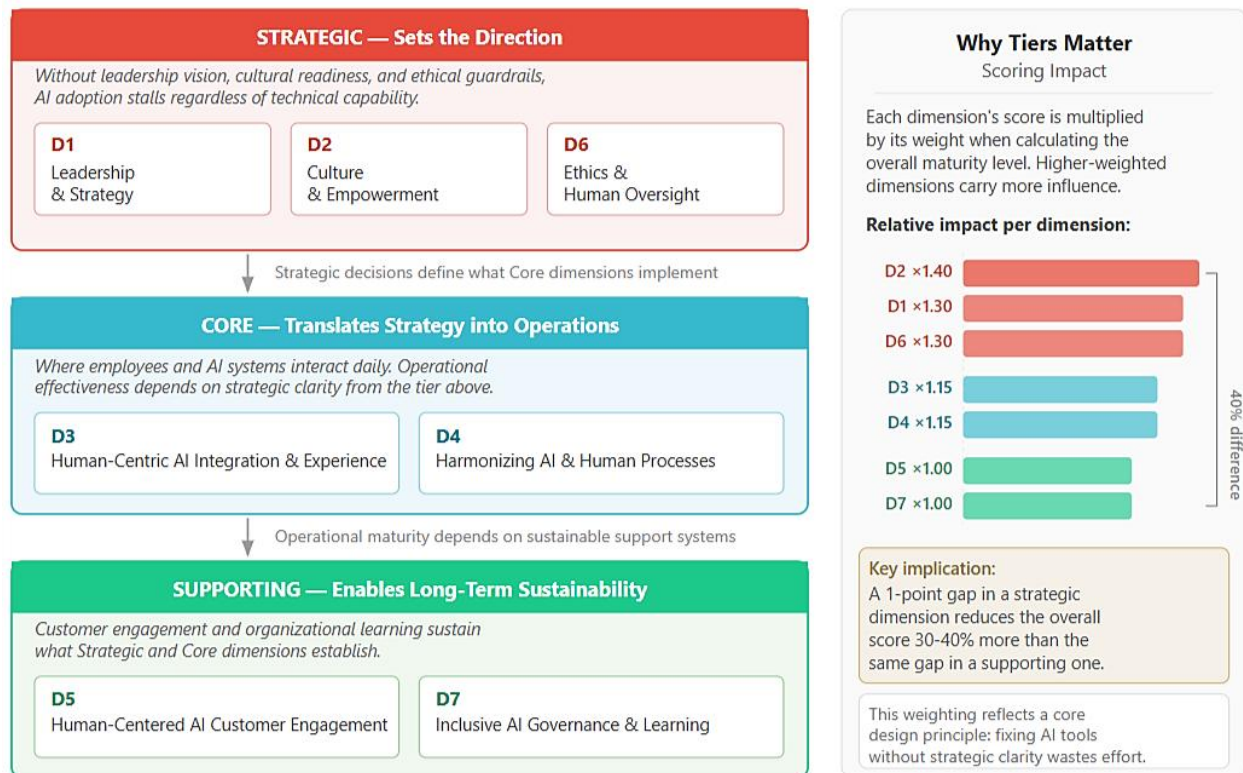


Figure 9: How Dimension Tiers Shape the Maturity Assessment

Strategic Dimensions (weight ≥ 1.40) are Dimensions 1, 2, and 6. These are the leadership, culture, and ethics dimensions. These carry the greatest weight because research and practitioner experience consistently show that AI adoption depends on these organizational foundations. Without leadership commitment, cultural readiness, and ethical oversight, technology investments produce limited results.

Core Dimensions ($1.10 \leq \text{weight} < 1.30$) are Dimensions 3 and 4. These represent the operational areas where AI becomes integrated into daily work. Process harmonization and human-centered design translate strategy into practice across the organization.

Supporting Dimensions (weight < 1.10) are Dimensions 5 and 7. These areas strengthen overall maturity but are not prerequisites for progress. An organization may perform well in

customer engagement, for example, but without strong leadership and ethical oversight, overall maturity will remain limited. Conversely, organizations with strong strategic foundations can still achieve meaningful maturity even if supporting areas develop more gradually.

This three-tier structure reflects a consistent finding in the literature: organizational commitment (leadership, culture, and ethics) is the strongest predictor of AI adoption success; operational execution is essential but secondary; and specialized areas such as customer engagement enhance maturity but are not the primary drivers.

4.3.3. Thirty-Two Capabilities with Weights

If the seven dimensions define the broad strategic areas of human-AI collaboration, the 32 capabilities define the specific, measurable elements within each area. A capability answers a focused question about what an organization can or cannot do. For example, Dimension 1 asks broadly how well leadership uses AI. Its capabilities break this into more specific questions: whether leaders make AI-informed decisions (*Augmented Decision Making*), understand AI well enough to guide initiatives and manage risks (*Leadership AI Literacy*), communicate the AI vision across the organization (*Inclusive AI Vision Communication*), align AI initiatives with business objectives (*AI Strategy Alignment*), and assess organizational readiness for adoption (*AI Adoption Readiness Assessment*).

Each capability is defined, weighted, and classified so the scoring algorithm reflects its relative importance. The 32 capabilities span all seven dimensions, with four to six capabilities per dimension. Table 14 presents the complete mapping.

Table 14: Capability Mapping with Weights and Classifications

#	Capability	Dimension	Weight	Classification	Description
1	Augmented Decision Making	D1: Leadership & Strategy	1.00	Supporting	Use AI and data analytics to enhance leaders' decision-making with data-driven insights
2	Leadership AI Literacy	D1: Leadership & Strategy	1.40	Strategic	Equip leaders with deep understanding of AI to champion initiatives and manage risks
3	Inclusive AI Vision Communication	D1: Leadership & Strategy	1.00	Supporting	Communicate the AI vision clearly across all levels, aligning with organizational goals
4	AI Strategy Alignment	D1: Leadership & Strategy	1.20	Core	Align AI initiatives with business objectives to maximize competitive advantage
5	AI Adoption Readiness Assessment	D1: Leadership & Strategy	1.00	Supporting	Assess readiness for AI by evaluating infrastructure, skills, and resources
6	Comprehensive AI Training & Development	D2: Culture & Empowerment	1.20	Core	Build AI-focused training programs to enhance collaboration and adaptability
7	AI Partnership Index	D2: Culture & Empowerment	1.00	Supporting	Develop metrics to assess the quality and effectiveness of human-AI collaboration
8	Workforce AI Adaptability	D2: Culture & Empowerment	1.20	Core	Enhance adaptability to AI-driven changes through targeted training and support
9	Psychological Safety in AI Collaboration	D2: Culture & Empowerment	1.00	Supporting	Create a safe environment for employees to interact openly with AI
10	Human-Centered AI Design	D4: Integration & Experience	1.20	Core	Design AI systems that prioritize user needs, ensuring usability and accessibility
11	AI Integration Effectiveness	D4: Integration & Experience	1.00	Supporting	Ensure smooth AI integration into workflows, minimizing disruptions
12	Employee Experience with AI Tools	D4: Integration & Experience	1.00	Supporting	Improve user interaction with AI through feedback-driven interface adjustments
13	Human-AI Collaboration Quality	D4: Integration & Experience	1.20	Core	Measure collaboration productivity by evaluating communication, task completion, and outcomes
14	Human Trust in AI Assessment	D4: Integration & Experience	1.00	Supporting	Assess and foster trust in AI through transparency, reliability, and employee involvement

15	AI-Driven Process Optimization	D3: Process Harmonization	1.20	Core	Use AI to optimize processes, increase efficiency, and reduce redundancies
16	Human-AI Collaboration Index	D3: Process Harmonization	1.00	Supporting	Create metrics to quantify collaboration effectiveness between humans and AI
17	Human-AI Task Flow	D3: Process Harmonization	1.00	Supporting	Design workflows that distribute tasks effectively between humans and AI
18	Adaptive Task Allocation	D3: Process Harmonization	1.00	Supporting	Use real-time assessments to dynamically assign tasks to humans or AI
19	AI-Enhanced Customer Engagement	D5: Customer Engagement	1.20	Core	Personalize customer interactions with AI, improving experience and satisfaction
20	Customer Insights on AI Experiences	D5: Customer Engagement	1.00	Supporting	Collect feedback on AI interactions to refine customer-facing AI tools
21	Human-AI Response Integration	D5: Customer Engagement	1.00	Supporting	Enable seamless coordination between humans and AI in customer service
22	Human-AI Collaborative Resolution Rate	D5: Customer Engagement	1.00	Supporting	Measure resolution success in issues solved through human-AI collaboration
23	AI Ethical Oversight	D6: Ethics & Oversight	1.40	Strategic	Establish governance structures to oversee ethical AI deployment
24	AI Data Compliance	D6: Ethics & Oversight	1.40	Strategic	Ensure AI operations comply with data protection laws and standards
25	AI Governance Effectiveness	D6: Ethics & Oversight	1.00	Supporting	Assess and strengthen AI governance for policy enforcement and risk management
26	AI Operational Transparency	D6: Ethics & Oversight	1.00	Supporting	Maintain transparent communication about AI operations to foster trust
27	Responsible AI Practices	D6: Ethics & Oversight	1.20	Core	Adopt best practices to ensure ethical, fair, and accountable AI usage
28	Equity and Fairness Assessment	D6: Ethics & Oversight	1.00	Supporting	Promote fairness in AI systems with inclusive policies and bias mitigation
29	Achieving Diversity in AI Training Data	D7: Governance & Learning	1.00	Supporting	Ensure diverse and representative data in AI training to reduce biases

30	Assessing AI Impact on Workforce Roles	D7: Governance & Learning	1.20	Core	Analyze how AI impacts job roles and plan reskilling as needed
31	Implementing Inclusive AI Decision-Making	D7: Governance & Learning	1.00	Supporting	Involve diverse perspectives in AI-related decisions to promote fairness
32	Adaptive AI Workforce Upskilling	D7: Governance & Learning	1.20	Core	Provide ongoing AI skill development to maintain a proficient workforce

The distribution is deliberate: 3 Strategic, 11 Core, and 18 Supporting capabilities. The three Strategic capabilities carry the highest weights because they represent the prerequisites on which everything else depends.

Leadership AI Literacy (weight = 1.40) is foundational. Without leaders who understand AI well enough to champion initiatives and manage risks, other capabilities develop unevenly. Leadership determines direction, allocates resources, and signals organizational priorities.

AI Ethical Oversight (weight = 1.40) is equally critical because trust failures can undermine AI adoption. If employees do not trust that systems are used responsibly, adoption slows; if customers perceive decisions as opaque or biased, reputational damage can follow.

AI Data Compliance (weight = 1.40) completes the Strategic tier because regulatory requirements directly constrain AI deployment. Data protection regulations such as GDPR, CCPA, and sector-specific rules impose strict conditions on how AI systems collect and process information. Non-compliance can lead to fines, legal exposure, and loss of customer trust.

The 11 Core capabilities (weight = 1.20) form the operational backbone of human-AI collaboration. These include training programs, process optimization, human-centered design, and workforce adaptability, the mechanisms that translate strategic intent into daily practice.

The 18 Supporting capabilities (weight = 1.00) strengthen maturity through metrics, feedback loops, transparency, and specialized functions. They enhance organizational capability but are not the primary drivers of progression.

This weighting structure means that two organizations with identical average scores can achieve different maturity outcomes depending on where their strengths lie. Organizations that perform well in Strategic and Core capabilities will progress further than those that score highly only in Supporting areas.

4.3.4. Five Maturity Levels

Every score in HAIC-MM maps to one of five maturity levels. Capabilities, dimensions, and the overall organization each receive a level. These levels serve two purposes, they indicate the organization's current position and describe the next stage of development. The scale ranges from 0.00 to 5.00. Table 15 presents the full maturity scale.

Table 15: HAIC-MM Maturity Levels

Level	Name	Score Range	Definition	Organizational Characteristics
L1	AI Exploration	0.00-1.99	Organizations experimenting with AI through small pilot projects	Minimal AI adoption; leadership mentions AI but lacks concrete plans; decision-making relies on conventional methods; no structured approach
L2	AI-Enabled	2.00-2.99	Organizations implementing AI tools to support existing processes	Emerging AI interest; basic AI projects in select departments; introductory training; inconsistent implementation
L3	AI-Embedded	3.00-3.79	Organizations with AI integrated as a core component of operations	Structured AI integration across departments; clear objectives from leadership; regular AI use in decision-making; established frameworks

L4	AI-Aligned	3.80-4.49	Organizations with comprehensive AI strategy aligned with business goals	Advanced AI integration; strategic AI initiatives with measurable outcomes; daily innovation using AI tools; comprehensive frameworks
L5	Symbiotic Partnership	4.50-5.00	Organizations where AI and humans work in complete harmony	Seamless AI integration at all levels; decision-making naturally combines AI insights with human judgment; continuous innovation

To clarify how the scale applies in practice, the following examples illustrate what each level may look like within an SME:

- *Level 1 (AI Exploration)*: A 30-person retail company where the owner has heard about AI chatbots but no one has tried them. Decisions are made as they always have been. Staff may be curious about AI, but there is no training, no tools, and no plan.
- *Level 2 (AI-Enabled)*: A 75-person logistics firm using AI for demand forecasting in one department. Some employees have received basic training and early results are promising, but the tools operate in isolation from the rest of the organization. There is no company-wide strategy connecting these experiments to broader goals.
- *Level 3 (AI-Embedded)*: AI is integrated into routine operations. A 100-person manufacturing firm uses AI-driven quality inspection across the production floor. Leadership sets clear AI objectives, multiple departments rely on AI in their workflows, and frameworks exist for performance evaluation and risk management.
- *Level 4 (AI-Aligned)*: Strategy and operations converge around AI as a core capability. A 60-person financial services firm continuously refines AI models based on performance outcomes. Cross-department collaboration is routine, and the organization measures the return on AI investments to guide future improvements.

- *Level 5 (Symbiotic Partnership)*: Humans and AI operate as adaptive partners. Workflows evolve through continuous interaction between AI insights and human judgment. Innovation becomes ongoing, and the boundary between human and AI work grows increasingly fluid.

Figure 10 shows progression across the five maturity levels and how scores contextualize an organization’s human-AI collaboration state. A consistent color scheme accompanies the levels across all ten assessment reports: red for L1, yellow for L2, green for L3, blue for L4, and purple for L5. This visual system allows readers to quickly recognize maturity status whether viewing a single capability, an entire dimension, or the organization’s overall score.

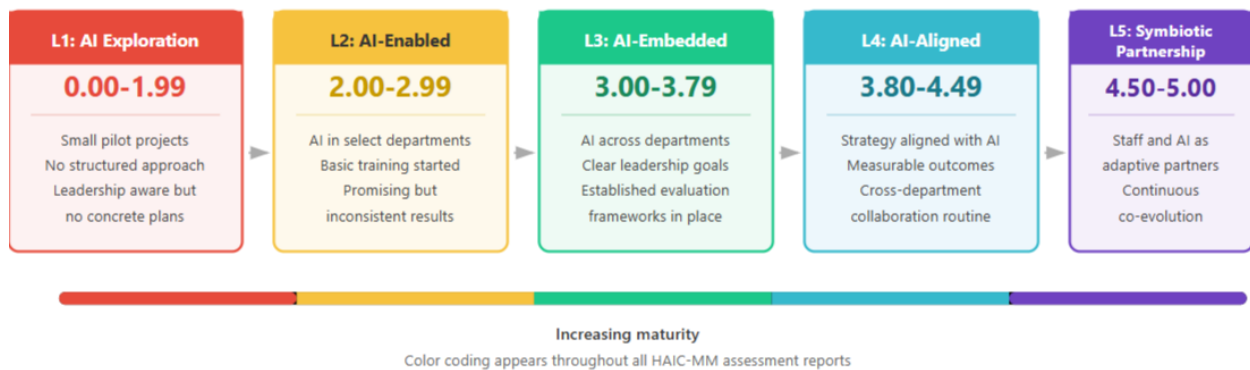


Figure 10: HAIC-MM Maturity Level Progression

So far, this chapter has described what HAIC-MM measures (dimensions and capabilities) and the scale used to measure it (maturity levels). The remaining sections explain how these measurements are calculated, the actions they inform, and the diagnostic overlays that deepen the assessment.

4.3.5. Focus Areas: Five Ways to Examine Each Capability

When a physician assesses a patient, they do not ask one question and rely on a single data point to form a diagnostic view. Instead, they examine multiple indicators, such as the heart, lungs, bloodwork, reflexes, and medical history. No single test tells the full story, but together they provide a reliable picture. HAIC-MM applies the same principle to each capability.

Consider “Augmented Decision Making,” which asks how effectively an organization uses AI to support decisions. The answer depends on several factors: whether the workforce is prepared, whether AI tools connect with existing decision processes, whether staff can use those tools effectively, whether the technical infrastructure supports them, and whether employees trust what the AI recommends. Five different questions, all aimed at the same capability. In HAIC-MM, those five angles are called Focus Areas:

1. *Organizational Readiness & Adaptation:* Is the organization prepared for AI adoption?
This lens examines leadership support, cultural readiness, and transition planning.
2. *Socio-Technical Integration:* Do AI tools integrate with existing work processes, or do they operate separately from daily workflows?
3. *Human-AI Interaction Design:* Are AI tools intuitive and usable for employees without specialized technical expertise?
4. *Systems Engineering Support:* Does the technical infrastructure (i.e., hardware, software, data pipelines, and engineering practices) reliably support AI systems?
5. *Human-AI Trust Dynamics:* Do employees trust the AI systems they are expected to use? This lens evaluates transparency, reliability, and fairness.

These five focus areas repeat across all 32 capabilities. The questions change to match each capability's subject matter, but the five lenses remain constant. Figure 11 illustrates this structure for Capabilities 1 and 15.

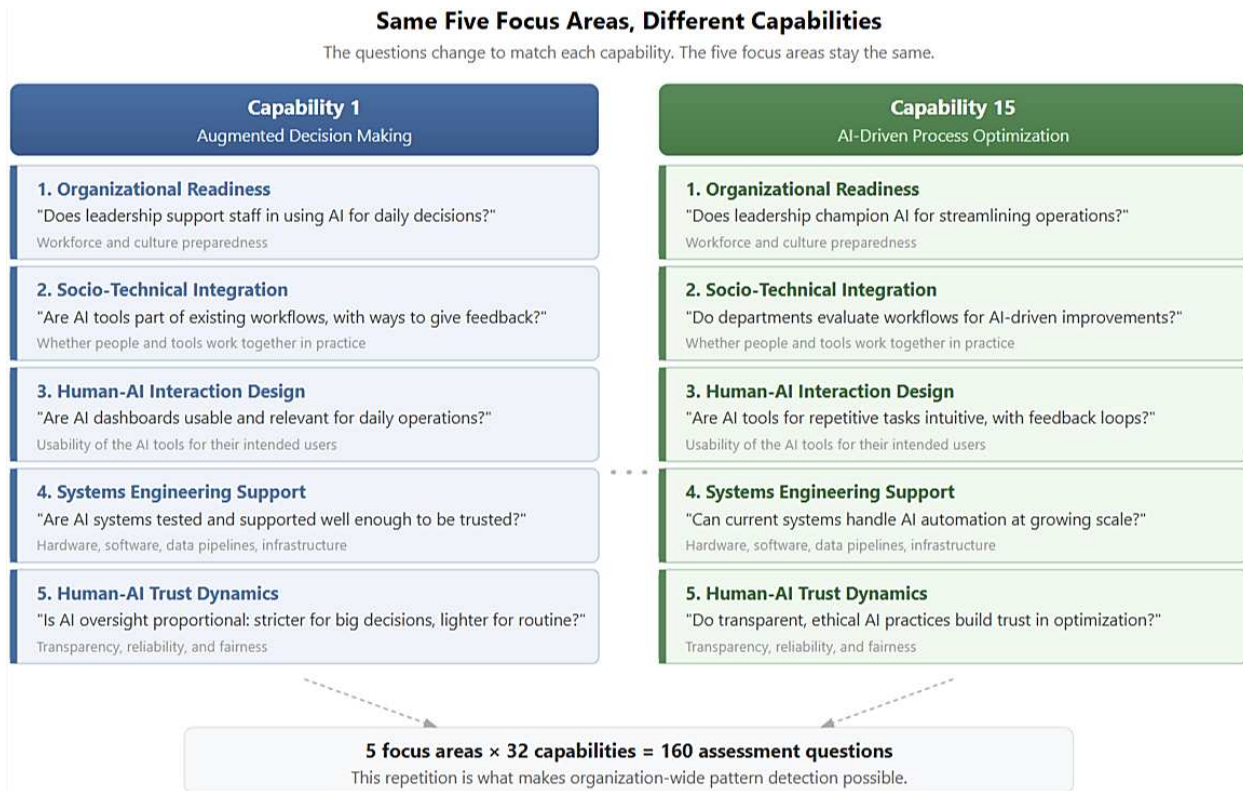


Figure 11: Focus Area Lenses Applied Across Capabilities

For example, when assessing Capability 1 (*Augmented Decision Making*), SME leaders answer five questions, one for each focus area. When they move to Capability 15 (*AI-Driven Process Optimization*), they answer five new questions using the same lenses. This repetition creates a consistent evaluation pattern, making it easier for respondents to complete the assessment efficiently.

The repeating structure also enables organization-wide pattern detection. For instance, if a logistics company scores poorly on “Human-AI Trust Dynamics” across many capabilities, the

platform identifies this as a systemic trust issue rather than isolated weaknesses. Addressing the problem at a single capability would not resolve a pattern that widespread.

The structure also generates the data used to calculate the Success Factors. Each of the 160 assessment questions carries a tag indicating whether it measures a human-centric, AI-centric, or collaborative aspect of performance. Because the same lenses repeat across all capabilities, the platform can aggregate these tagged responses to produce organization-wide scores for each aspect. Section 4.3.8 explains the Success Factors in detail, and Section 4.3.9 describes how they integrate into the full framework.

The calculation is straightforward. Five Focus Areas per capability, 32 capabilities, and 160 questions in total. Each is rated on a 1-to-5 scale, producing the raw data that feeds the scoring methodology described in Section 4.4.

4.3.6. Advancement Practices: From Diagnosis to Action

A maturity score indicates where an organization stands, but it does not explain what to do next. An SME leader who learns that a capability scores at Level 2 knows the organization has begun using AI to support existing processes, but the score alone does not indicate whether to invest in tools, train the workforce, redesign processes, or pursue some combination of these. The gap between knowing where you stand and knowing what to do about it is where most maturity models stop, and where many SMEs stall.

Advancement practices bridge that gap. Each of the 160 focus areas contains four practices, producing 640 across the full model. An advancement practice is a specific, named initiative for strengthening one aspect of a capability. While focus areas structure the diagnostic process, advancement practices structure the response.

The number 640 may appear excessive for organizations with 20 to 200 employees. In practice, this granularity makes the model usable rather than burdensome. A broad recommendation such as “improve your AI processes” offers little practical guidance. Leadership would still need to determine what improvement means, which processes to address, and in what sequence; an analysis requiring time and expertise many SMEs lack. HAIC-MM reduces this burden by dividing each focus area into four defined practices that progress from foundational to advanced.

SME leaders do not confront all 640 practices at once. The assessment identifies the focus areas requiring attention, and within each one, the four practices provide a clear starting point and sequence of improvement. A 40-person firm with limited resources and no dedicated AI team, for example, might begin with Practice 1 under its weakest focus area this quarter, move to Practice 2 the next quarter, and continue building capability incrementally rather than attempting a comprehensive transformation at once.

This design is intentional. Granularity at the practice level creates flexibility at the organizational level. SMEs can focus on the areas that matter most given their current scores, address them in manageable increments, and expand their efforts as capacity grows and earlier improvements take hold.

4.3.6.1. Advancement Practice Structure

Table 16 shows how advancement practices are organized. It presents all 20 advancement practices for Capability 1 (Augmented Decision Making), grouped by their parent focus area. Within each group, the four practices are sequenced so that each one builds on the work of the previous, providing a clear progression for organizational improvement.

Table 16: Twenty Advancement Practices for Capability 1 (Augmented Decision Making)

Focus Area	#	Advancement Practice	What It Addresses
1. Organizational Readiness	1	AI Readiness and Transformation	Assessing whether the organization is prepared to adopt AI and planning the transition
	2	Human-AI Collaboration Development	Building the workforce's capacity to work productively alongside AI systems
	3	AI Change Management and Leadership Engagement	Managing the organizational change AI adoption requires, with active leadership involvement
	4	AI Adoption and Workforce Evolution	Reshaping roles and workflows as AI becomes embedded in daily operations
2. Socio-Technical Integration	5	Digital Capability Advancement	Developing the digital skills staff need to work with AI tools
	6	Process and Task Optimization	Improving individual processes through AI-assisted efficiency gains
	7	Human-AI Workflow Intelligence	Designing workflows in which human judgment and AI analysis complement each other
	8	AI-Enhanced Service Delivery	Applying AI-enhanced processes across the organization's service operations
3. Human-AI Interaction Design	9	AI Tool Proficiency Development	Ensuring staff can use AI tools competently in their daily work
	10	Human-AI Partnership Growth	Moving from basic tool use to productive human-AI working partnerships
	11	Digital Interaction Advancement	Improving the quality and effectiveness of human-AI interactions
	12	AI Solution Adaptation Skills	Adapting AI solutions to new situations and changing business requirements
4. Systems Engineering Support	13	Systems Engineering Practices	Establishing foundational engineering discipline for AI systems
	14	Digital Engineering Enablement	Building the digital infrastructure required to support AI tools
	15	Human-AI Systems Integration	Connecting human workflows with AI systems so both can operate effectively together
	16	Technology and Infrastructure Evolution	Upgrading the technology foundation to support growing AI capabilities
5. Human-AI Trust Dynamics	17	Human-AI Trust Index	Measuring and tracking employee trust in AI systems
	18	Ethical AI Governance	Establishing governance structures to ensure ethical AI deployment

19	AI Transparency Management	Making AI decision processes visible and understandable to staff
20	AI Equity and Bias Mitigation	Identifying and reducing bias in AI systems to ensure fair outcomes

Within each focus area, the four practices follow a logical progression. For example, an organization cannot integrate human and AI systems (Practice 15) without first establishing engineering foundations (Practice 13) and developing the supporting digital infrastructure (Practice 14). Across the five focus areas, the sequence reflects the broader framework structure: readiness, integration, interaction, infrastructure, and trust.

This structural pattern repeats across all 32 capabilities, although the practices themselves differ. Each capability addresses a distinct aspect of human–AI collaboration, and the recommended initiatives are written specifically for that context. For instance, the readiness practice under *Augmented Decision Making* (Capability 1) addresses a different challenge than the readiness practice under *AI-Driven Process Optimization* (Capability 15) or *AI Ethical Oversight* (Capability 23). The focus area defines the lens of evaluation, while the capability defines the subject matter. As a result, each of the 640 practices provides guidance tailored to its specific capability.

Practice numbering is sequential across the framework: Capability 1 includes Practices 1-20, Capability 2 includes Practices 21-40, and this pattern continues through Capability 32 (Practices 621-640).

Because practices are organized by the same five Focus Areas used in the assessment, the improvement plan mirrors the diagnostic structure. If an organization scores low on *Systems Engineering Support* within *AI-Driven Process Optimization*, the four practices under that focus

area target that weakness with initiatives specific to process optimization rather than generic engineering guidance.

4.3.6.2. Targeting Identified Gap at the Correct Level

Identifying the right gap is necessary but not sufficient. The guidance must also match the organization’s maturity level. Each advancement practice provides different recommendations at Level 1 than at Level 4 because the needs of organizations beginning their AI journey differ fundamentally from those of more advanced adopters. As a result, practices are customized along two dimensions: the capability defines the subject of improvement, and the maturity level determines the depth and complexity of the guidance. Figure 12 illustrates this relationship.

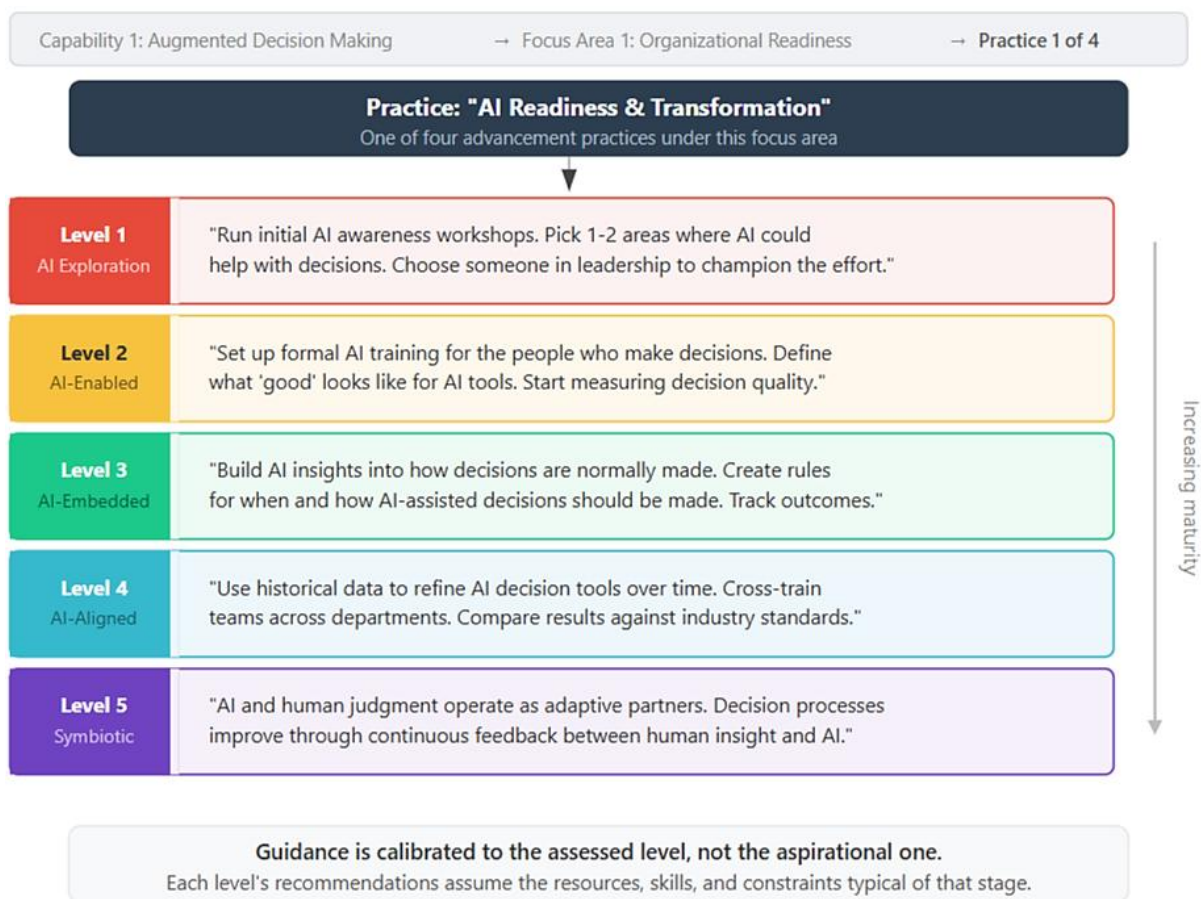


Figure 12: Level-Specific Advancement Practice Guidance

Consider a 60-person accounting firm that scores Level 2 (AI-Enabled) on *AI-Driven Process Optimization*. The advancement practices for that capability present guidance written specifically for Level 2 organizations. The firm does not see recommendations about adaptive feedback loops or continuous AI-driven workflow evolution. Those recommendations apply to Level 4 and Level 5 organizations. Instead, it receives practical next steps appropriate to its current stage, such as establishing formal training for staff, defining what effective AI tool use looks like, and beginning to measure decision quality so progress can be tracked.

In this way, the improvement plan reflects both the organization's current maturity and the specific capability requiring attention.

4.3.6.3. What the Organization Receives

For each capability, the reports present three outputs: where the organization stands (its current maturity level and what that level typically looks like in practice), what effective performance looks like at that level (not at Level 5, but at the level the organization has actually reached), and what the next level requires as an advancement target. The advancement practices under each capability provide the specific, sequenced initiatives to close the distance between the current level and the next.

4.3.7. Advancement Practice Structure

Most maturity models treat AI adoption as a single trajectory. An organization invests in technology, trains its workforce, and gradually moves upward through maturity levels. HAIC-MM recognizes that this view is incomplete. The 30 source frameworks synthesized in Chapter 3 came from three distinct research domains, and each domain emphasized a different aspect of what makes AI adoption succeed. HMT research focused on whether people are prepared; AI maturity

models focused on whether the technology performs; DT frameworks focused on whether the integration between the two works. These perspectives do not overlap neatly. An organization can have a highly skilled workforce that distrusts an AI system deployed without adequate transparency regarding its outputs, or sophisticated AI tools that sit unused because processes were never redesigned to incorporate them. Rather than blending these perspectives into a single composite score, as every model reviewed in Chapter 2 does, HAIC-MM maintains them as three separate measurement streams. These became the HAIC pillars.

- *Human-Centric Pillar [H]* assesses workforce readiness for AI. It draws on capabilities such as Leadership AI Literacy, Workforce AI Adaptability, and Psychological Safety in AI Collaboration. Questions tagged [H] evaluate workforce skills, governance, and cultural readiness.
- *AI-Centric Pillar [A]* addresses the technology dimension, including AI deployment, system integration, and data management. Questions tagged [A] evaluate the capabilities of AI systems, the supporting infrastructure, and the effectiveness of data management. Capabilities contributing to this pillar include AI-Driven Process Optimization, AI Integration Effectiveness, and AI Data Compliance.
- *Collaborative Pillar [C]* examines how effectively humans and AI work together. It does not measure workforce skills alone or technology performance alone. Instead, it focuses on the interaction between them. Capabilities such as Human-AI Collaboration Quality, Human-AI Task Flow, and Adaptive Task Allocation contribute to this pillar.

Each of the 160 assessment questions carries one of these three tags. Respondents answer the questions on a 1-to-5 scale. The platform then uses these tags to calculate separate [H], [A], and [C] scores for each capability. Figure 13 illustrates this structure.

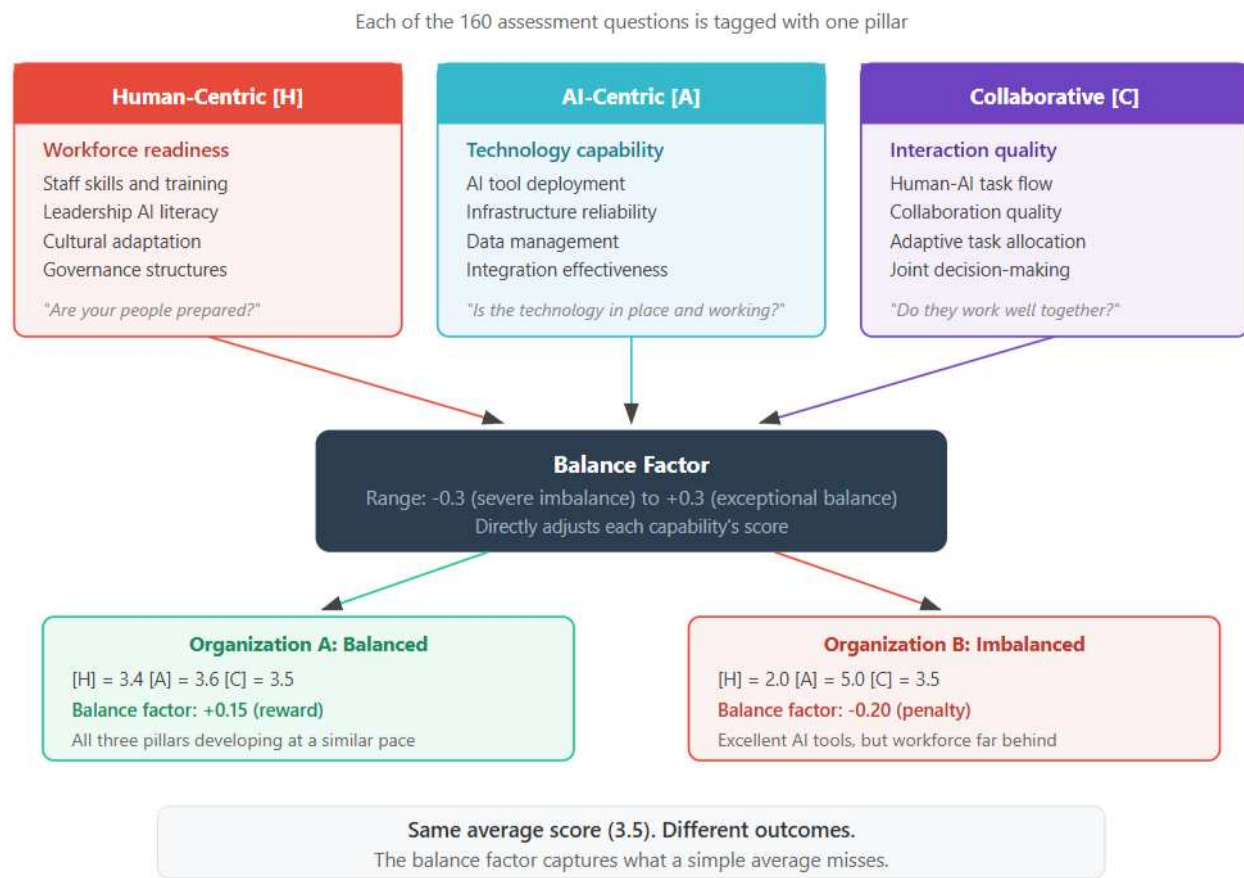


Figure 13: Three HAIC Pillars and the Balance Factor

4.3.7.1. Importance of the Three Separate Scores

Maintaining three separate pillar scores, rather than combining them into a single average, allows the model to determine whether the organization is developing all aspects of collaboration at a similar pace. A traditional maturity model typically averages all responses and reports a single value. However, that average can conceal important differences. An organization where the workforce, AI tools, and their interaction develop together is in a fundamentally different position than one where technology advances faster than the people who use it, even if the numerical average appears identical.

HAIC-MM addresses this through a Balance Factor that rewards balanced development and penalizes uneven investment. The Balance Factor is calculated for each capability and applied directly to the capability score. Scores increase when the three pillars are aligned and decrease when they diverge.

Section 4.4 presents the mathematical framework for this calculation, including the collaboration bonus, the variance penalty formulas, parameter ranges, and a worked comparison of two organizations with identical averages but different collaboration outcomes.

The pillar scores also support a second diagnostic layer. The five Success Factors, described in the next section, evaluate whether the organization's underlying structure can sustain the maturity level suggested by the scores.

4.3.8. Five Success Factors: The Organizational Foundation

Capability scores indicate how an organization performs in specific areas. They do not reveal whether the organization has the underlying conditions needed to sustain that performance. The five HAIC Success Factors cut across all dimensions and capabilities. These five factors were not selected arbitrarily. They emerged from a pattern observed across the 30 source frameworks during the synthesis in Chapter 3. Regardless of domain, models that addressed long-term capability sustainment identified a common set of organizational enablers: HMT research emphasized trust and transparency, AI maturity models highlighted process integration and risk governance, and digital transformation frameworks identified change readiness and knowledge circulation as determinants of whether technology investments persist or erode. These five themes recurred with enough consistency across all three domains to justify treating them as cross-cutting factors:

- *Trust & Communication* measures employee trust in AI systems and the quality of organizational communication about AI. Organizations score highly when employees understand how AI recommendations are generated and feel comfortable raising concerns. Scores decline when AI tools are introduced without explanation or when employees are expected to follow AI outputs without question.
- *Process Integration* measures how effectively AI is embedded in existing business processes. It assesses not whether an organization possesses AI tools, but whether those tools are integrated into everyday operations.
- *Risk Management* evaluates the organization's ability to identify and manage risks associated with AI adoption. These include technical risks (such as incorrect AI outputs), workforce risks (changes to roles or responsibilities), and ethical risks related to fairness and accountability.
- *Change Readiness* measures whether employees view AI as an opportunity or a threat and whether the organization provides adequate support for the transition. During pilot testing, this factor showed the greatest variability across participating SMEs, which aligns with broader research on organizational resistance to change.
- *Knowledge Sharing* measures how effectively AI-related knowledge circulates across teams. When successful practices remain isolated within individual departments, scores decline. When lessons learned and effective approaches spread across the organization, scores improve.

4.3.8.1. *Where Success Factors Come From*

The Success Factors are not a separate assessment. They are derived from the same 160 responses, analyzed through the three HAIC pillars. For each capability, the scoring engine

calculates pillar scores [H], [A], and [C], along with a Balance Factor [B]. These values are averaged across the 32 capabilities to produce overall scores. Each Success Factor then applies a different weighting formula to these values, reflecting which pillar contributes most to that organizational condition.

For example, *Trust & Communication* weights the collaborative pillar most heavily because trust develops when employees and AI systems evolve together. *Risk Management* places greater weight on the workforce pillar because employees ultimately make risk decisions, even when AI identifies potential issues.

Different weightings allow Success Factors to reveal weaknesses that individual capability scores may conceal. Consider a 40-person marketing agency that performs well on several risk-related capabilities: AI Ethical Oversight at 3.8, AI Data Compliance at 3.6, and AI Governance Effectiveness at 3.2. However, the *Risk Management* Success Factor returns a score of 2.5. This occurs because the calculation draws heavily from workforce pillar scores across all capabilities, and the broader organization lacks sufficient workforce readiness. Individual teams may manage AI risks effectively, but the wider workforce does not yet have the skills to manage those risks consistently. The Success Factor exposes this gap.

Capability scores measure specific skills. Success Factors measure whether the organization has the foundation to make those skills last.

4.3.8.2. Success Factors as Gatekeepers

Success Factors also serve as a verification step. After the scoring engine calculates the overall score and maps it to a maturity level, it checks whether the Success Factors meet the minimum threshold required for that level. Table 17 presents these thresholds.

Table 17: Success Factor Thresholds by Maturity Level

Maturity Level	Minimum Required Average for Success Factors
L1: AI Exploration	2.0
L2: AI-Enabled	2.5
L3: AI-Embedded	3.0
L4: AI-Aligned	3.5
L5: Symbiotic Partnership	4.0

If the average Success Factor score falls below the threshold, the maturity level is reduced. The system lowers the level by one step, checks the threshold again, and continues until it finds a level the organization can sustain.

Figure 14 illustrates this process. An organization receives an overall score of 3.5, which initially corresponds to Level 3. However, its Success Factor average is 2.7, below the Level 3 requirement of 3.0. The system therefore reduces the rating to Level 2, where the threshold is 2.5. Because the score of 2.7 meets this requirement, Level 2 becomes the verified maturity level.



Figure 14: Success Factor Checkpoint

This checkpoint functions like a building inspection. Capability scores represent visible elements such as finishes or fixtures. Success Factors represent the foundation and supporting structure. An organization may appear mature based on capability scores alone, but if the underlying conditions cannot support that performance, the maturity level cannot be sustained. The Success Factor checkpoint ensures that reported maturity levels reflect both current capability and the organizational capacity to maintain it.

4.3.9. Framework Summary

The framework layers are now established. *Dimensions* define the seven strategic areas of human-AI collaboration. *Capabilities* break these areas into 32 measurable aspects weighted by strategic importance. *Focus Areas* structure the assessment through five consistent lenses. *Advancement Practices*, 640 in total and each unique to its parent capability, provide sequenced improvement guidance calibrated to the organization's assessed maturity level.

Two diagnostic overlays add analytical depth. The *HAIC Pillars* measure whether collaboration is balanced across the workforce, the technology, and their interaction. The *Success Factors* assess whether the organizational foundation can sustain the assessed maturity level. Together, these structural layers and diagnostic overlays produce the full HAIC-MM scale shown in Figure 15: 32 capabilities decomposed into 160 focus areas, 640 advancement practices, and 3,200 unique level-specific guidance items.



Figure 15: HAIC-MM Hierarchical Structure and Full Framework Scale

4.4. Scoring Methodology

The dimensions, capabilities, and maturity levels define what HAIC-MM assesses. This section describes how the assessment generates scores. It introduces the mathematical framework that converts the 160 responses into capability scores, dimension scores, Success Factor ratings, and an overall maturity level. The methodology accounts for imbalances across capability areas that traditional averaging approaches often conceal.

4.4.1. Hierarchical Scoring Structure

HAIC-MM uses a bottom-up scoring approach. Scores flow upward through four levels, from individual question responses to an overall organizational maturity assessment. Figure 16 illustrates this flow.



Figure 16: HAIC-MM Scoring Flow

4.4.2. Score Calculations

HAIC-MM yields an overall HAIC-MM maturity level for the organization, for each dimension, for each Success Factor, and for each capability. Scores are computed and then assigned a maturity level based on the thresholds listed in Table 18.

Table 18: Maturity Level Thresholds

Maturity Level	Score Range
L1	0.00 - 1.99
L2	2.00 - 2.99
L3	3.00 - 3.79
L4	3.80 - 4.49
L5	4.50 - 5.00

4.4.2.1. Pillar Score Calculations

The first step is converting responses into Human, AI, and Collaborative scores, representing the three HAIC Pillars, for each capability. This is achieved by computing the average score of the human-centric questions (Equation 1), AI-centric questions (Equation 2), and collaborative-centric questions (Equation 3).

$$\text{Human Score} = \frac{Q_{H1} + Q_{H2}}{2} \quad (1)$$

$$\text{AI Score} = \frac{Q_{A1} + Q_{A2}}{2} \quad (2)$$

$$\text{Collab Score} = Q_C \quad (3)$$

4.4.2.2. Balance Factor Calculation

Then, the Balance Factor (Equation 4) is computed for each capability to reward human-AI collaboration and penalize human-AI imbalance. This Balance Factor is HAIC-MM's core scoring innovation. It addresses a practical problem that traditional maturity models ignore: two organizations can have identical average scores but completely different collaboration effectiveness.

$$\text{Balance Factor} = \left(\frac{\text{Collab Score}}{5} \right)^{1.5} \times 0.2 - \left(\frac{|\text{Human Score} - \text{AI Score}|}{5} \right)^{1.5} \times 0.3 \quad (4)$$

4.4.2.3. Dependency Impact Factor

Next, a dependency correction factor (Equations 5 and 6) is computed to account for prerequisite capabilities to ensure realistic progression. Specifically, when a capability requires a certain level of maturity of another capability. Figure 17 illustrates how this correction operates: each unmet prerequisite reduces a capability's score in proportion to its impact level, so capabilities that depend on underdeveloped foundations cannot inherit an inflated rating from their own performance alone.

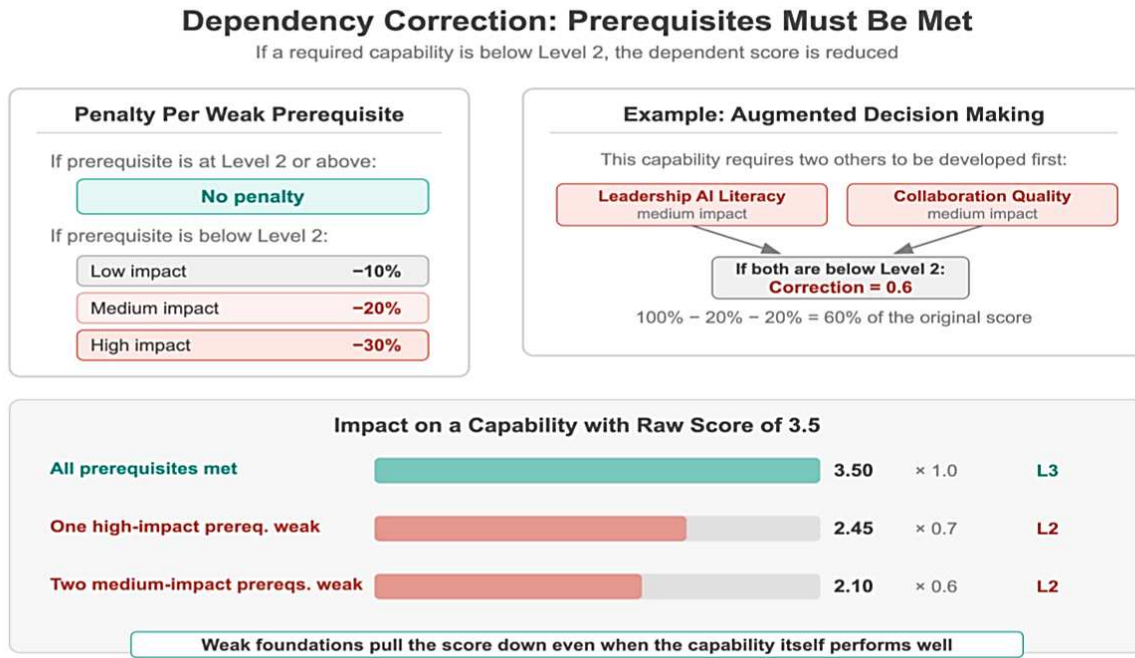


Figure 17: Dependency Correction Factor: Penalty per Unmet Prerequisite

$$\text{Impact}_{\text{req}} = \begin{cases} 0.1, & \text{if Capability Level}_{\text{req}} < 2 \text{ and Impact Level} = \text{Low} \\ 0.2, & \text{if Capability Level}_{\text{req}} < 2 \text{ and Impact Level} = \text{Medium} \\ 0.3, & \text{if Capability Level}_{\text{req}} < 2 \text{ and Impact Level} = \text{High} \\ 0, & \text{if Capability Level}_{\text{req}} \geq 2 \end{cases} \quad (5)$$

$$\text{Dependency Correction} = 1 - \sum \text{Impact}_{\text{req}} \quad (6)$$

These capability prerequisite requirements are provided in Table 19.

Table 19: Dimensions, Capabilities, Weights, and Dependencies

Dimension	Capability ID	Capability Weight	Required Capability capability ID (impact)
1: AI-Enhanced Leadership and Strategy <i>Dimension Weight = 1.4</i>	1	1	2 (medium), 13 (medium)
	2	1.4	4 (low)
	3	1	14 (high)
	4	1.2	5 (high), 7 (high)
	5	1	--
2: Adaptive AI Culture and Empowerment <i>Dimension Weight = 1.2</i>	6	1.2	3 (high)
	7	1	6 (medium), 13 (medium)
	8	1.2	5 (high), 6 (low)
	9	1	--
3: Human-Centric AI Integration and Experience <i>Dimension Weight = 1.0</i>	10	1.2	15 (high), 16 (high)
	11	1	10 (high), 15 (high)
	12	1	9 (high), 11 (medium)
	13	1.2	11 (high), 12 (high)
	14	1	12 (high), 13 (medium)
4: Harmonizing AI and Human Processes <i>Dimension Weight = 1.2</i>	15	1.2	5 (high), 9 (high)
	16	1	15 (medium)
	17	1	15 (high), 16 (high)
	18	1	17 (high)
5: Human-Centered AI Customer Engagement <i>Dimension Weight = 1.2</i>	19	1.2	10 (high), 17 (High)
	20	1	15 (medium), 19 (high)
	21	1	17 (medium), 20 (high)
	22	1	13 (medium), 21 (high)
6: AI Ethics and Human Oversight <i>Dimension Weight = 1.4</i>	23	1.4	31 (high)
	24	1.4	--
	25	1	24 (high)
	26	1	14 (medium), 25 (high)
	27	1.2	25 (high), 26 (high)
7: Inclusive AI Governance and Learning	28	1	27 (high)
	29	1	24 (high), 28 (high)
	30	1.2	8 (high)

<i>Dimension Weight = 1.0</i>	31	1	13 (medium), 29 (high)
	32	1.2	6 (high), 30 (high)

4.4.2.4. Organization Size Adjustment

A 12-person consulting practice and a 200-person manufacturing firm both qualify as SMEs, but their capacity to adopt AI differs considerably. The smaller firm likely has no dedicated IT staff and operates with a technology budget limited to subscriptions; the larger firm may have a small IT department and enough operational volume to justify dedicated automation investments. Scoring both against the same expectations would penalize the smaller firm for constraints outside its control.

HAIC-MM addresses this through an organization size factor. During assessment registration, organizations identify whether they are small (1 to 50 employees) or medium (51 to 250 employees), and the scoring engine applies the corresponding adjustment factor from Table 20.

Table 20: Organization Size Adjustment Factors

Organization Size	Employee Range	Adjustment Factor
Small	1 to 50	0.8
Medium	51 to 250	1.0

The 0.8 factor for small organizations reflects that firms with fewer than 50 employees typically lack dedicated AI expertise and must rely on staff covering multiple roles. Medium organizations serve as the baseline at 1.0. In practice, a small firm scoring 4.0 on a capability receives an adjusted 3.2, moving from Level 4 (AI-Aligned) to Level 3 (AI-Embedded), which better represents what a 12-person firm can realistically sustain. The calibration ensures that a

given maturity level carries the same meaning regardless of organization size, given that both categories face resource constraints but at different scales. These factors are configurable parameters in the assessment system and can be adjusted as AI tools become more accessible to smaller firms.

4.4.2.5. *Capability Level Calculations*

The capability score can then be calculated using Equation 7, which integrates the Balance Factor (Equation 4), the Dependency Correction (Equation 6), and the Organization Size Factor (Table 20). The maturity level for that capability is assigned based on the thresholds in Table 18.

$$\text{Capability Score} = \frac{\text{Human Score} + \text{AI Score} + \text{Collab Score}}{3} \times \text{Balance Factor} \times \text{Dependency Correction} \times \text{Org Size Factor} \quad (7)$$

Since the adjustments are multiplicative, their effects compound. A capability with weak prerequisites in a small organization where the HAIC Pillar scores also diverge will receive a score that reflects all of these constraints at once, preventing the methodology from assigning maturity levels that the organization's actual conditions cannot support.

4.4.2.6. *Dimension Level Calculations*

A maturity level for each of the seven dimensions is computed based on the scores for the capabilities within the dimension, which are weighted based on the relative importance of each capability. Table 19 provides the weight for each capability, as well as the capabilities within each dimension. The dimension score from Equation 8 can then be used to identify the maturity level using Table 18.

$$\text{Dimension Score} = \frac{\sum \text{Capability Score} \times \text{Capability Weight}}{\sum \text{Capability Weight}} \quad (8)$$

4.4.2.7. Overall Level Calculations

The overall organizational maturity score combines all dimension scores using weighted averaging that reflects each dimension's strategic importance to business success. These weights are provided in Table 19. This overall score can then be used to obtain the organization's overall maturity level using Table 18.

$$\text{Overall Score} = \frac{\sum \text{Dimension Score} \times \text{Dimension Weight}}{\sum \text{Dimension Weight}} \quad (9)$$

4.4.2.8. Success Factor Calculations

Each of the five Success Factors are first computed at the capability level and then averaged across all capabilities to obtain a single value for that Success Factor, see Equation 10. No weighting is applied in these calculations, such that all capabilities contribute equally to each Success Factor.

$$\text{Success Factor}_i = \frac{\sum_{j=1}^{32} \text{Capability Score}_j}{32} \quad \text{for } i = 1, \dots, 5 \quad (10)$$

Trust & Communication (Equation 11) measures stakeholder confidence in human-AI systems and communication effectiveness. For SMEs, this directly affects customer retention and employee engagement because smaller organizations cannot afford the reputation damage from poor AI experiences.

$$\text{Trust and Comm.} = (\text{Collab Score} \times 0.5) + (\text{Balance Factor} \times 0.3) + (\text{Capability Score} \times 0.2) \quad (11)$$

Process Integration (Equation 12) measures operational efficiency and workflow coordination quality. SMEs depend on streamlined operations with minimal waste, making human-AI process integration a competitive necessity rather than an optimization opportunity.

$$\text{Process Integ.} = (\text{Human Score} \times 0.2) + (\text{AI Score} \times 0.4) + (\text{Collab Score} \times 0.3) + (\text{Balance Factor} \times 0.1) (12)$$

Risk Management (Equation 13) measures governance effectiveness and oversight capability. SMEs face amplified risk because they lack the resources to recover from significant AI-related failures, requiring proactive risk management approaches.

$$\text{Risk Manag.} = (\text{Human Score} \times 0.4) + (\text{AI Score} \times 0.3) + (\text{Collab Score} \times 0.2) + (\text{Balance Factor} \times 0.1) (13)$$

Change Readiness (Equation 14) measures adaptation capability and innovation readiness. SMEs must adapt quickly to market changes, and their ability to evolve human-AI collaboration directly determines their market responsiveness.

$$\text{Change Read.} = (\text{Human Score} \times 0.4) + (\text{AI Score} \times 0.1) + (\text{Collab Score} \times 0.3) + (\text{Balance Factor} \times 0.2) (14)$$

Knowledge Sharing (Equation 15) measures learning effectiveness and continuous improvement capability. SMEs rely on institutional knowledge retention and cross-training more than larger organizations, making effective human-AI knowledge sharing critical for operational continuity.

$$\text{Knowl. Shar.} = (\text{Human Score} \times 0.3) + (\text{AI Score} \times 0.2) + (\text{Collab Score} \times 0.4) + (\text{Balance Factor} \times 0.1) (15)$$

4.5. Discussion

4.5.1. How the Scoring Methodology Operationalizes the Model's Principles

The scoring methodology translates the theoretical principles of HAIC-MM into measurable outputs. Three design choices are particularly important.

First, the 2-2-1 question structure of the HAIC Pillars enables the Balance Factor. Each capability includes two human-centric questions, two AI-centric questions, and one collaborative question. The distribution reflects the nature of what each pillar measures: human readiness and AI capability each involve multiple facets that a single question cannot adequately capture, while collaboration quality is a joint property that emerges from the interaction between the two sides. During focus group testing, a single focused question about the working relationship proved more diagnostically useful than attempts to decompose collaboration into subcomponents. This structure produces separate pillar scores rather than a single blended value, allowing the assessment to detect whether capabilities are developing in alignment or diverging.

Second, the Balance Factor directly addresses the existing gap in many maturity models, which rely on simple averages for defining maturity levels. Specifically, traditional models calculate a single composite score that treats balanced and unbalanced organizations as equivalent. HAIC-MM instead evaluates how well human, AI, and collaborative capabilities develop together.

Lastly, realistic progression is enforced through the dependency system. Organizations cannot claim advanced capabilities if the necessary prerequisites are underdeveloped. For example, an organization cannot demonstrate AI-driven innovation without first establishing data quality or workforce AI literacy. The dependency map reduces capability scores when prerequisite capabilities remain weak. This prevents inflated maturity classifications that can occur when capability development is treated as an independent checklist rather than a connected progression.

4.5.2. Balance-Based Scoring vs. Traditional Averaging

The value of balance-based scoring becomes clearer when compared with traditional averaging approaches. In a traditional model, Organization A (balanced: Human 3.6, AI 3.4, Collaborative 3.4) and Organization B (unbalanced: Human 2.3, AI 4.8, Collaborative 2.8) would receive nearly identical scores of about 3.45. Both organizations would likely be placed at the same maturity level and given similar recommendations.

HAIC-MM produces a different outcome. Organization A is classified at Level 4 (AI-Aligned), while Organization B is classified at Level 2 (AI-Enabled). The Balance Factor category also provides actionable insight. Organization A falls into the Excellent Partnership category, indicating that its current development approach is effective. Organization B falls into the Significant Gap category, showing that AI investment has outpaced workforce readiness and collaboration processes. The appropriate response for Organization B is therefore not additional technology investment, but improvements in human training and collaboration design. Figure 18 visualizes this contrast across the three pillars and the resulting maturity classification, demonstrating how the gap between Human and AI readiness in Organization B is invisible to a simple average but determinative under HAIC-MM.

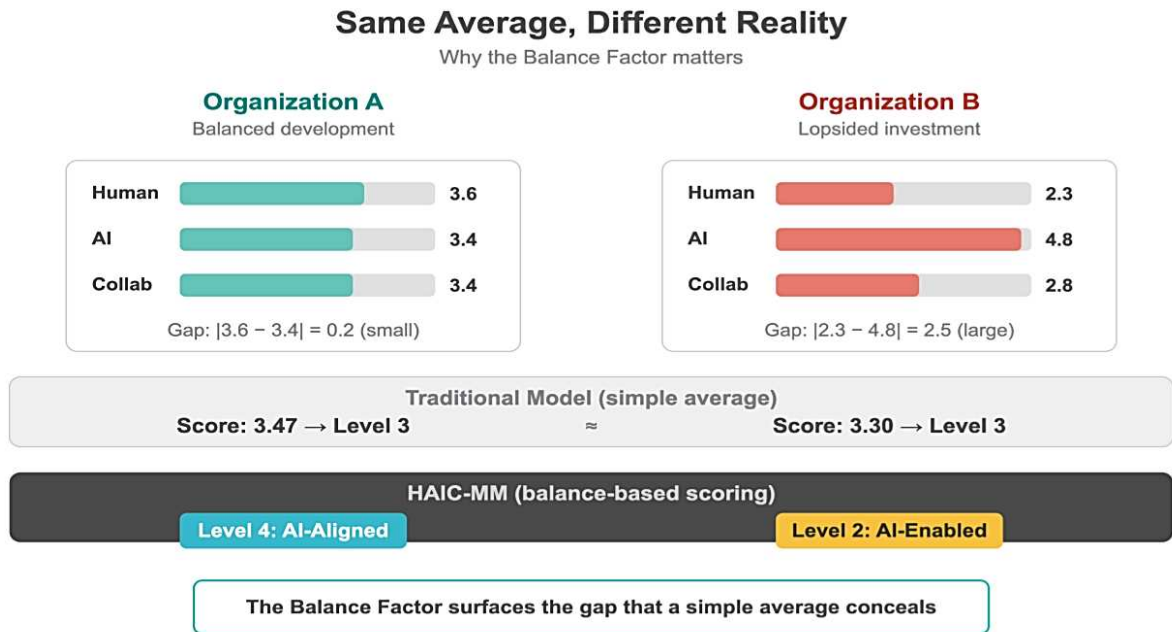


Figure 18: Difference Between Traditional Averaging and HAIC-MM Balance Factor

This distinction is particularly important for SMEs. Large enterprises can often correct misallocated investments in later budget cycles. SMEs typically operate with far more limited resources. Investing in additional AI technology when the primary constraint is workforce readiness may prevent them from realizing the intended benefits of AI adoption.

4.5.3. Dependencies and Realistic Progression

The dependency system addresses a common failure pattern in AI adoption: organizations pursuing advanced initiatives before establishing the foundations required to support them. The complete dependency map highlights several important patterns.

Some foundation capabilities have no prerequisites and serve as natural starting points. *AI Adoption Readiness Assessment* (Capability 5) and *AI Data Compliance* (Capability 24) fall into this category. These capabilities can be developed independently and support multiple downstream

capabilities. For example, AI Adoption Readiness Assessment supports AI Strategy Alignment, Workforce AI Adaptability, and AI-Driven Process Optimization. AI Data Compliance supports AI Governance Effectiveness, which then extends to AI Operational Transparency, Responsible AI Practices, and eventually to Equity and Fairness Assessment and Inclusive AI Decision-Making.

Other capabilities appear at the end of longer dependency chains. Examples include *Adaptive AI Workforce Upskilling* (Capability 32), which depends on Capabilities 6 and 30, and *Implementing Inclusive AI Decision-Making* (Capability 31), which depends on Capabilities 13 and 29. These represent advanced maturity states that require earlier capabilities to be established first.

By enforcing these relationships, the dependency system encourages realistic capability development and prevents organizations from claiming maturity levels that are not supported by the necessary foundations.

4.5.4. The Integrated System: From Assessment to Actionable Output

The preceding sections described the individual components of the scoring methodology: pillar scores, the Balance Factor, dependency corrections, organization size adjustments, capability and dimension scoring, and Success Factor calculations. Each component addresses a limitation of traditional maturity models. This section explains how these elements operate together as an integrated system and what the SME practitioner experiences when using the platform.

The framework includes seven dimensions, 32 capabilities, 160 focus areas, and 640 advancement practices. At first glance, this structure may appear complex for an SME with fewer than 100 employees. In practice, the complexity is handled by the platform rather than the

practitioner. The SME leader answers 160 questions in approximately 60-90 minutes, while the platform performs the remaining analysis.

4.5.4.1. Two Parallel Analysis Streams

The 160 responses generate two analytical streams that together produce the final result. Figure 19 presents this scoring architecture at a glance, showing how the framework structure and the diagnostic overlays converge at the Success Factor checkpoint to produce a verified maturity level. Figure 20 then traces the path from those assessment responses to a prioritized improvement plan.

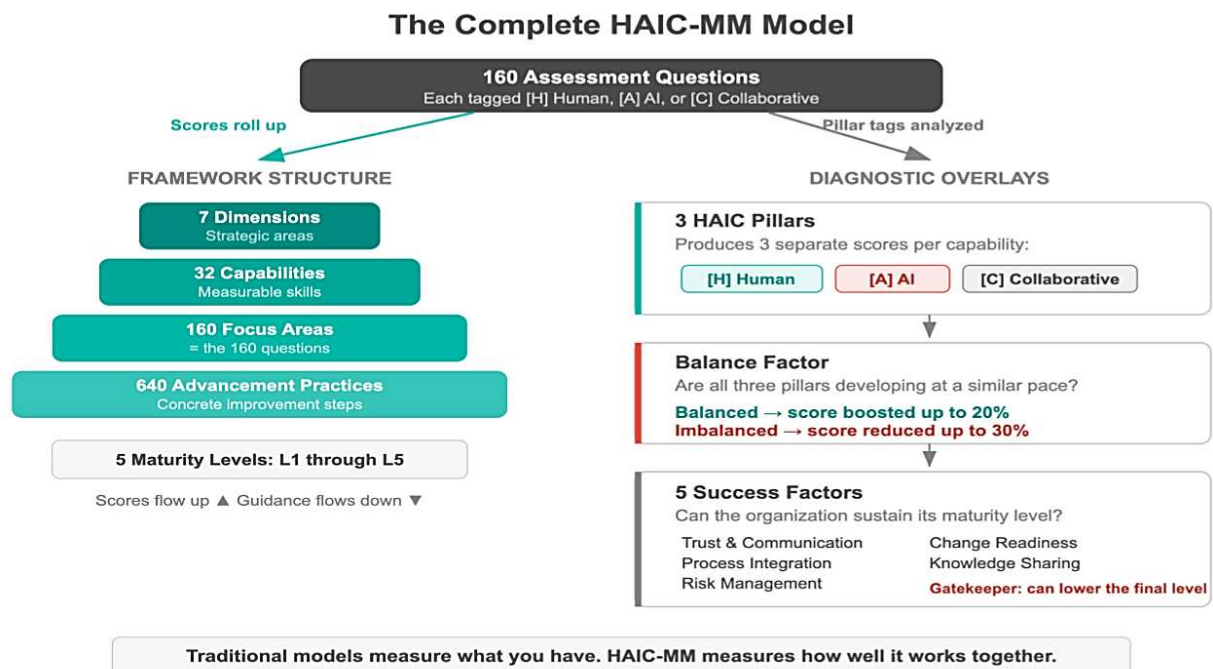


Figure 19: Diagnostic Overlays Converging at the Success Factor Checkpoint

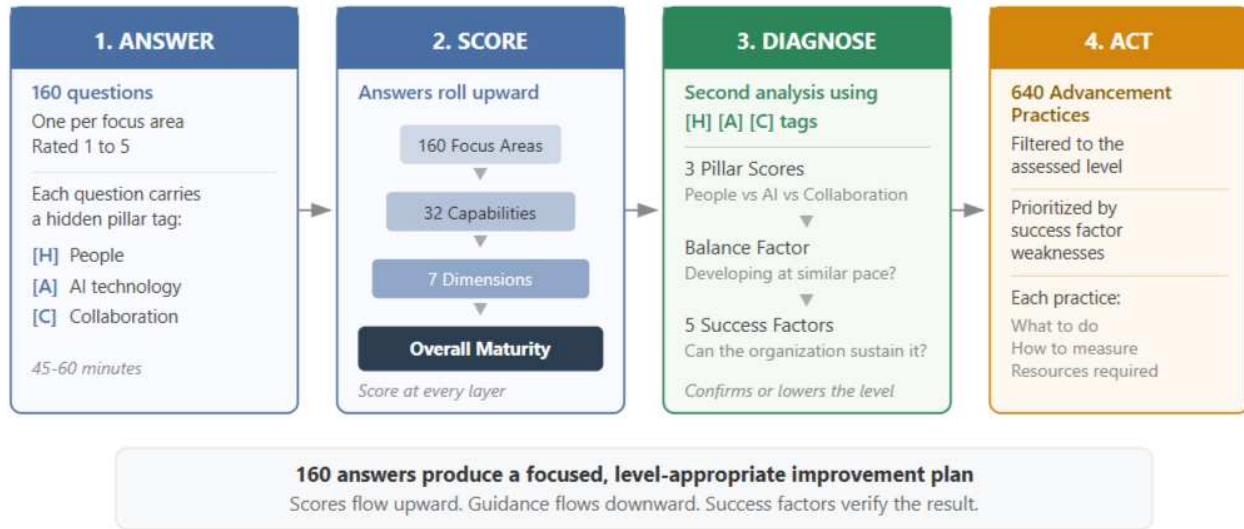


Figure 20: From 160 Questions to a Prioritized Action Plan

The first stream follows the hierarchical structure of the model. Focus area scores aggregate into capability scores, adjusted for dependencies, balance, and organization size (Equations 5–7). Capability scores combine into dimension scores (Equation 8), which then produce an overall maturity level (Equation 9). This stream establishes the organization’s position across each layer of the framework.

The second stream analyzes the same responses through the HAIC pillar tags. Because each question is tagged as human-centric [H], AI-centric [A], or collaborative [C], the platform calculates pillar performance across the organization. This analysis produces the Balance Factor and the five Success Factors. These metrics reveal patterns that hierarchical scores alone cannot detect, such as whether workforce readiness, AI capability, and collaborative processes are developing at similar rates.

The two streams converge at the Success Factor checkpoint. The hierarchical analysis proposes a maturity level based on capability performance. The cross-cutting analysis verifies whether the organization can sustain that level. If Success Factor scores fall below the required

threshold, the system lowers the maturity level until the organizational foundation supports the result. The outcome is a verified maturity level reflecting both capability performance and organizational readiness.

4.5.4.2. From Verified Level to Improvement Plan

The verified maturity level drives the model's prescriptive output. Each focus area's maturity score selects the appropriate version of its four advancement practices, ensuring that recommendations match the organization's current stage. Success Factor scores help prioritize which areas require attention. Figure 21 shows the complete system.

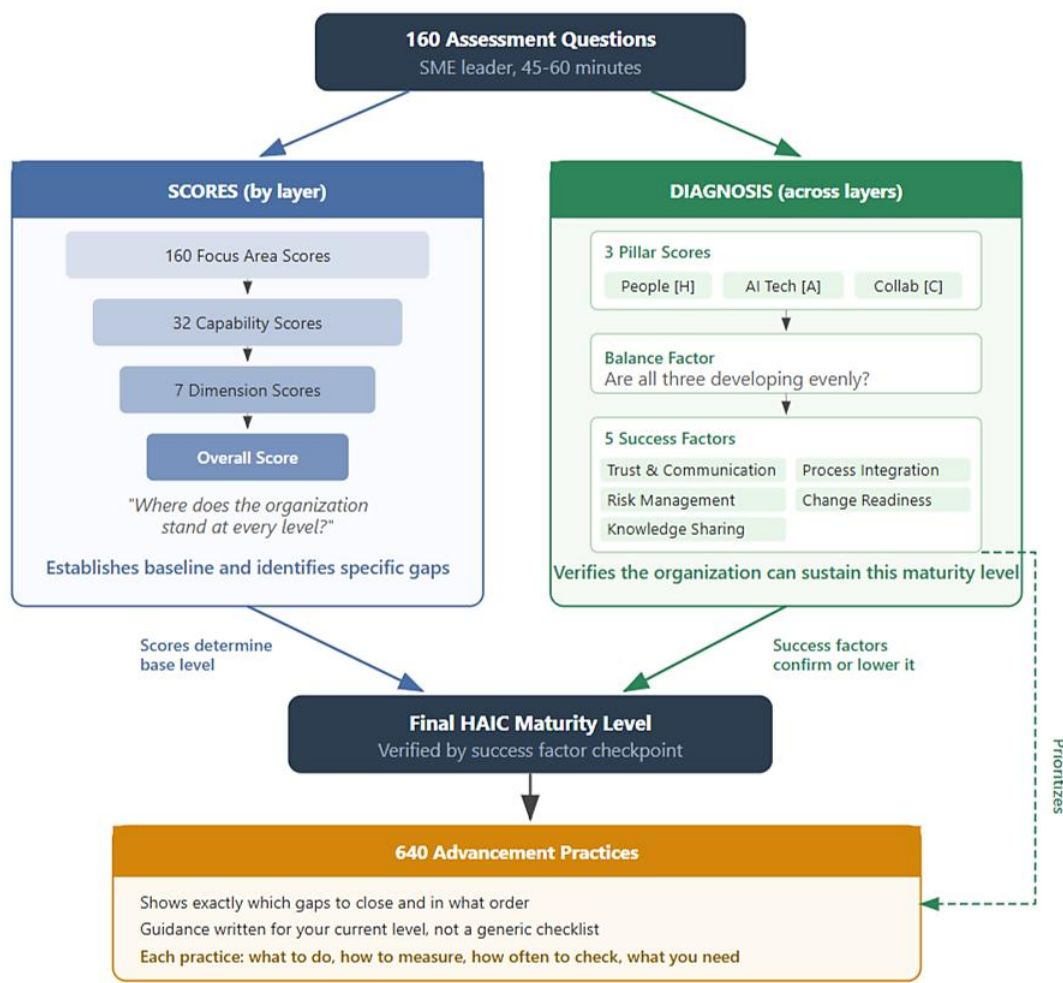


Figure 21: The Complete HAIC-MM System

Consider the accounting firm example introduced in Section 4.3.6. The platform identifies an overall Level 3, but Level 2 in AI-Driven Process Optimization and a weak Change Readiness Success Factor. The resulting improvement plan emphasizes Level 2 practices for process optimization and organizational readiness initiatives to prepare staff for operational change.

This output results from the interaction of multiple scoring mechanisms. Hierarchical scoring identifies weak capabilities. The Balance Factor reveals whether weaknesses arise from misalignment between workforce and technology. Dependency analysis indicates whether missing prerequisites are responsible. Success Factors identify organization-wide conditions such as trust or change readiness. Advancement practices translate these findings into sequenced improvement steps tailored to the organization's maturity level.

4.5.4.3. Why This Matters for SMEs

The multi-layered structure exists to convert a broad question into specific, actionable guidance. Instead of asking only, “How effective is our human–AI collaboration?”, the system can identify concrete issues such as low employee trust in AI-generated recommendations and propose targeted initiatives to address them.

For SMEs without dedicated AI strategy teams, this distinction is critical. Traditional maturity models often produce a score but leave interpretation to the organization. HAIC-MM generates a score, verifies that it reflects operational reality through Balance and Success Factor checks, and converts the result into a prioritized improvement plan that accounts for organization size, capability dependencies, and cross-cutting organizational conditions.

The SME leader answers 160 questions. The integrated system performs the analysis and produces the improvement roadmap.

The framework was structurally validated through a 100-participant survey and refined through five practitioner focus groups. The resulting scoring methodology converts assessment responses into actionable maturity scores that distinguish genuine human–AI collaboration from superficial AI adoption. Chapter 5 presents the pilot deployment used to evaluate the framework in practice.

Chapter 5. Aim 2 - Refinement of HAIC-MM

5.1. Introduction

Chapter 3 produced the preliminary HAIC-MM framework. Although this structure was grounded in existing research, it had not yet been tested against the judgment of practitioners responsible for AI adoption in SMEs. A framework derived solely from literature risks being theoretically sound but practically disconnected from operational realities. For this reason, an empirical refinement process was required to transform the preliminary model into a validated and deployable assessment tool.

Two rounds of empirical refinement were conducted to evaluate and improve the model's clarity, relevance, and usability. The first round used a survey study with 100 professionals to provide broad quantitative validation that the model's dimensions and capabilities resonated with practitioners involved in AI adoption. The second round used five focus group sessions with ten industry practitioners to provide deeper qualitative refinement by testing descriptions, identifying gaps, and revising content to better reflect SME operational realities.

These methods formed a sequential mixed methods refinement process that combined broad practitioner feedback with deeper collaborative evaluation. The results of this chapter have been published in the INCOSE Systems Engineering journal, titled "Advancing human-AI collaboration in small and medium-sized enterprises: A systems engineering approach" (Ortolano & Gallegos, 2025). This chapter addresses Research Aim 2 through the following research questions.

- **RQ2.1:** How do stakeholder survey responses inform the refinement of the HAIC-MM's capabilities?

- **RQ2.2:** How do insights from practitioner focus groups contribute to improving the clarity, relevance, and practical applicability of HAIC-MM dimensions and assessment questions?

5.2. Round 1 – Validation and Refinement of Dimensions and Capabilities

A quantitative analysis via an online survey was conducted to validate the dimensions (7) and capabilities (28) of the proposed HAIC-MM framework. This survey targeted industry experts, subject matter specialists, and AI practitioners to assess the model's applicability, relevance, and construct validity within professional settings.

5.2.1. Methodology

A total of 100 participants (50 males, 50 females) completed the survey. Participants represented diverse organizational roles: middle management (N=29), senior management (N=9), director (N=51), and c-level executive (N=11). There was also a wide range of age groups represented: 25-34 years old (N=22), 35-44 y.o. (N=43), 45-54 y.o. (N=21), and 55+ y.o. (N=14). They were recruited through a paid panel via PollFish, targeting working professionals in the United States who met the following inclusion criteria: (1) at least 18 years old; (2) completed at least a bachelor's degree; (3) currently employed at a company with 100-500 employees; and (4) at least some involvement with AI adoption, usage, or planning within their organization.

The survey took on average 14.5 minutes to complete. The survey included demographic questions, and 47 questions related to their perceptions of AI within their organization. Specifically, there were 14 questions used to assess our HAIC-MM dimensions (2 questions per dimension) and 27 questions to assess our HAIC-MM capabilities (1 question per capability).

The questions were asked using a 6-point Likert scale, with higher scores indicating stronger agreement or perceived importance. Participants were asked questions related to each dimension and capability without being presented with the HAIC-MM directly. For example, to assess the "Collaborative Strategy and Leadership" dimension, participants responded to statements about the importance of integrating AI into strategic planning and leaders being knowledgeable about AI tools.

5.2.2. Results

5.2.2.1. Participant Experience with AI within Organizations

Participants reported varying levels of involvement with AI in their organizations. The majority (65%) reported “direct involvement in strategic planning and decision-making for technology, including AI.” There were 17% that reported that they “contribute to the evaluation and selection of technology and AI-based solutions.” And 9% each to the categories of “participate in discussions or provide input on adoption new technologies or AI-based solutions” and “regularly use technology or AI-based solutions as part of job functions.”

5.2.2.2. Validation of HAIC-MM Dimensions

Participants were asked about their perceptions of each dimension relative to successful integration of human-AI teaming within the workplace. Each dimension was assessed across two questions. Depending on the wording of the question, participants were asked on a 6-point Likert scale to assess the importance, significance, agreement, criticality, essentialness, beneficial, or vitalness of the statement. Results indicate that across all seven dimensions, mean scores were above 4.3 out of 6, displaying support for inclusion in the HAIC-MM, see Table 21.

Table 21: Summary of Participant Scores on 6-Point Likert Scale for Each Dimension

HAIC-MM Dimension	Question 1		Question 2	
	<i>Mean</i>	<i>Scale</i>	<i>Mean</i>	<i>Scale</i>
Collaborative Strategy Leadership	5.2	Importance	5.0	Agreement
Empowerment and Adaptive Culture	4.4	Importance	4.2	Criticality
Integrated Tech. and User Experience	4.8	Importance	4.7	Essential
Process Harmonization	4.8	Importance	4.8	Beneficial
Human-Centric Customer Engagement	4.3	Significance	4.5	Essentialness
Data Ethics and Human Oversight	4.8	Importance	4.5	Vitalness
Inclusive Goals and Continuous Learning	4.6	Importance	4.6	Significance

5.2.2.3. Validation of HAIC-MM Capabilities

Similarly, 6-point Likert scale questions were used to assess each capability. Given the relatively large number of capabilities, only one question per capability was asked. Each question described the capability, and asked participants about their perceived significance of the statement on integrating humans with AI effectively. Figure 22 presents these mean scores for each capability within their respective dimensions. This visualization demonstrates a consistently high level of significance assigned to individual capabilities across dimensions, reflecting positive evaluations of the framework’s approach to measuring effective human-AI collaboration.

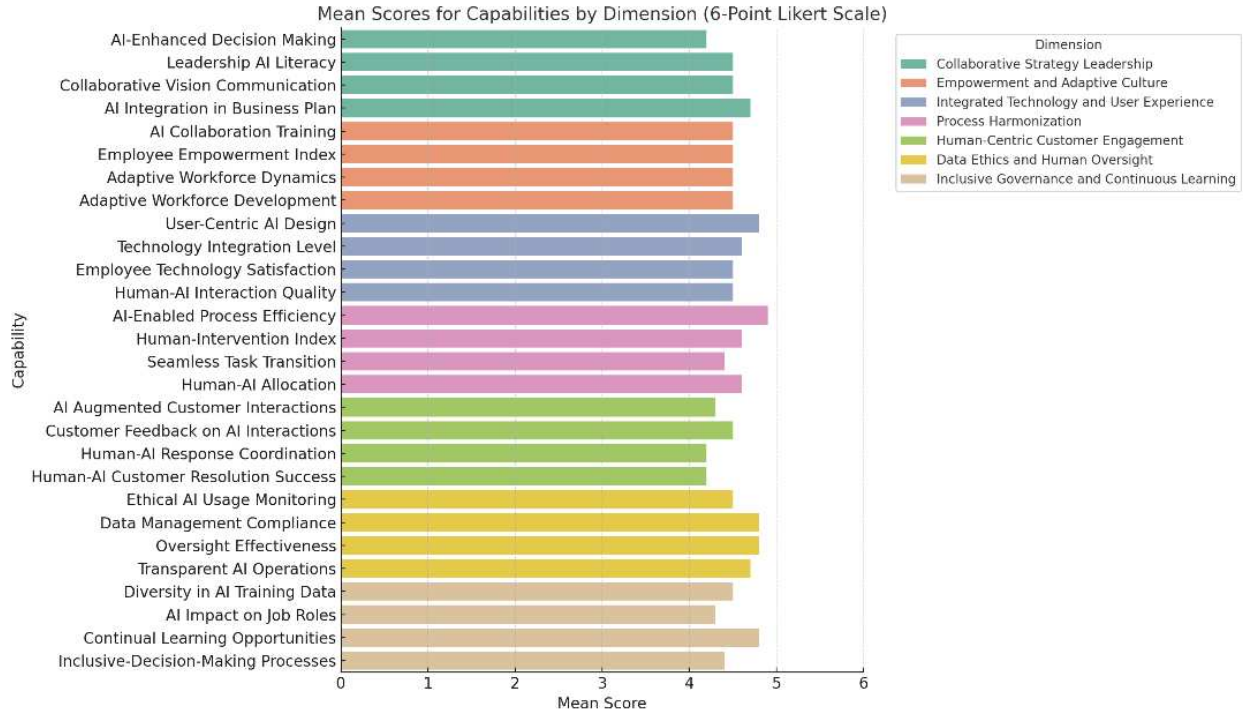


Figure 22: Mean Scores (out of 6) for Capabilities by Dimension

5.2.3. Summary

While the survey results indicated consistently high perceived importance across most capabilities rather than sharp differentiation, this quantitative analysis (N=100) served a crucial purpose: it provided broad validation that the fundamental dimensions and capabilities identified for the HAIC-MM resonated as relevant and comprehensive with industry professionals involved in AI adoption. This confirmation provided a solid foundation for the subsequent, more in-depth qualitative refinement through focus groups, where nuances and specific contextual factors could be explored in greater detail.

5.3. Round 2 – Validation and Refinement of Dimensions and Assessment Questions

There were five focus group sessions conducted to further validate and refine the HAIC-MM. The first set (Sessions 1 and 2) focused on reviewing the model's dimensions, capabilities,

and maturity levels to establish their necessity and comprehensiveness. The second set (Sessions 3, 4, and 5) concentrated on refining the 'current state' descriptions for each capability across the five maturity levels, ensuring they accurately reflect small and medium-sized enterprises (SMEs) realities. These current state descriptions provide the context within each capability and maturity level cross section for an SME to identify how they score for each capability.

5.3.1. Methodology

A total of 10 participants from various leadership roles and industry backgrounds participated in the focus groups. The job position of each participant is as follows: Director of IT Operations; VP of Engineering; Director of Process Improvement; VP of Human Resources; VP of Claims Management; Director of Customer Service; Marketing Manager; Digital Product Manager; Finance Director; and VP of Sales.

All participants attended both sessions 1 and 2 all together. In these sessions, participants reviewed the HAIC-MM dimensions, capabilities, and maturity levels. Each session took approximately 90-minute. Discussions in these focus groups were guided by two primary questions: (1) Is there a clear and defined need for a Human-AI Collaboration Maturity Model, and (2) Do the proposed capabilities in the HAIC-MM comprehensively assess the ways in which humans and AI collaborate.

Participants were then divided into smaller groups for the subsequent set of focus group sessions, where each participant only participated in one session. In session 3 (N=3), session 4 (N=4), and session 5 (N=3), participants reviewed the current state descriptions for each capability within each of the five maturity levels. To allow for deeper discussion, each session only evaluated a subset of the current state descriptions. Specifically, session 3 evaluated the first 11 capabilities, session 4 evaluated the next 11 capabilities, and session 5 evaluated the last 10 capabilities. Since

each capability had a current state description across all five maturity levels, each session reviewed 55, 55, and 50 current state descriptions, respectively. Discussion in these focus groups were guided by three key questions: (1) Do the current state descriptions accurately reflect SME realities; (2) Are the descriptions realistic and relevant for SMEs; and (3) Do they demonstrate a logical progression across maturity levels.

The audio of participant discussions was recorded for all five sessions with participant consent. Each recording was then transcribed verbatim using Google Gemini's audio-to-text capabilities, producing one written transcript per session. Each transcript was then reviewed against its audio recording to correct misheard terms, speaker attribution errors, and any artifacts of the automated transcription process before coding began. The reviewed transcripts were imported into MAXQDA, a qualitative data analysis tool, using the free version available for academic use. Within MAXQDA, every comment was reviewed and tagged to support a sentiment analysis that captured participants' positive, neutral, and negative assessments of the HAIC-MM components. A sentiment score was then calculated using Equation 16, which ranges from -1 (entirely negative) to +1 (entirely positive).

$$Sentiment\ Score = \frac{N_{Positive\ Comments} - N_{Negative\ Comments}}{N_{Total\ Comments}} \quad (16)$$

Sentiment analysis was conducted through manual coding of the focus group transcriptions inside MAXQDA. Each comment was reviewed and classified as positive, neutral, or negative based on the expressed sentiment toward the HAIC-MM dimensions, capabilities, or maturity levels. Positive comments indicated agreement, support, or positive evaluation of the model components. Negative comments expressed disagreement, criticism, or identified weaknesses.

Comments that were factual, clarifying, or did not express a clear positive or negative evaluation were classified as neutral. Two researchers coded each transcript, and any discrepancies in classification were resolved through discussion to ensure consistency in the final sentiment assignment.

5.3.2. Results

5.3.2.1. Focus Groups Sessions 1 & 2

The initial two focus group sessions were conducted to gather essential feedback on the HAIC-MM's purpose and to refine the value and scope of its capabilities, laying a foundation for aligning the model with real-world human-AI collaboration needs.

A sentiment analysis was performed across all the comments that each participant said throughout Sessions 1 & 2, see Table 22. This revealed varying feedback across roles. Marketing (0.78) and Engineering (0.77) recorded the highest scores, showing strong model support in technical and customer-facing roles. The lowest score (0.00) from IT Operations, which was neutral, indicated a balanced, cautious view. The overall 0.54 sentiment score from the 185 comments reflected broad support for the HAIC-MM model, while highlighting the need for attention in technical and operational areas. This feedback distribution indicates that the model aligns with diverse stakeholder needs yet required targeted refinements.

Table 22: Sentiment Analysis by Participant for Sessions 1 and 2

Participant	Positive	Neutral	Negative	Total	Sentiment Score
Manager, Marketing	15	2	1	18	0.78
VP Engineering	18	3	1	22	0.77
VP Sales	13	2	2	17	0.65
Manager, Digital Products	11	2	1	14	0.71
Dir. Customer Service	12	2	2	16	0.63

VP Human Resources	12	3	1	16	0.69
Dir. Process Improvement	14	4	2	20	0.60
Dir. Finance	8	5	1	14	0.50
VP of Claims Management	10	8	2	20	0.40
Dir. IT Operations	8	12	8	28	0.00
Total	121	43	21	185	0.54

The analysis in Table 23 revealed considerable sentiment improvement across all HAIC-MM dimensions following the review and refinement of their purposes and descriptions. Initial sentiments were notably negative toward overall purposes, ranging from -0.5 (Harmonizing Processes) to -0.1 (Governance & Learning), indicating substantial initial concerns. Post-refinement, all dimensions achieved positive sentiments, with Ethics & Oversight and Customer Engagement showing the most dramatic improvements, reaching 0.9 from -0.3 and -0.2 respectively. The observed improvement in initial to final sentiment scores across all dimensions demonstrates the successful refinement of the model's dimensions purposes and strong stakeholder alignment with their final concept.

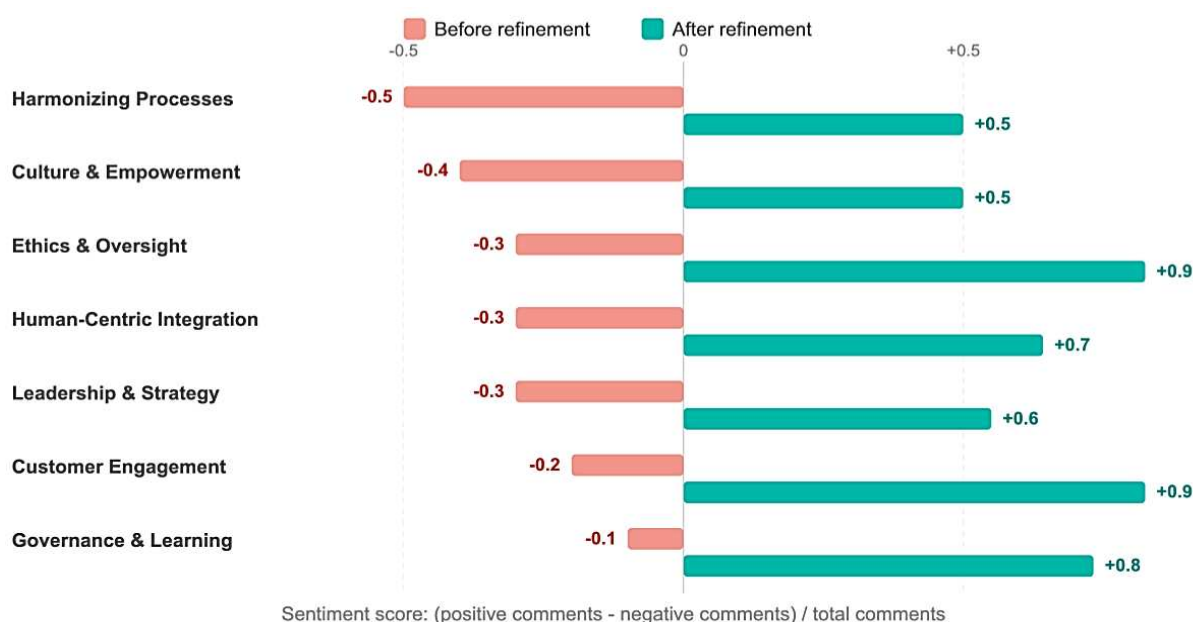


Figure 23: Dimension Sentiment Before and After Refinement

Table 23: Sentiment Analysis of HAIC-MM Dimensions Before and After Refinement

Dimension	Before			After			Initial Score	Final Score
	+	0	-	+	0	-		
Harmonizing Processes	1	3	6	6	3	1	-0.5	0.5
Empowerment & Culture	1	4	5	6	3	1	-0.4	0.5
Ethics & Oversight	2	3	5	9	1	0	-0.3	0.9
Human-Centric Integration	2	3	5	8	1	1	-0.3	0.7
AI-Enhanced Leadership	2	3	5	7	2	1	-0.3	0.6
Customer Engagement	2	4	4	9	1	0	-0.2	0.9
Governance & Learning	3	3	4	8	2	0	-0.1	0.8

A similar analysis for the capabilities is shown in Table 24, which also revealed significant improvements post-refinement. Of the original 28 capabilities, conversations led to 24 of the capabilities getting revised. These revised capabilities showed substantial enhancement, moving from -0.5 initial sentiment to 0.6 final sentiment. The four unchanged capabilities maintained a consistent 80% sentiment throughout, validating their original design.

During the focus group sessions, four new capabilities were identified as missing aspects of human-AI collaboration and were added to strengthen the model: AI Adoption Readiness Assessment, Human Trust in AI Assessment, Data Quality Assurance for AI, and Equity and Fairness Assessment. These new additions achieved a 0.6 final sentiment, indicating successful integration into the model.

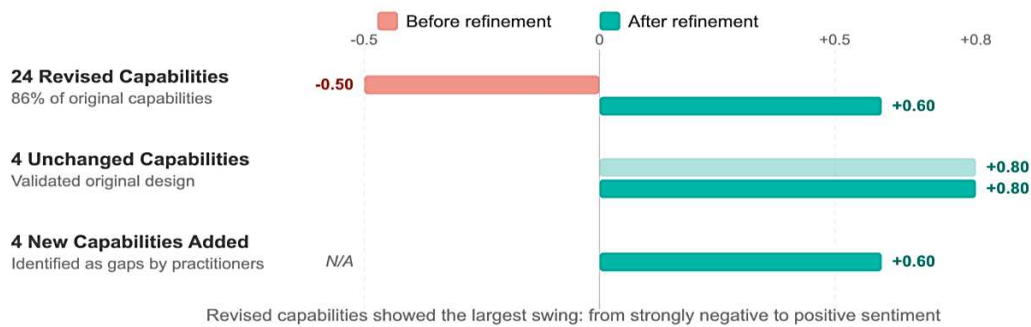


Figure 24: Capability Sentiment Before and After Refinement

Table 24: Sentiment Analysis of HAIC-MM Capabilities Before and After Refinement

Category	# of Capabilities	Before			After			Initial Score	Final Score
		+	0	-	+	0	-		
Revised Capabilities	24	1	2	5	7	2	1	-0.50	0.60
Unchanged Capabilities	4	8	2	0	8	2	0	0.80	0.80
New Capabilities Added	4	--	--	--	7	2	1	--	0.60

A similar analysis of HAIC-MM maturity levels is shown in Table 25, also illustrating significant improvements following the refinement of level descriptions and titles against their relevancy within human-AI collaboration. Four of the five levels showed substantial positive changes in sentiment, with initial negative scores improving to positive scores. The most dramatic improvement was seen in Level 4, which evolved from "Strategic" to "AI-Aligned." Notably, Level 5 "Symbiotic" maintained its strong positive sentiment of 0.8 throughout, requiring no revision and validating its original conceptualization as the model's highest maturity level. These improvements demonstrate the effectiveness of the refinement process in creating more clearly defined and meaningful maturity levels.

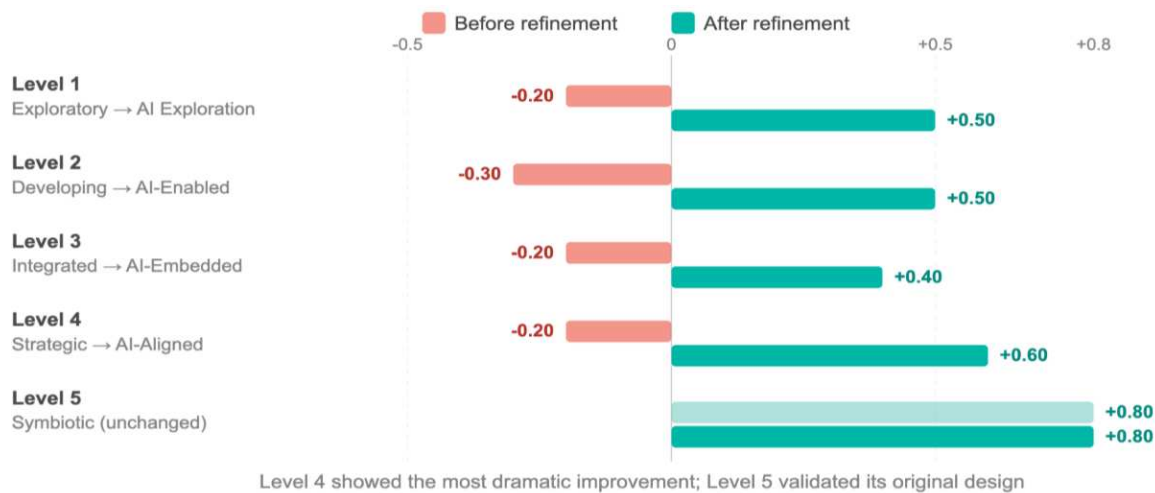


Figure 25: Maturity Level Sentiment Before and After Refinement

Table 25: Sentiment Analysis and Changes to Maturity Levels Before and After Refinement

Level	Initial Title	Initial Score	Revised Title	Revised Score
1	Exploratory	-0.20	AI Exploration	0.50
2	Developing	-0.30	AI-Enabled	0.50
3	Integrated	-0.20	AI-Embedded	0.40
4	Strategic	-0.20	AI-Aligned	0.60
5	Symbiotic	0.80	Symbiotic	0.80

Lastly, the analysis of stakeholder responses to the two primary questions, Table 26, revealed strong support for the HAIC-MM. Regarding the question relating to the need for the HAIC-MM, seven participants expressed positive support, with two neutral responses and one negative response, achieving a moderate consensus level. The second question regarding the comprehensiveness of HAIC-MM demonstrated even stronger support with eight positive responses, one neutral, and one negative position, reaching a high consensus level. The higher consensus on comprehensiveness suggests that while there is solid agreement on the need for the model, there is even stronger confirmation that the proposed model effectively captures the essential elements of human-AI collaboration. Only IT Operations maintained consistent concerns, while Finance remained neutral, indicating potential areas for technical and operational consideration in future refinements.

Table 26: Sentiment Analysis towards Primary Questions

Overall Questions	Positive	Neutral	Negative	Total	Sentiment Score
Need for HAIC-MM	7	2	1	10	0.60
HAIC-MM Comprehensiveness	8	1	1	10	0.70

In Summary, focus group sessions 1 and 2 demonstrated substantial improvement in the HAIC-MM's structure and stakeholder acceptance. Initial sentiment analysis revealed strong

support from technical and customer-facing roles, while highlighting concerns in IT Operations. All seven dimensions progressed from negative sentiments to achieve positive final sentiments, while capability refinement showed similar success and introduced four new capabilities. Maturity level refinement saw four of five levels improve significantly. The strong consensus on the model's need and comprehensiveness (7 and 8 positive responses) validates the model's foundation while identifying key areas for technical implementation refinement.

5.3.2.2. Focus Group Sessions 3, 4, and 5

The final three focus group sessions concentrated on validating and refining the HAIC-MM current state descriptions to better align them with the specific needs of SMEs. The primary objectives of this qualitative analysis were to assess participants' level of agreement on the accuracy of the maturity state descriptions, evaluate their realism and progression, and ensure that the HAIC-MM's capabilities were applicable to real-world SME contexts.

Each participant was asked to complete a pre-session evaluation, in which they were provided the current state descriptions for each of the capability + maturity level combinations that their group was assessing. They were asked if they agreed or disagreed with the description. For example, the original current state description for “Capability 1: Augmented Decision Making - Level 3” stated:

"Organization achieves 45% AI-supported decision-making across core operations. Standardized data processes and improved AI models deliver consistent insights. Cross-functional teams regularly leverage AI analysis, though advanced applications remain limited."

Prior to each focus group session, we identified the descriptions that did not have consensus and focused discussion only on these descriptions. Hence, each of these sessions centered around

resolving these disagreements on the descriptions. Disagreement was defined such that at least one participant disagreed with the current state description.

For example, during the focus group discussion on the previous current state description, participants highlighted that the 45% metric was arbitrary and difficult to measure, the assumption of standardized data processes was too ambitious for SMEs, and the description needed clearer criteria for AI-supported decisions. This feedback led to the following revised current state description that better reflected SME realities:

"Organization achieves 30% AI-supported decision-making across core operations, with clear criteria defining AI-supported decisions. Basic data quality standards and governance processes enable reliable insights. Cross-functional teams pilot AI analysis in specific departments, with documented success cases driving wider adoption. Focus remains on building trust and ensuring data quality while gradually expanding AI applications."

This revision process exemplifies how the focus groups helped refine the HAIC-MM to be more practical and achievable for SMEs. While a table visualizing the agreement across all 160 current state descriptions would be lengthy, Table 27 summarizes this feedback at the dimension level. This table shows the number and percent of current state descriptions within each dimension that had complete agreement (all participants approved). The current state descriptions with disagreement were evaluated in the focus groups.

Table 27: Agreement Counts and Proportions by Dimension Across Maturity Levels

Dimension	Number of Capabilities	Maturity Level				
		1	2	3	4	5
AI-Enhanced Leadership & Strategy	5	4 (80%)	1 (20%)	3 (60%)	4 (80%)	5 (100%)
Adaptive AI Culture & Empowerment	4	4 (100%)	3 (75%)	0 (0%)	4 (100%)	4 (100%)
Human-Centric AI Integration	5	4 (80%)	2 (40%)	1 (20%)	3 (60%)	3 (60%)
Harmonizing AI & Human Processes	4	2 (50%)	1 (25%)	2 (50%)	3 (75%)	4 (100%)
Human-Centered AI Customer Engagement	4	1 (25%)	0 (0%)	1 (25%)	1 (25%)	1 (25%)
AI Ethics & Human Oversight	6	4 (67%)	0 (0%)	1 (17%)	5 (83%)	6 (100%)
Inclusive AI Governance & Learning	4	1 (25%)	0 (0%)	1 (25%)	4 (100%)	4 (100%)

Based on these current state descriptions that required revision, we performed the focus group sessions 3, 4, and 5 focusing on evaluating and improving the descriptions based on three key criteria: accuracy, clarity, and achievability. The analysis of these sessions is summarized in Table 28, revealing significant improvements after revisions. Specifically, sentiment scores improved from all negative towards the current state descriptions to all positive, achieving scores above 0.65 across all criteria.

Table 28: Sentiment Analysis of Current State Descriptions Before and After Refinement

Focus Group	Current State Description	Before			After			Initial Score	Final Score
		+	0	-	+	0	-		
Session 3	Accuracy	2	3	12	14	2	1	-0.59	0.76
	Clarity	1	2	14	15	1	1	-0.76	0.82
	Achievability	3	2	12	13	3	1	-0.53	0.71
Session 4	Accuracy	1	4	19	20	3	1	-0.75	0.79
	Clarity	0	3	21	19	4	1	-0.88	0.75
	Achievability	2	3	19	18	4	2	-0.71	0.67

Session 5	Accuracy	1	2	14	15	1	1	-0.76	0.82
	Clarity	0	3	14	14	2	1	-0.82	0.76
	Achievability	1	2	14	13	3	1	-0.76	0.71

The validation process across these three sessions revealed both strengths and areas for improvement in the HAIC-MM framework. Analysis exposed a clear pattern of stronger validation at foundational levels with decreasing consensus as maturity levels increased. This pattern indicated challenges in describing advanced maturity states for SMEs. However, the subsequent revision process proved highly effective across accuracy, clarity, and achievability criteria among participants. The dramatic shift from predominantly negative responses pre-revision to strongly positive responses post-revision validates the iterative development approach and suggests the final framework better aligns with SME needs and practical implementation requirements.

5.4. Discussion

5.4.1. Complementary Value of Survey and Focus Groups

The survey and focus groups served complementary functions in the refinement process. The survey provided the breadth needed to confirm that the model's structural design was sound; all seven dimensions and the full capability set were validated as relevant by 100 professionals across diverse organizational roles. This broad quantitative confirmation established a solid foundation for the more targeted qualitative work that followed.

The focus groups provided the depth needed to improve the model's practical content. Where the survey confirmed *what* to include, the focus groups refined *how* to describe it. The sentiment analysis showed dramatic improvements across every model component. Dimensions improved from predominantly negative sentiment (ranging from -0.50 to -0.10) to consistently

positive scores (ranging from +0.50 to +0.90). Similarly, revised capabilities improved from −0.50 to +0.60 and current state descriptions improved from as low as −0.88 to a range of +0.67 to +0.82.

5.4.2. Model Revisions

The refinement process produced four categories of changes: structural expansion, maturity level evolution, content calibration, and current state description refinement.

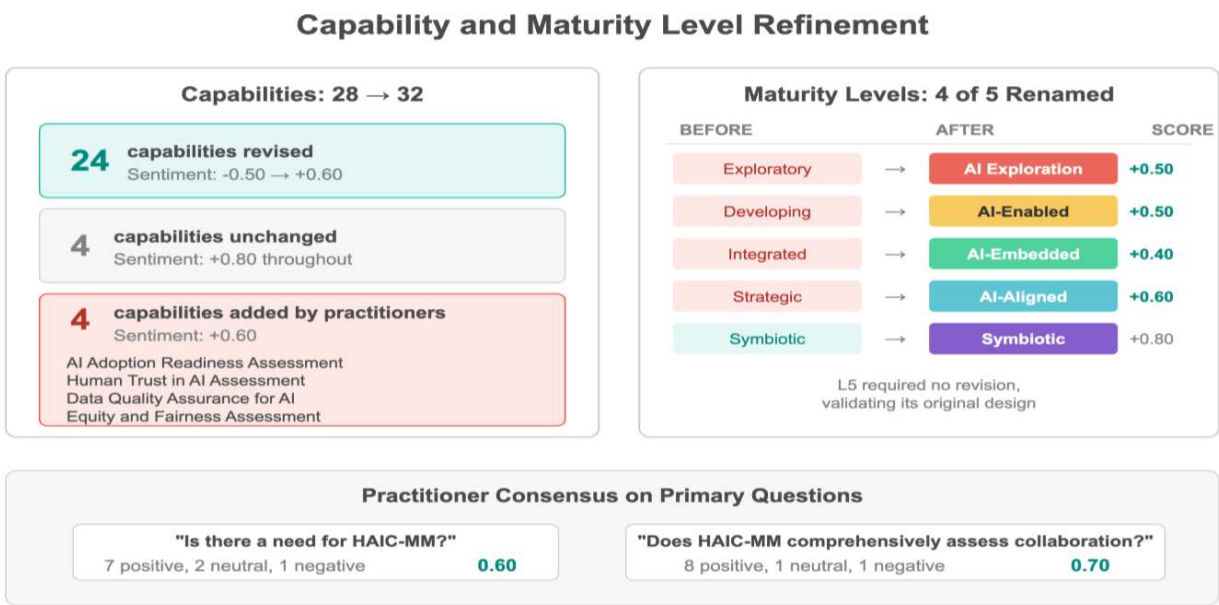


Figure 26: Summary of Refinement Changes Across the HAIC-MM Model

5.4.2.1. Structural Expansion

The model expanded from 28 to 32 capabilities with the addition of four capabilities that practitioners identified as essential. These included “AI Adoption Readiness Assessment,” “Human Trust in AI Assessment,” “Data Quality Assurance for AI,” and “Equity and Fairness Assessment.” The additions addressed gaps in readiness assessment, trust measurement, data quality, and fairness that were not surfaced through the literature synthesis.

5.4.2.2. *Maturity Level Evolution*

Four of the five maturity level names were revised to better describe the organizational state at each level. The revised names are “AI Exploration,” “AI Enabled,” “AI Embedded,” “AI Aligned,” and “Symbiotic Partnership,” which provide clearer language for practitioners assessing their own organizations.

5.4.2.3. *Content Calibration*

Across all components, descriptions were recalibrated to reflect the operational realities of organizations with 50 to 500 employees, rather than the large-enterprise assumptions that characterized the initial literature-derived content.

5.4.2.4. *Current State Description Refinement*

All 160 current state descriptions were reviewed, and most were revised to reduce unrealistic targets, clarify definitions, and better reflect conditions typical of small and medium-sized enterprises. The revisions generally lowered quantitative thresholds, introduced clearer qualifying criteria, and grounded the descriptions in observable organizational behaviors rather than abstract metrics.

The following examples illustrate the types of refinements that occurred across the three sessions. Each example describes the original description, the practitioner critique, and the resulting revision.

Example 1 comes from Session 3 and concerns Augmented Decision Making at Level 3 regarding reducing arbitrary metrics. The original state description was as follows:

Original State Description: *"Organization achieves 45% AI-supported decision-making across core operations. Standardized data processes and improved AI*

models deliver consistent insights. Cross-functional teams regularly leverage AI analysis, though advanced applications remain limited."

The Director of IT Operations noted that the 45 percent threshold appeared arbitrary and explained that SMEs often struggle to quantify AI supported decisions in practice. He emphasized the need for clearer criteria defining what constitutes an AI supported decision. The Director of Customer Service added that decisions in operational contexts often blend AI insights with human judgment, making it difficult to determine whether a decision should be classified as AI supported. The assumption of standardized data processes was also identified as overly ambitious. The IT Operations director observed that many SMEs lack mature data governance and suggested focusing first on establishing basic data quality standards.

The revised description lowered the threshold to 30 percent AI supported decision making across core operations and introduced clear criteria defining AI supported decisions. It also emphasized the establishment of basic data quality standards and governance processes to enable reliable insights. Cross functional teams were described as piloting AI analysis within specific departments, with documented success cases supporting broader adoption while maintaining a focus on building trust and improving data quality. The updated state description for Augmented Decision Making at Level 3 was revised to:

Revised State Description: *"Organization achieves 30% AI-supported decision-making across core operations, with clear criteria defining AI-supported decisions. Basic data quality standards and governance processes enable reliable insights. Cross-functional teams pilot AI analysis in specific departments, with documented success cases driving wider adoption. Focus remains on building trust and ensuring data quality while gradually expanding AI applications."*

Example 2 comes from Session 4 and addresses Human AI Collaboration Quality at Level 3 regarding correcting content misalignment. The original state description was as follows:

Original State Description: "Organization maintains comprehensive customer feedback systems tracking AI interactions across all channels. Advanced analytics generate actionable insights on customer preferences..."

The Vice President of Engineering identified a fundamental misalignment, noting that the description focused primarily on customer feedback rather than the quality of collaboration between employees and AI systems. The capability was intended to assess internal collaboration practices rather than customer experience. This issue was one of two instances in Session 4 where the description content did not align with the capability being assessed, likely due to mapping errors during the initial description generation.

The revised description therefore focused on structured measurement systems designed to evaluate human AI collaboration effectiveness, which was changed to:

Revised State Description: "Organization implements structured measurement systems to evaluate human-AI collaboration effectiveness. Teams track key performance indicators including task completion rates, accuracy improvements, error reduction, and time savings."

Example 3 comes from Session 5 and concerns Ethical AI Governance at Level 2 regarding embedding ethics in design rather than oversight. The original description as follows:

Original State Description: "Organization implements basic AI governance framework with defined roles and policies. Oversight committee established to monitor AI projects."

Practitioners argued that the description focused too heavily on oversight rather than integration with development processes. The Digital Product Manager emphasized the need to embed ethical considerations directly within product development cycles rather than relying solely on oversight after deployment. The Director of Claims Management added that governance descriptions should also address incident response and compliance breach protocols. Another practitioner noted that without measurable indicators the governance framework risked becoming largely symbolic.

The revised description introduced a standardized AI governance framework with clearly defined roles, policies, and shared ethical protocols across departments. It also clarified accountability structures for the oversight committee and incorporated basic data protection measures and ethical checkpoints supported by transparent documentation of ethical decision making practices. The revised text changed to:

Revised State Description: "Organization implements standardized AI governance framework with clearly defined roles, policies, and unified ethical protocols across departments. Oversight committee established with clear accountability structures. Basic data protection measures and ethical checkpoints implemented, with transparent documentation of ethical decision-making frameworks."

Lastly, Example 4 comes from Session 5 and addresses Assessing AI Impact on Workforce Roles at Level 1 regarding workforce displacement fears. The original description stated:

Original State Description: "Organization has limited understanding of AI's impact on workforce roles. Employee concerns about job displacement remain unaddressed."

Practitioners argued that acknowledging the issue without outlining action steps was insufficient. The Director of Claims Management recommended including preliminary communication strategies that emphasize AI's role in supporting rather than replacing employees. This concern was widely shared across the session, with participants identifying proactive workforce communication as a missing element in the governance and learning capabilities.

The revised description therefore introduced an initial structured assessment of AI's workforce impact through role mapping and skills analysis. It also incorporated basic communication and change management strategies designed to address workforce concerns and highlight opportunities for human AI collaboration. Specifically:

Revised State Description: "Organization begins structured assessment of AI's workforce impact through initial role mapping and skills analysis. Basic communication and change management strategies implemented to address concerns and emphasize AI's supportive role, with focus on identifying opportunities for human-AI collaboration rather than replacement."

Across the full set of 160 descriptions, these four examples illustrate the dominant revision patterns observed during the sessions. Practitioners consistently reduced unrealistic metrics to more achievable targets, corrected content misalignments, shifted governance descriptions from reactive oversight toward integration within design processes, and introduced a stronger human dimension that was largely absent from the literature derived descriptions.

5.4.3. Next Steps in Development Process

The survey and focus groups validated what HAIC-MM measures. Three specific findings from the empirical work then drove how the scoring methodology was designed.

The focus groups revealed that practitioners consistently evaluated capabilities from three distinct angles: whether the organization's people were ready (human readiness, skills, trust), whether the AI technology was adequate (infrastructure, data, integration), and whether the two actually worked together (collaboration quality, task flow, communication). This pattern became the foundation for the three-pillar assessment structure (Human-Centric, AI-Centric, Collaborative). Each capability is assessed through questions mapped to all three pillars, ensuring that no assessment captures only one perspective.

The literature gaps identified in Chapter 2 and confirmed by practitioner feedback pointed to a deeper problem: traditional maturity models average scores across areas, producing a single number that treats a balanced organization and a lopsided one as equivalent. Practitioners described this directly when they noted that strong AI investment without corresponding workforce readiness creates friction rather than productivity. The HAIC-MM Balance Factor was designed as the mathematical response to this insight, rewarding organizations that develop all three pillars in alignment and penalizing those with significant imbalances.

Practitioners also emphasized repeatedly that SMEs cannot skip developmental steps. An organization cannot claim AI-driven innovation when it has not established basic data quality or employee AI literacy. The HAIC-MM dependency impact system enforces this progression by checking whether prerequisite capabilities have reached sufficient maturity before a dependent capability can score fully.

Chapter 6. Aim 3 - Validation of HAIC-MM

6.1. Introduction

Research Aim 2 produced a refined HAIC-MM; specifically, 32 validated capabilities across seven dimensions, with a scoring methodology that captures collaboration quality through the Balance Factor, enforces realistic progression through dependency checking, and adjusts for organizational context through size-based scaling. The model was structurally validated through a 100-person survey and qualitatively refined through five focus group sessions. What remained untested was whether the complete, assembled framework works in practice: can SME practitioners complete the full assessment, understand the results, and use the outputs to guide organizational improvement?

This chapter addresses Research Aim 3: to pilot test the deployable HAIC-MM to determine whether it can be effectively applied by SME practitioners. Ten practitioners from SMEs across multiple industries completed the full HAIC-MM assessment via the haicmm.com web platform and provided structured feedback on three evaluation dimensions: usability of the assessment process, usefulness of the generated outputs, and applicability to SME operational realities. The results of this chapter have been submitted for review with a peer-reviewed journal, titled “Empirical validation of a human-AI collaboration maturity model for small and medium enterprises” (Ortolano & Gallegos, 2026). Three research questions guided this work:

- **RQ3.1:** How effectively can SME practitioners complete and interpret the HAIC-MM assessment?
- **RQ3.2:** How does the HAIC-MM output support SMEs in identifying priorities and guiding organizational improvement?

- **RQ3.3:** How well does the HAIC-MM align with the operational realities and constraints typical of SMEs?

6.2. Methods

6.2.1. Participants

Ten professionals across diverse organizational contexts participated in the validation study. All participants were employed by a small (fewer than 50 employees) or medium-sized (50 to 250 employees) enterprise and were based in Canada or the United States. The sample included 40% operational directors, 30% executive leadership, and 30% technical or program management. Table 29 summarizes participant characteristics, including job role, organization type, industry, and organizational size.

Table 29: Participant Characteristics

Job Title	Organization Type	Industry	Organization Size
Grant Program Administrator	Non-Profit	Community Development	Small (1-10)
Business Owner	For-Profit	Accounting Services	Small (11-50)
CEO	For-Profit	Logistics/Distribution	Medium (51-250)
Technical Program Manager	For-Profit	Technology Services	Medium (51-250)
VP of Engineering	For-Profit	Technology/Software	Medium (51-250)
Director, Process Improvement	For-Profit	Insurance	Medium (51-250)
VP of Claims Management	For-Profit	Insurance	Medium (51-250)
Director, Customer Service	For-Profit	Insurance	Medium (51-250)
Director, Payroll and Finance	For-Profit	Insurance	Medium (51-250)
Director, IT Operations	For-Profit	Insurance	Medium (51-250)

6.2.2. Procedure

All ten participants completed the full HAIC-MM assessment (i.e., completed all 160 questions) using the haicmm.com web platform. On average, it took participants about 2 hours to complete the assessment. Participants were instructed to respond based on the practices and conditions of their specific business unit rather than their broader organization, ensuring that responses reflected operational reality rather than aspirational statements about the organization as a whole. Figure 27 shows an example of the assessment interface as experienced by participants, illustrating the five questions for a single capability with the Likert scale response options and the capability description providing context.

The screenshot displays the 'AI Ethical Oversight' section of the HAIC-MM assessment. At the top, a header reads 'AI Ethics and Human Oversight » AI Ethical Oversight'. Below this, a descriptive paragraph states: 'This Capability establishes a practical framework for ethical AI adoption that builds trust and confidence across the organization. It guides SMEs in developing clear oversight practices, fostering responsible AI use, and ensuring fair outcomes while empowering teams to work effectively with AI tools. Through transparent guidelines and measurable standards, it creates lasting partnerships between humans and AI that align with business values and stakeholder expectations.'

The assessment consists of five questions (q1 to q5) with Likert scale response options:

- q1** How actively does leadership support ethical AI adoption, making staff confident in guidelines that ensure fair, responsible usage? (Help icon) The scale ranges from 'Never' to 'Always', with 'Sometimes' selected.
- q2** How effectively does the organization review workflows for alignment with ethical standards, and maintain transparency to build trust in AI-driven services? (Help icon) The scale ranges from 'Not Effective' to 'Highly Effective', with 'Effective' selected.
- q3** To what extent do employees agree that AI interfaces reflect ethical principles in daily tasks, and that dedicated training reinforces fairness? (Help icon) The scale ranges from 'Strongly Disagree' to 'Strongly Agree', with 'Neutral' selected.
- q4** How satisfied is your team that systems support responsible AI use, including human review for important or risky decisions? (Help icon) The scale ranges from 'Very Dissatisfied' to 'Very Satisfied', with 'Very Dissatisfied' selected.
- q5** How frequently does robust oversight sustain trust in AI initiatives, ensuring bias mitigation and transparency remain consistently upheld? (Help icon) The scale ranges from 'Never' to 'Always', with 'Sometimes' selected.

At the bottom left, there is a 'Save & Exit' button. At the bottom right, there is a 'Next' button with a right-pointing arrow.

Figure 27: Screenshot of Assessment Interface (AI Ethical Oversight Capability)

After completing the assessment, participants reviewed the auto-generated HAIC-MM reports summarizing maturity scores across all seven dimensions, five Success Factors, overall

maturity level, and individualized recommendations for improvement. Participants completed the assessment in approximately two hours on average.

6.2.3. Surveys

Participants completed three structured feedback forms designed to evaluate the framework's usability, output quality, and applicability to SME contexts. Together, these surveys provided a comprehensive evaluation of HAIC-MM, covering framework design, implementation fidelity, user experience, and perceived business value. Most questions asked for feedback using a 5-point Likert scale, while some questions asked for open-ended feedback.

Specifically, the first survey (framework design) asked questions related to perceptions of the model architecture, scoring methodology, maturity descriptions, Success Factors, and implementation feasibility. The second survey (user experience) included questions about the platform usability, clarity of the assessment process, perceived assessment burden, report readability, and overall satisfaction. The third survey (SME applicability and value) captured perceptions of the framework's relevance to SME environments, usefulness of recommendations, strategic value, and likelihood of adoption. Survey responses were then analyzed using Microsoft Excel.

6.3. Results

Results are organized by research question, examining framework usability (RQ3.1), output usefulness (RQ3.2), and SME applicability (RQ3.3) through both quantitative metrics and qualitative practitioner feedback.

6.3.1. Framework Usability

All ten participants completed the full 160-question assessment without assistance. No participant abandoned the assessment or required technical support. Figure 28 presents consolidated participant ratings across seven usability dimensions. For each item, the majority of participants reported agreement or strong agreement, with no instances of disagreement. Overall satisfaction reached 90%, with 10% neutral, and 80% indicated they would use the assessment again for longitudinal tracking. All participants (100%) found instructions clear and that questions progressed logically. Question clarity emerged as the primary area for improvement, with 70% of participants reporting satisfaction and 30% providing neutral ratings.

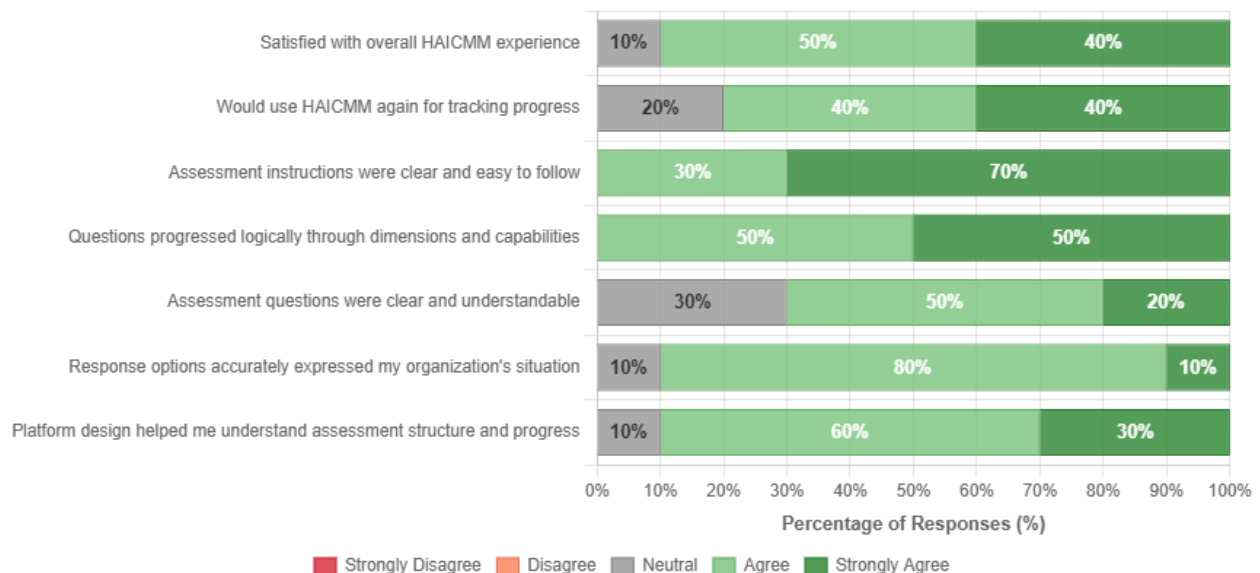


Figure 28: Usability Evaluation of the HAIC-MM Platform

6.3.2. Framework Usefulness

Usefulness was evaluated across four areas: the framework's architecture, the effectiveness of the generated reports, the clarity of the scoring methodology, and the value of the Success Factor outputs.

6.3.2.1. Framework Architecture

Participants evaluated the structural design of HAIC-MM, including its dimensions, capabilities, hierarchical organization, and the distinction between of human-centric, AI-centric, and collaborative perspectives. Figure 29 presents participant assessment of HAIC-MM's structural design. All participants agreed the seven dimensions comprehensively cover key aspects of human-AI collaboration, with 60% strongly agreeing. Capability descriptions were rated clear by 80% of participants, and the overall HAIC-MM hierarchical structure was unanimously perceived as logical and easy to follow. Participants also endorsed the model's measurement approach. Ninety percent agreed that separating human-centric, AI-centric, and collaborative-centric factors was useful for assessment. Perceptions of maturity level progression (i.e., L1-L5) were generally positive, with 70% agreeing that the progression was logical; however, 30% of participants provided neutral ratings, suggesting some uncertainty in distinguishing adjacent maturity levels.

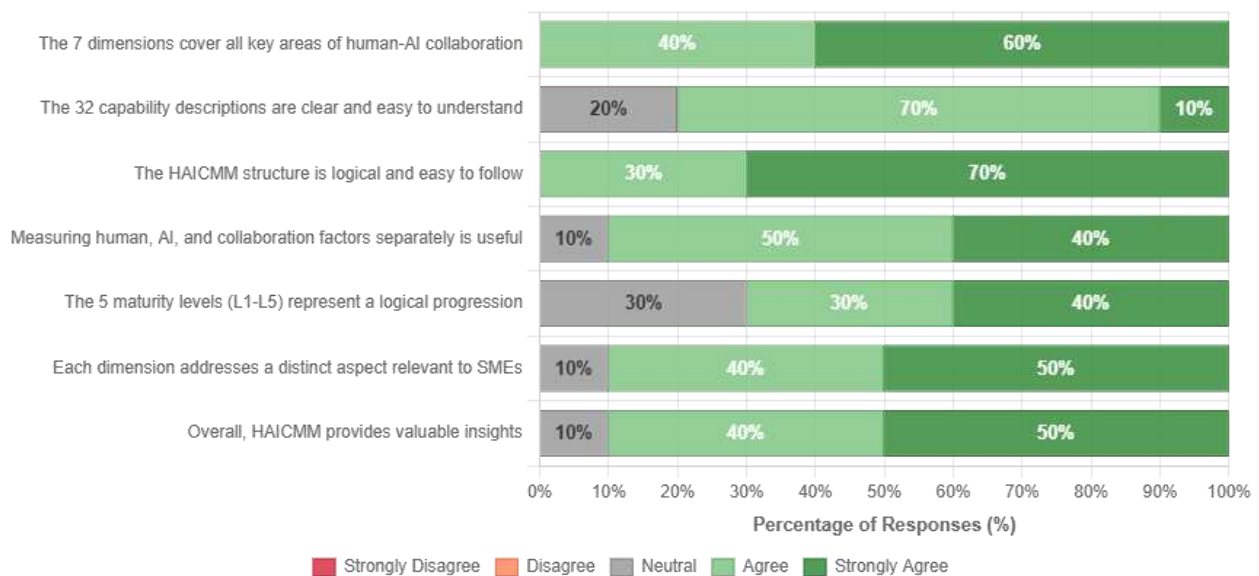


Figure 29: Architecture Evaluation of the HAIC-MM Framework

6.3.2.2. Capability Prioritization

When asked to identify the capabilities most critical for SMEs to focus on, participants' selections revealed clear priorities. The top priorities cluster around two themes: strategic AI leadership (Decision Making, Strategy Alignment, Training) and governance (Data Compliance, Responsible Practices, Transparency). This pattern reinforces the weighted scoring system of HAIC-MM, where Leadership AI Literacy, AI Ethical Oversight, and AI Data Compliance carry the highest Strategic weight (1.40). Practitioners independently prioritized the same areas that the framework weights most heavily, providing convergent validity for the weight allocation. The top-ranked capabilities are presented in Table 30.

Table 30: Most Critical Capabilities for SMEs

Capability	Selections	Dimension
Augmented Decision Making	5	D1: Leadership & Strategy
AI Data Compliance	5	D6: Ethics & Oversight
AI Strategy Alignment	4	D1: Leadership & Strategy
Comprehensive AI Training & Development	4	D2: Culture & Empowerment
Human-Centered AI Design	3	D4: Integration & Experience
AI-Driven Process Optimization	3	D3: Process Harmonization
Workforce AI Adaptability	3	D3: Process Harmonization
Responsible AI Practices	3	D6: Ethics & Oversight
AI Operational Transparency	3	D6: Ethics & Oversight

6.3.2.3. Dimension Prioritization

When asked which dimensions were most relevant to their organization, participants' selections revealed a clear hierarchy, as shown in Table 31. AI Ethics and Human Oversight was selected by seven of ten participants, more than any other dimension. For SME practitioners,

governance and ethical oversight are not theoretical concerns; they are operational necessities that determine whether AI adoption is sustainable.

Table 31: Most Critical Dimensions for SMEs

Dimension	Selections
D6: AI Ethics and Human Oversight	7
D2: Adaptive AI Culture and Empowerment	5
D3: Harmonizing AI and Human Processes	4
D4: Human-Centric AI Integration and Experience	4
D1: AI-Enhanced Leadership and Strategy	3
D5: Human-Centered AI Customer Engagement	3
D7: Inclusive AI Governance and Learning	3

6.3.2.4. Report Effectiveness

After completing the assessment, participants reviewed the auto-generated HAIC-MM reports and evaluated their usefulness for decision making. Figure 30 shows an example of an Executive Overview report that participants saw first. The report presents the overall maturity score, maturity level, partnership quality classification, and all five Success Factor scores with color-coded maturity level indicators.

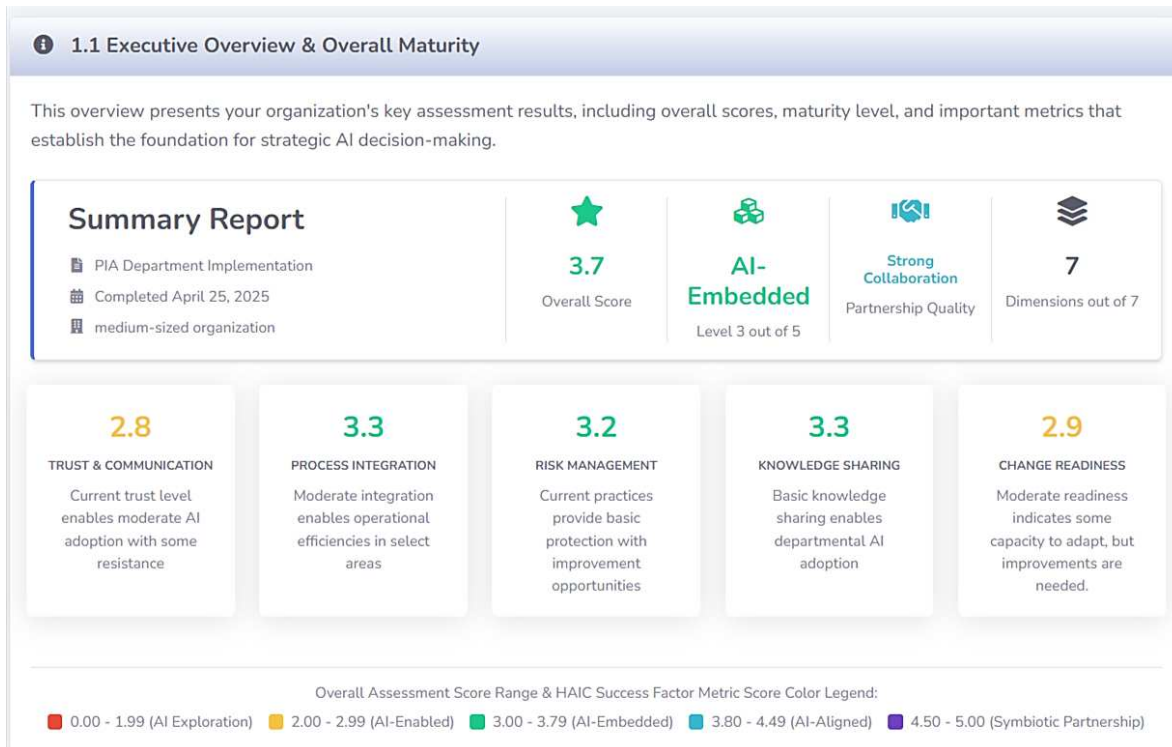


Figure 30: Screenshot of HAIC-MM Executive Overview Report

Table 32 presents the overall effectiveness of the report and shows that most responses were positive. The lowest ratings were associated with the immediate actionability of the report, with 60% positive responses, 30% neutral responses, and 10% negative responses. This suggests that the report could benefit from clearer guidance on how organizations can improve their performance.

Table 32: Overall Report Effectiveness of HAIC-MM Output

Report Metric	Positive	Neutral	Negative
Framework provides valuable insights	90%	10%	0%
Reports provide actionable guidance	90%	10%	0%
Recommendations are useful for organization	90%	0%	10%
Can take immediate action on findings	60%	30%	10%

HAIC-MM provided users with a variety of six individual reports, such as an Executive Summary, Gap Analysis Report, Balance Factor Report, AI Trust & Fairness Report, Tactical Action Plan Report, and Dimension Deep Dive Report. A sample Gap Analysis Report is provided in Figure 31, illustrating how the report presents the current maturity level, the next target level, a ranked view of top capabilities by current score, and a dimension gaps overview that identifies where the largest improvement opportunities exist. This diagnostic function, showing practitioners exactly where they stand and where to focus, is what SME leaders valued most.

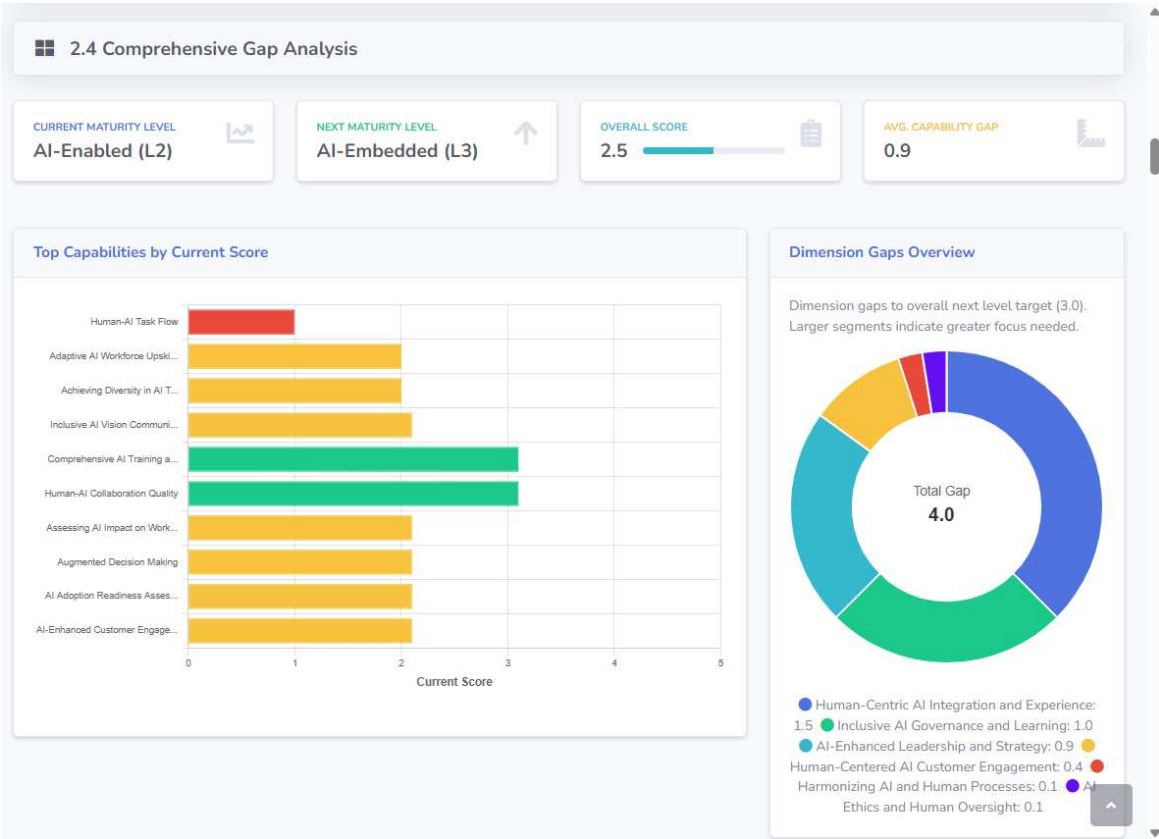


Figure 31: Example of HAIC-MM Gap Analysis Report

Figure 32 summarizes participant ratings of the effectiveness and actionability of the six HAIC-MM reports. Across all report types, the majority of participants reported agreement or

strong agreement, indicating generally positive perceptions of report value. Reports supporting prioritization and high-level decision-making received the strongest agreement, particularly the Gap Analysis and Executive Summary reports. In contrast, reports requiring deeper interpretation, such as the Dimension Deep Dive, showed a higher proportion of neutral responses, indicating reduced perceived effectiveness for some participants. Overall, most participants agreed that the reports provided realistic and actionable guidance, though neutral responses indicate that additional support may be needed to translate insights into immediate action in some cases.

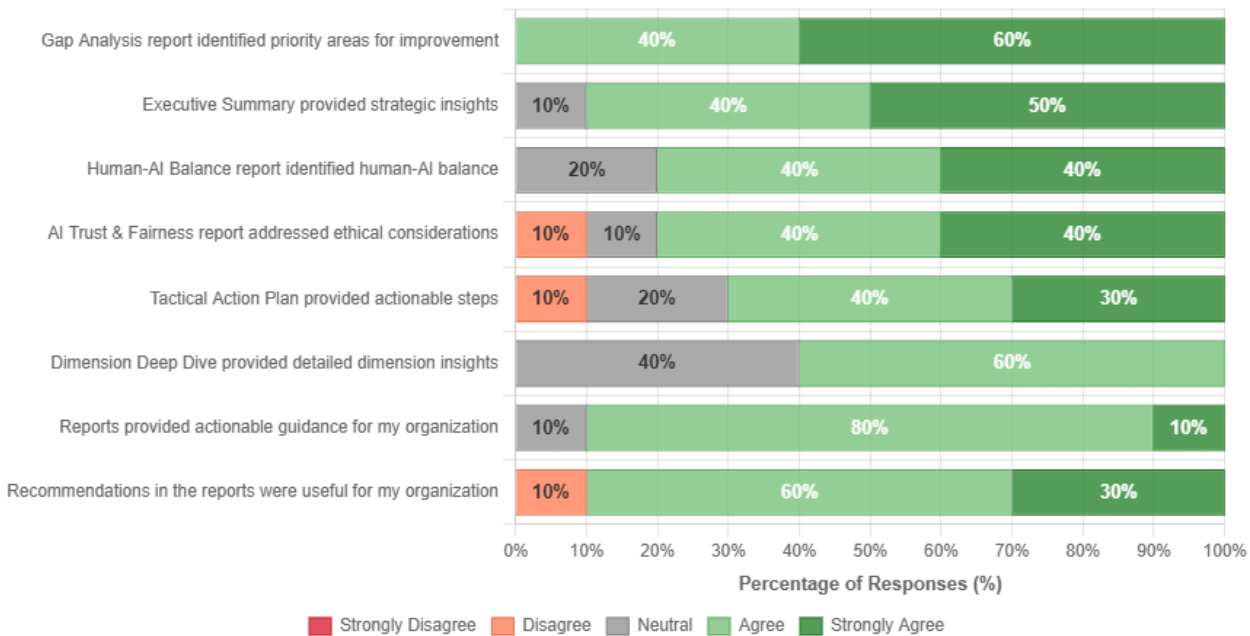


Figure 32: Individual Report Effectiveness and Actionability

6.3.2.5. Scoring Methodology Clarity

Figure 33 summarizes participant understanding of the HAIC-MM scoring methodology. Overall, results indicate strong conceptual endorsement of the bottom-up scoring approach (70%), alongside more mixed understanding of the underlying calculation mechanics. Specifically, only

30% fully understood the calculation mechanics. The Balance Factor was rated useful by 60%, and 90% agreed it reflected their organizational reality.

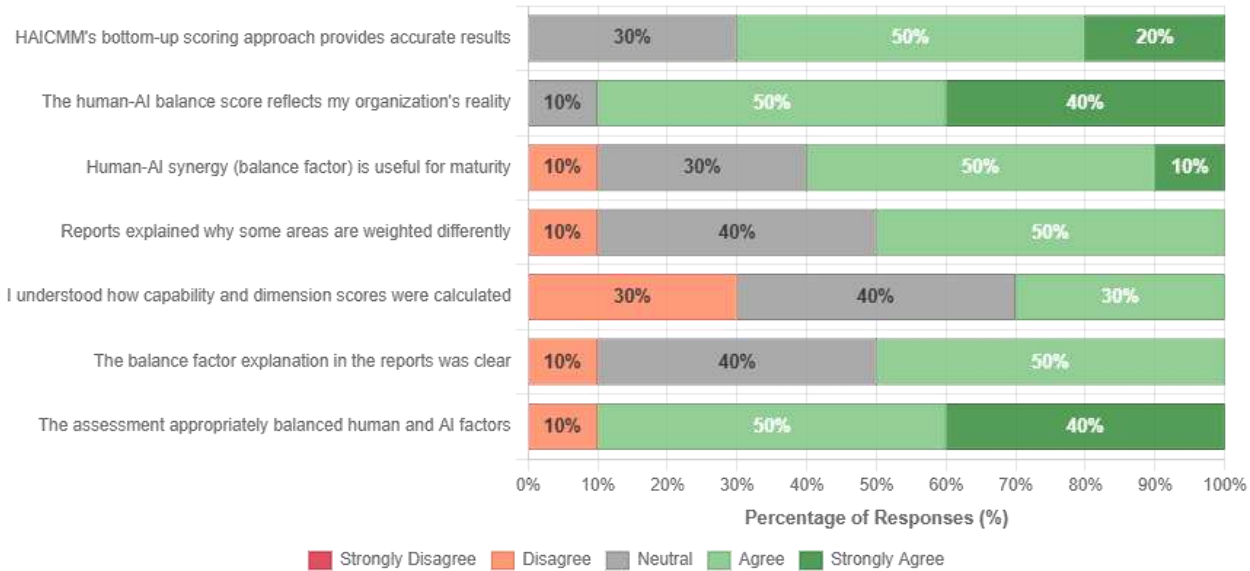


Figure 33: Clarity of Scoring Methodology and Balance Factor

The results highlight a distinction between trusting the scoring approach and understanding how it operates. Seven of the ten participants endorsed the bottom-up scoring logic in which scores flow from individual questions through capabilities and dimensions to an overall maturity level. Nine participants also agreed that the Balance Factor reflects their organizational reality, indicating that the concept of rewarding balanced human AI development aligns with practitioner experience.

Understanding of the calculation mechanics was more divided. Only 30% of participants reported fully understanding how scores are calculated, while 40% were neutral and 30% disagreed that they understood the process. This distribution suggests that the scoring methodology produces outputs that practitioners trust even though many users cannot easily trace how the results are generated. One participant noted that the derivation of Success Factor scores could be more clearly linked to the underlying capability scores. The participant explained that the concept was clear,

but the quantitative linkage was not immediately obvious. This feedback suggests a need for clearer explanations of score derivation, particularly for non-technical users and in contexts where auditability or regulatory justification requires traceability from questions to final scores.

Participants also evaluated the five focus areas that structure each capability assessment. Seven of the ten participants agreed that these focus areas cover the key domains required to develop each capability, while three selected a neutral response. No participant disagreed. This suggests that the structure is generally accepted as comprehensive, although the neutral responses may indicate that some practitioners found the focus area categories less intuitive than the dimension and capability levels that appear higher in the framework hierarchy.

6.3.2.6. Success Factor Utility

Figure 34 summarizes participant perceptions of the utility of the HAIC-MM Success Factors. Eighty percent of participants agreed that the five Success Factors were useful for tracking progress over time, and 70% agreed that the metric supports effective measurement of human-AI collaboration. Participants also reported that the Success Factors helped identify actionable steps for improvement (70%) and supported strategic decision-making related to human-AI collaboration (60%), although higher proportions of neutral responses suggest some variability in perceived strategic impact across organizations.

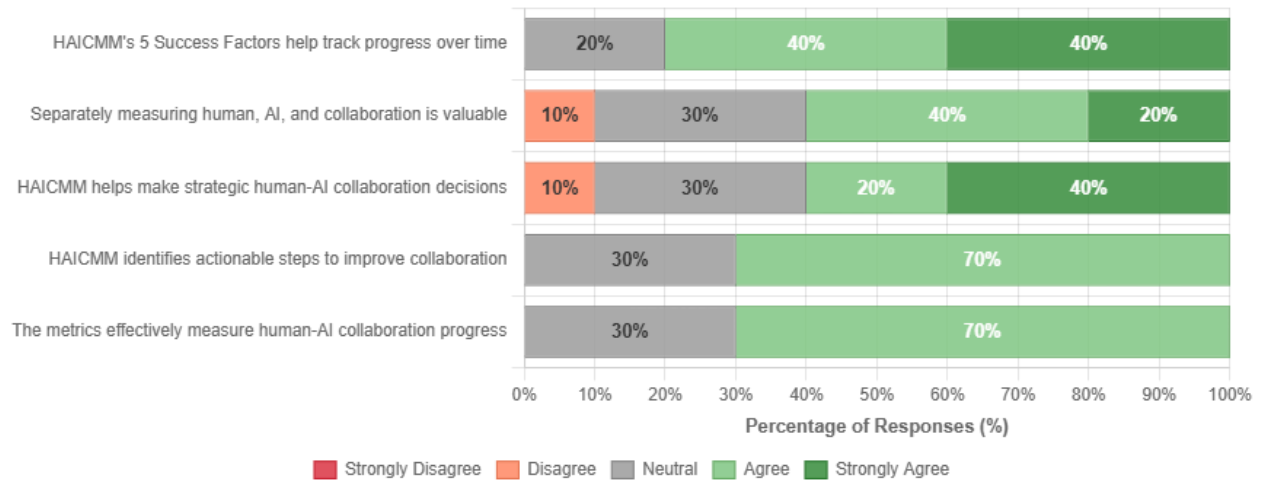


Figure 34: Utility of Success Factors and Strategic Decision Support

Participants were asked to identify the most critical Success Factor for their organization. Respondents favored Risk Management (N=4), followed by a two-way tie between Trust and Communication (N=2) and Process Integration (N=2), and lastly Change Readiness (N=1) and Knowledge Sharing (N=1). Risk Management emerged as the dominant priority, reflecting the risk-aware orientation that characterizes SME approaches to AI adoption. SMEs lack the financial reserves and operational redundancy to recover from significant AI-related failures. A compliance violation, a biased algorithm affecting customers, or a system failure disrupting operations can have disproportionate impact on a smaller organization. The emphasis on Risk Management suggests that SME practitioners view proactive risk governance not as an optional best practice but as a prerequisite for sustainable AI adoption.

6.3.3. Applicability for SMEs

The most critical test for HAIC-MM is whether it reflects the operational reality of SMEs, organizations that face tighter budgets, fewer specialists, and less formalized processes than the large enterprises that most existing frameworks were designed for SMEs.

Figure 35 presents participant assessment of HAIC-MM's applicability in SME settings. Most participants (90%) reported agreement that the framework captures the human-AI collaboration challenges faced by their organizations and is relevant to current AI adoption challenges (90%). A large majority (80%) also agreed that the maturity level descriptions reflect realistic stages of AI adoption for SMEs. Perceptions of cross-context applicability were more mixed. While most participants (60%) agreed that HAIC-MM could be applied across industries and organizational sizes, a higher proportion of neutral (30%) and even one disagree (10%) responses suggests interest in greater industry-specific customization. This perspective was reflected in qualitative feedback, with one participant noting: *“In finance, regulators mandate full audit trails for AI-driven decisions,”* highlighting the importance of domain-specific capabilities such as model explainability and auditability.

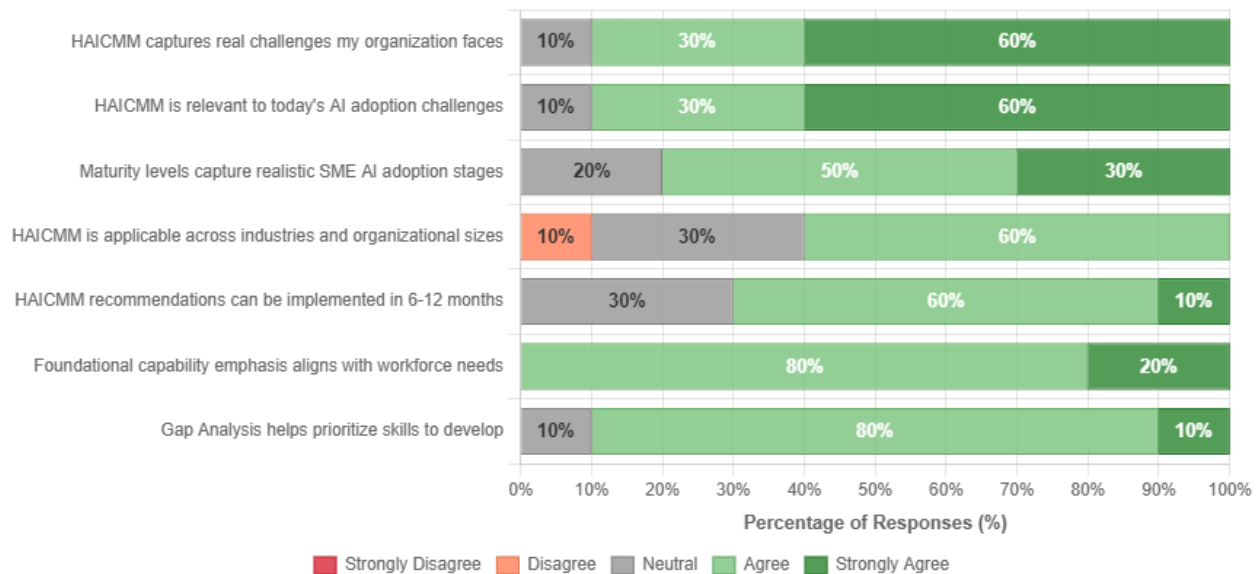


Figure 35: Relevance and Implementation Feasibility for SME Contexts

6.3.4. Summary of Validation Findings

Table 33 summarizes the validation results across all three evaluation dimensions (usability, usefulness, and applicability) mapped to the three research questions.

Table 33: Consolidated Validation Metrics

Evaluation Dimension	Metric	Positive	Neutral	Negative
Usability (RQ3.1)	Overall satisfaction	90%	10%	0%
	Instruction clarity	100%	0%	0%
	Question progression	100%	0%	0%
	Would use again	80%	20%	0%
Usefulness (RQ3.2)	Framework value	90%	10%	0%
	Actionable guidance	90%	10%	0%
	Report effectiveness	70%	30%	0%
	Success Factor utility	80%	20%	0%
Applicability (RQ3.3)	Captures SME challenges	90%	10%	0%
	Implementation feasibility	70%	30%	0%
	Contemporary relevance	90%	10%	0%
	Foundational emphasis	100%	0%	0%

Across all twelve metrics, positive responses ranged from 70% to 100%, with no negative responses observed on any metric. This consistent pattern (positive or neutral, never negative) indicates that HAIC-MM meets a baseline standard of quality across all three evaluation dimensions while identifying specific areas where targeted improvements would strengthen the framework.

Four areas were identified for enhancement: (1) improved explanation of the scoring methodology for non-technical users, (2) greater clarity in how the Balance Factor affects scores, (3) refinement of detailed analytical reports for broader audiences, and (4) clearer pathways for industry-specific customization.

6.4. Discussion

6.4.1. Validation Outcomes

The pilot deployment provides empirical evidence that HAIC-MM functions as intended across all three evaluation dimensions. All ten practitioners completed the full 160-question assessment without assistance. That alone is a meaningful result because many maturity frameworks require external consultants or facilitators, creating access barriers that put them out of reach for resource-constrained SMEs (Kalleparambil & Akoum, 2025; Naheed et al., 2025). HAIC-MM avoids this barrier. Satisfaction was high (90%), instructions were rated unanimously clear, and 80% of participants expressed intent to use the assessment again for longitudinal tracking.

The outputs were also perceived as actionable, which is important because research has shown that perception strongly influences behavior (Pourfalatoun et al., 2025; Ahmed et al., 2024). Nine out of ten participants confirmed the framework provided valuable insights, and the same proportion found the guidance actionable. Executive-level reports (i.e., Gap Analysis, Executive Summary) received the strongest endorsement for prioritization. The Success Factors add an analytical layer that dimension scores alone cannot provide because they highlight cross cutting issues. For example, a risk management gap that spans multiple dimensions can be identified before it compounds across the organization.

Applicability to SME contexts was similarly strong. Nine of the ten participants confirmed that the framework captures collaboration challenges they encounter in practice, and the emphasis on foundational capabilities received unanimous endorsement. HAIC-MM avoids two common weaknesses in existing frameworks. Some models reduce maturity assessment to simplified checklists that offer limited explanatory power, while others assume enterprise scale resources that

SMEs do not possess. By prioritizing organizational readiness and people rather than technology first prescriptions, the framework aligns with research showing that sustainable AI transformation in SMEs depends more on human and organizational investments than on technological sophistication alone (Peretz-Andersson et al., 2024).

6.4.2. Trust vs. Understanding

The results reveal a distinction with practical implications for how HAIC-MM is deployed and communicated. Participants broadly endorsed the bottom-up scoring logic and the balance-oriented approach (70-90% positive) even when they did not fully understand the underlying quantitative calculations (only 30% fully understood the mechanics). This pattern suggests that the framework produces outputs that practitioners recognize as credible based on their organizational experience, even when the mathematical derivation is not immediately clear.

In many deployment contexts, this level of face validity may be sufficient. An SME leader who receives a maturity report that accurately identifies strengths and breakdowns in human AI collaboration can act on those findings even without understanding the detailed calculations behind the Balance Factor.

Transparency becomes more critical in two specific contexts. The first involves regulated industries where audit trails are required, as noted by the financial services participant. The second involves organizations where leadership needs to justify AI investment decisions to boards or stakeholders who will ask "how did you arrive at these numbers?" For these contexts, HAIC-MM needs clearer score derivation explanations: not changes to the scoring methodology itself, but better communication of how each score connects back to specific question responses through the pillar scores, Balance Factor, and dependency adjustments.

6.4.3. Risk Management as the Priority

Risk Management was selected as the most critical Success Factor by four of ten participants, which is twice the rate of any other factor. This finding reflects the risk-aware orientation that characterizes SME approaches to AI adoption. Unlike large enterprises with dedicated risk management teams and financial reserves to absorb failures, SMEs face amplified consequences from AI-related problems: a compliance violation, a biased algorithm, or a system failure can disproportionately damage a smaller organization's reputation, finances, and operations.

This emphasis on Risk Management validates HAIC-MM's design decision to weight AI Ethics and Human Oversight as a Strategic dimension (weight 1.4) and to include capabilities like AI Ethical Oversight and AI Data Compliance at the highest weight level (1.40). The practitioners' prioritization of risk aligns with the framework's structural emphasis on governance and oversight as prerequisites for sustainable AI adoption.

Chapter 7. Conclusions

7.1. Introduction

This dissertation addressed a specific gap. Small and medium sized enterprises lack a practical and validated framework for assessing and improving how their people and AI systems work together. Existing maturity models are primarily designed for large enterprises, treating human readiness and AI capability as separate factors, and producing averaged scores that often conceal the collaboration imbalances that determine whether AI adoption actually delivers value.

The Human AI Collaboration Maturity Model (HAIC-MM) was developed to address this gap. The framework applies a systems engineering perspective to assess collaboration quality across seven dimensions and 32 capabilities. HAIC-MM incorporates balance-based scoring to identify and penalize collaboration imbalances and uses dependency checks to enforce realistic capability progression. The model also provides actionable guidance through a self-service web platform designed for direct use by practitioners.

This chapter summarizes the research contributions, answers each research question, discusses the study limitations, and identifies the publications resulting from this work.

7.2. Research Contributions

7.2.1. Theoretical Contributions

No existing maturity model treated human AI collaboration as a system-level property worthy of direct measurement. HAIC-MM addresses this gap through four theoretical contributions.

7.2.1.1. A Unified Human-AI Collaboration Framework

Prior to HAIC-MM, no single model integrated human machine teaming, AI maturity, and digital transformation within an SME context. HAIC-MM brings together insights from these three domains within a unified framework consisting of seven dimensions, 32 capabilities, 160 focus areas, and 640 advancement practices. The framework spans leadership and strategy, organizational culture, technology integration, process harmonization, customer engagement, ethics and oversight, and governance and learning.

7.2.1.2. Balance-Based Scoring and Three-Pillar Assessment

Traditional maturity models typically produce composite scores that conceal critical imbalances. For example, an organization with strong human expertise but weak AI infrastructure can receive the same score as one with balanced but moderate capabilities. HAIC-MM addresses this limitation through two linked innovations. The three-pillar structure (i.e., human centric, AI centric, and collaborative) evaluates each capability through questions that measure human readiness, AI capability, and the quality of interaction between them. The Balance Factor then uses these pillar scores to penalize uneven development rather than averaging across areas, making lopsided investment visible and measurable.

7.2.1.3. Five-Level Collaboration Progression

HAIC-MM defines maturity levels from “L1 AI Exploration” to “L5 Symbiotic Partnership.” Unlike traditional maturity scales that track technology deployment, these levels assess the quality and depth of human AI collaboration. The model therefore captures AI’s evolution from an experimental tool to an integrated collaborative partner.

7.2.2. Methodological Contributions

7.2.2.1. Synthesis Methodology for Maturity Model Development

Building a maturity model from 30 source frameworks across three unrelated domains required a replicable integration process. By combining Becker et al.'s (2009) structured eight-step methodology with Hevner et al.'s (2004) design science research principles, this research developed such a process. The approach involved systematic decomposition of ten AI maturity models, ten digital transformation frameworks, and ten human machine teaming assessments through metamodels, pivot models, and concept matrices. Researchers developing integrated maturity models across multiple domains can apply this decomposition methodology.

7.2.2.2. Multi-Stage Scoring and Dependency-Aware Progression

Most maturity assessments produce a single summary score. HAIC-MM instead converts 160 question responses into maturity scores through a four-level hierarchy. Pillar scores feed into capability scores, which are adjusted by balance, dependency, and organization size factors. Capability scores aggregate into dimension scores, which produce the overall maturity level. This structure preserves diagnostic information that would otherwise be lost in simple aggregation. Within this hierarchy, the dependency system enforces realistic capability progression by reducing scores when prerequisite capabilities remain underdeveloped. Dependency factors operate within a range of 0.5 to 1.0 across all 32 capabilities and three impact levels. This prevents inflated maturity classifications when advanced capabilities are built on weak foundations.

7.2.2.3. Configurable Parameter System

Key parameters including emphasis factors, balance sensitivity, dependency strictness, organization size adjustments, and dimension scaling are configurable. This design allows the

framework to be adapted to different industries and organizational contexts without structural redesign.

7.2.2.4. 2-2-1 Question Structure

Each capability is assessed through five questions consisting of two human centric questions, two AI centric questions, and one collaborative question. This structure ensures that each capability captures all three perspectives and generates the pillar level data required for the Balance Factor calculation.

7.2.3. Practical Contributions

7.2.3.1. Self-Service Assessment Platform and Validated Instrument

Most maturity frameworks remain locked in consulting engagements or academic publications. HAIC-MM is available for free at haicmm.com as a self-service web platform where practitioners complete the 160-question assessment online and receive auto-generated reports without consultant support or specialized training. Pilot deployment confirmed that all participants completed the assessment without assistance.

7.2.3.2. Ten Auto-Generated Reports

Pilot participants rated the platform's reports as providing valuable insights (90%) and actionable guidance (90%). Ten report types serve different organizational audiences and purposes: executive summaries for leadership, detailed gap analyses for operational managers, and strategic roadmaps for planning teams.

7.2.3.3. Capability Dependency Map and Success Factor Profiles

Two practical tools translate HAIC-MM scores into action. The complete dependency map across all 32 capabilities gives SMEs a realistic improvement sequence, showing which capabilities must be developed before others and converting directly into prioritized action plans. Separately, five Success Factors (Trust & Communication, Process Integration, Risk Management, Change Readiness, and Knowledge Sharing) provide cross-cutting assessments that complement dimension-specific scores and help leaders identify systemic issues spanning multiple dimensions.

7.2.4. Empirical Contributions

7.2.4.1. Survey Validation

All seven HAIC-MM dimensions and the capability structure were confirmed as relevant and comprehensive by 100 professionals with direct AI adoption experience.

7.2.4.2. Focus Group Refinement

The focus groups reshaped the model. Five sessions with ten industry practitioners revised 24 of 28 original capabilities, added four new capabilities (bringing the total to 32), renamed four of five maturity levels for clarity, and revised all 160 current state descriptions.

7.2.4.3. Pilot Deployment and Balance Factor Face Validity

Ten SME practitioners completed the full HAIC-MM assessment and provided structured feedback across three evaluation dimensions, establishing usability (90% overall satisfaction, 100% instruction clarity), usefulness (90% valuable insights, 90% actionable guidance), and SME applicability (90% captures real challenges, 100% foundational emphasis appropriate). No negative responses were recorded on any of the twelve consolidated validation metrics. Of

particular note, nine out of ten participants confirmed that the Balance Factor reflects their organizational reality, recognizing in their own maturity reports the collaboration dynamics that the scoring mechanism measures. This 90% endorsement represents the strongest validation of HAIC-MM's core innovation.

7.3. Summary of Research Findings Relative to Research Questions

This section answers each research question based on the findings presented in this dissertation.

7.3.1. Aim 1: Development of HAIC-MM

RQ1.1: What frameworks exist for developing new maturity models?

Answer: Seven established procedural frameworks exist for developing maturity models, ranging from De Bruin et al.'s (2005) iterative six-phase strategy to Von Wangenheim et al.'s (2018) DESRIST methodology. These frameworks vary in their emphasis on validation rigor, accessibility, and stakeholder involvement. The most effective approach for developing HAIC-MM combined Becker et al.'s (2009) structured eight-step methodology, which scored highest on rigor, with Hevner et al.'s (2004) design science research principles, which ensure practical, real-world grounding. This hybrid approach provided the structured process needed for systematic model construction while maintaining focus on genuine SME challenges rather than theoretical abstractions.

RQ1.2: How do the strengths and limitations of existing maturity models guide the development of the HAIC-MM?

Answer: The analysis of 30 existing frameworks across three domains (ten AI maturity models, ten digital transformation frameworks, and ten human-machine teaming assessments)

revealed five critical gaps: (1) HMT frameworks treat AI as a tool rather than a collaborative partner; (2) AI maturity models oversimplify SME needs; (3) DT models ignore collaborative dynamics between humans and AI; (4) no existing model integrates all three perspectives; and (5) existing models treat components independently, concealing imbalances through averaging. These five gaps directly drove HAIC-MM's key innovations: the five-level collaboration progression from AI Exploration to Symbiotic Partnership, the three-pillar assessment structure, the Balance Factor that penalizes uneven development, and the dependency-based scoring system that enforces realistic capability progression.

7.3.2. Aim 2: Refinement of HAIC-MM

RQ2.1: How do stakeholder survey responses inform the refinement of the HAIC-MM's capabilities?

Answer: The online survey with 100 professionals confirmed that all seven HAIC-MM dimensions and the capability structure are relevant and comprehensive for assessing human-AI collaboration. All dimension mean scores exceeded 4.3 on a 6-point Likert scale, with no dimension falling below the "important" threshold. This broad quantitative validation established that the synthesis-derived framework captured the right areas of human-AI collaboration, providing the foundation for the deeper qualitative refinement that followed.

RQ2.2: How do insights from practitioner focus groups contribute to improving the clarity, relevance, and practical applicability of HAIC-MM dimensions and assessment questions?

Answer: Five focus group sessions with ten industry practitioners transformed the model through structural changes, content refinement, and scoring methodology development. Structurally, 24 of 28 original capabilities were revised and four new capabilities were added (AI Adoption Readiness Assessment, Human Trust in AI Assessment, Data Quality Assurance for AI,

and Equity and Fairness Assessment), producing the final 32-capability framework. All 160 current state descriptions were revised to replace unrealistic targets with achievable SME-specific metrics, bringing sentiment scores from a range of -0.88 to -0.53 up to $+0.67$ to $+0.82$. The focus groups also informed the development of the scoring methodology, including the Balance Factor, dependency checking, and organization size adjustments that make HAIC-MM's scores reflect collaboration quality rather than simple capability averages.

7.3.3. Aim 3: Validation of HAIC-MM

RQ3.1: How effectively can SME practitioners complete and interpret the HAIC-MM assessment?

Answer: All ten pilot participants completed the full 160-question assessment in approximately two hours without assistance. Usability ratings were consistently high: 90% overall satisfaction, 100% instruction clarity, 100% logical question progression, and 80% intent to reuse the assessment for longitudinal tracking. The assessment is deployable as a self-service tool without requiring specialized training or external support.

RQ3.2: How does the HAIC-MM output support SMEs in identifying priorities and guiding organizational improvement?

Answer: HAIC-MM's outputs support decision-making at multiple organizational levels. The seven-dimension architecture was rated comprehensive by 100% of participants, and the hierarchical structure was unanimously rated as logical and easy to follow. Reports were rated as providing valuable insights (90%) and actionable guidance (90%). Success Factors were rated useful for tracking progress (80%) and identifying improvement steps (70%). Risk Management was identified as the most critical Success Factor by 40% of participants, reflecting the risk-aware orientation that characterizes SME approaches to AI adoption. The Balance Factor was endorsed

by 90% as reflecting organizational reality, though only 30% fully understood the calculation mechanics, indicating a need for clearer score derivation explanations.

RQ3.3: How well does the HAIC-MM align with the operational realities and constraints typical of SMEs?

Answer: HAIC-MM shows strong alignment with SME realities. Nine out of ten participants confirmed that HAIC-MM captures the human-AI collaboration challenges they face, and the same proportion found it relevant to their current AI adoption stage. AI Ethics and Human Oversight was the dimension rated most relevant by practitioners (selected by 7 of 10), reinforcing the governance-first orientation that HAIC-MM's weight system encodes. The emphasis on foundational capabilities received unanimous endorsement (100%), validating the dependency-based progression system. Implementation resource needs revealed a distinctly SME profile: staff time (90%), training budget (80%), and leadership commitment (70%) dominated, while technology investment and consulting support ranked far lower. Participants estimated 6 to 12 months for implementation (50%), with 70% rating feasibility positively. Cross-context applicability was the area of most mixed feedback: 60% agreed the framework could work across industries, 30% were neutral, and 10% disagreed, with specific feedback pointing to the need for industry-specific capabilities in regulated sectors.

7.4. Limitations and Future Work

7.4.1. Limitations

Several limitations should be considered when interpreting the results of this research. The current validation provides strong evidence that the framework functions as intended, but it should be interpreted as proof of concept rather than definitive evidence of broad generalizability.

The most significant limitation concerns sample composition. The survey phase included 100 respondents and provided sufficient evidence to validate the relevance and completeness of the framework dimensions and capabilities. However, this sample size was not large enough to support detailed subgroup analysis by industry, organization size, or region. The subsequent qualitative stages, including focus groups and pilot deployment, provided valuable practitioner insight but involved only ten participants in each stage. With small samples, individual responses have a greater influence on reported percentages, which limits the statistical generalizability of the findings.

Industry representation also introduces a potential source of bias. Five of the ten pilot participants were drawn from the insurance sector. While this provided useful depth within a single industry, it may influence how certain findings should be interpreted. For example, the strong prioritization of Risk Management as a Success Factor may partly reflect the insurance sector's emphasis on regulatory compliance and risk oversight. Additional validation across industries such as manufacturing, healthcare, retail, and professional services would help determine whether the same priorities emerge in contexts with different operational and regulatory environments.

A related limitation involves organizational size. Eight of the ten pilot participants represented medium-sized organizations with between 51 and 250 employees. Although the two participants from smaller organizations provide preliminary evidence that the framework can apply to smaller contexts, the alignment of the model with very small organizations, particularly those with fewer than 50 employees, remains only lightly tested.

Geographic scope presents another limitation. All participants were located in Canada or the United States. AI adoption patterns, regulatory environments, and organizational cultures vary across regions, and the current validation does not capture these differences. Additional validation

across Europe, Asia, and other regions would help determine whether the framework performs consistently in different institutional and regulatory environments.

The study also reflects the early stage of empirical validation. The pilot deployment represents a single assessment cycle. As a result, the research cannot yet evaluate whether the framework accurately tracks maturity progression over time or whether improvements in maturity scores correspond to measurable improvements in organizational outcomes.

The thirty frameworks synthesized to build HAIC-MM were all published before generative AI became common in organizations in late 2022 and 2023. The ten digital transformation models in particular treat AI as part of a broader analytics and automation stack, not as a conversational partner that can generate content, draft code, or act as an autonomous agent. The source literature therefore reflects an older view of human-AI collaboration shaped by predictive analytics, narrow machine learning, and rule-based systems rather than the conversational, generative tools SMEs use today. The core structure of HAIC-MM still holds: separating human and AI capability, checking prerequisites, and using the balance factor are not tied to any one generation of AI. The capability descriptions, advancement practices, and current state descriptions will need periodic refresh as generative AI continues to change how people and AI work together. This is a limitation of timing, not of design.

Two additional constraints relate to the interpretation and use of the scoring methodology. Although 90 percent of pilot participants reported that the Balance Factor reflected their organizational reality, only 30 percent reported fully understanding of the underlying scoring mechanics. This gap between conceptual trust and methodological transparency may limit the framework's usefulness in contexts where audit trails or regulatory justification require detailed explanations of how scores are derived.

Finally, the framework was designed specifically for small and medium-sized enterprises. Its applicability to large enterprises has not been empirically tested and may require structural adjustments to reflect the governance complexity and resource availability typical of larger organizations.

Overall, these limitations indicate that the results should be interpreted as strong initial validation of the framework's design and usability rather than definitive confirmation of its performance across all organizational contexts.

7.4.2. Future Research Directions

The most immediate next step is longitudinal validation: tracking organizations through multiple HAIC-MM assessment cycles to measure actual maturity progression over time and to determine whether higher maturity levels correlate with measurable business outcomes. The current validation confirms that the framework produces face-valid results at a single point in time. Whether it accurately tracks change remains an open question.

Expanding the validation sample is equally important. Priority should go to industries with distinct AI adoption patterns (manufacturing for Industry 4.0, healthcare for regulatory complexity, professional services for knowledge work augmentation) and to geographic regions outside North America, where organizational culture and regulatory environments may influence how human-AI collaboration develops. Pilot feedback also pointed toward industry-specific adaptations: domain extensions that retain HAIC-MM's core scoring structure while adding sector-specific assessment content for regulated industries where audit trails and explainability requirements shape AI decisions.

The AI landscape will not wait for validation to catch up. Generative AI and agentic AI systems are already changing what human-AI collaboration looks like, and the assessment content

will need periodic revision to reflect those changes. The configurable parameter system handles scoring adjustments without structural redesign, but the questions themselves may need updating as new collaboration patterns emerge.

Two research priorities address specific weaknesses surfaced during validation. Clearer scoring explanations, including visualization tools and interactive score derivation displays, would close the gap between the 90% who trust the Balance Factor and the 30% who fully understand how it works. Comparative studies testing HAIC-MM's balance-based scoring against traditional averaging using real organizational data would provide empirical evidence for or against the core methodological claim that balance-aware scoring produces more accurate assessments than conventional approaches.

7.5. Publications of Results

The research presented in this dissertation has been disseminated through peer reviewed venues and a publicly deployed web platform. The outputs include one conference presentation, two journal publications (one accepted and one currently under review), and the HAIC-MM assessment platform available at www.haicmm.com. These dissemination outputs are described below:

1. Ortolano, F., & Gallegos, E. (2024). Towards A Human-AI Collaboration Maturity Model (HAIC-MM) for Small and Medium-Sized Enterprises. *Presented at the Systems Engineering Research Center (SERC) AI4SE & SE4AI Workshop*. Arlington, VA: Sept 2024.
2. Ortolano, L.F., & Gallegos, E.E. (2025). Advancing human-AI collaboration in small and medium-sized enterprises: A systems engineering approach. *Systems Engineering*, 29(3), 477-494. <https://doi.org/10.1002/sys.70031>

3. Ortolano, L.F., & Gallegos, E.E. (under review). Empirical validation of a human-AI collaboration maturity model for small and medium enterprises.
4. Ortolano, L.F., & Gallegos, E.E. (2026). HAIC-MM Assessment Platform.
<https://www.haicmm.com>

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APPENDIX A: DIMENSIONS AND CAPABILITIES OF HAIC-MM

Dimension	Capability	Condensed Description
AI-Enhanced Leadership and Strategy	Augmented Decision Making	Use AI and data analytics to enhance leaders' decision-making with accurate, data-driven insights.
	Leadership AI Literacy	Equip leaders with a deep understanding of AI to champion initiatives and leverage AI effectively.
	Inclusive AI Vision Communication	Communicate the AI vision clearly across all levels, fostering alignment with organizational goals.
	AI Strategy Alignment	Align AI initiatives with business objectives to maximize competitive advantage and ROI.
	AI Adoption Readiness Assessment	Assess readiness for AI by evaluating infrastructure, skills, and available resources.
Adaptive AI Culture and Empowerment	Comprehensive AI Training & Development	Build an AI-focused training program to enhance collaboration and adaptability.
	AI Partnership Index	Develop metrics to assess the quality and effectiveness of human-AI collaboration.
	Workforce AI Adaptability	Enhance adaptability to AI-driven changes through targeted training and support.
	Psychological Safety in AI Collaboration	Create a safe environment for employees to interact openly with AI, promoting innovation.
Human-Centric AI Integration and Experience	Human-Centered AI Design	Design AI systems that prioritize user needs, ensuring usability and accessibility.
	AI Integration Effectiveness	Ensure smooth AI integration into workflows, minimizing disruptions and enhancing productivity.
	Employee Experience with AI Tools	Improve user interaction with AI through feedback-driven interface adjustments.
	Human-AI Collaboration Quality	Measure collaboration productivity by evaluating communication, task completion, and outcomes.
	Human Trust in AI Assessment	Assess and foster trust in AI through transparency, reliability, and employee involvement.
Harmonizing AI and Human Processes	AI-Driven Process Optimization	Use AI to optimize processes, increase efficiency, and eliminate redundancies.
	Human-AI Collaboration Index	Create metrics to quantify collaboration effectiveness between humans and AI.
	Human-AI Task Flow	Design workflows that distribute tasks effectively between humans and AI.
	Adaptive Task Allocation	Use real-time assessments to dynamically assign tasks to humans or AI, optimizing resources.
Human-Centered AI Customer Engagement	AI-Enhanced Customer Engagement	Personalize customer interactions with AI, improving experience and satisfaction.
	Customer Insights on AI Experiences	Collect feedback on AI interactions to refine and improve customer-facing AI tools.
	Human-AI Response Integration	Enable seamless coordination between humans and AI in customer service for efficient support.
	Human-AI Collaborative Resolution Rate	Measure resolution success in issues solved through human-AI collaboration.

AI Ethics and Human Oversight	AI Ethical Oversight	Establish governance structures to oversee ethical AI deployment.
	AI Data Compliance	Ensure AI operations comply with data protection laws and standards.
	AI Governance Effectiveness	Assess and strengthen AI governance for policy enforcement and risk management.
	AI Operational Transparency	Maintain transparent communication about AI operations to foster trust.
	Responsible AI Practices	Adopt best practices to ensure ethical, fair, and accountable AI usage.
Inclusive AI Governance and Learning	Equity and Fairness Assessment	Promote fairness in AI systems with inclusive policies and bias mitigation.
	Achieving Diversity in AI Training Data	Ensure diverse and representative data in AI training to reduce biases.
	Assessing AI Impact on Workforce Roles	Analyze how AI impacts job roles and plan reskilling/upskilling as needed.
	Implementing Inclusive AI Decision-Making	Involve diverse perspectives in AI-related decisions to promote fairness.
	Adaptive AI Workforce Upskilling	Provide ongoing AI skill development to maintain a proficient and adaptable workforce.

APPENDIX B: SURVEY QUESTIONNAIRE

Question	Answer Options
Q1 Please select the category that best describes your current organizational role:	- C-level Executive (Business Owner, CEO, CFO, CIO, COO, etc.) - Vice-President / Director - Senior Manager / Manager - Head of Department/Division - Project Manager / Program Manager - Supervisor - Non-Leadership Role - None of the above
Q2 Please describe your level of influence or involvement in adopting, using, or planning technology (including AI) in your organization:	- I am directly involved in strategic planning and decision-making for technology within my area, including the use of AI. - I contribute to the evaluation and selection of technology and automation tools, including AI-based solutions. - I participate in discussions or provide input for adopting new technologies, improving automation practices, or testing new AI-based solutions. - I am involved in pilot programs or initial testing phases of new technology, including intelligent software tools and AI-based solutions. - I regularly use technology, software automation tools or AI-based solutions as part of my job functions. - I have no direct involvement or influence on technology usage, including AI-based solutions in my organization.
Q3 How important do you believe it is for an organization to integrate AI into its strategic planning to gain a competitive advantage?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q4 To what extent do you agree that an in-depth understanding of AI tools is necessary for company leaders to enhance team performance and roles?	- Strongly Agree - Agree - Somewhat Agree - Somewhat Disagree - Disagree - Strongly Disagree

Q5 How would you rate the significance of actively empowering employees to utilize AI technologies in their daily roles?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q6 Evaluate the criticality of upskilling programs in equipping employees to effectively collaborate with emerging technologies like AI.	- Absolutely Critical - Critical - Fairly Critical - Moderately Critical - Slightly Critical - Not Critical at All
Q7 How would you rate the importance of designing AI tools that are user-friendly and facilitate collaboration?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q8 Please indicate how essential it is for employees to have a positive interaction experience with any AI systems they might use.	- Absolutely Essential - Essential - Fairly Essential - Moderately Essential - Slightly Essential - Not Essential at All
Q9 How beneficial do you think AI can be in improving process efficiency in an organization?	- Extremely Beneficial - Beneficial - Somewhat Beneficial - Slightly Beneficial - Not Very Beneficial - Not Beneficial at All
Q10 How important is it to have a smooth transition of tasks between AI systems and human employees?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q11 Please rate the significance of AI in supporting customer interactions within a business.	- Highly Significant - Significant - Fairly Significant - Moderately Significant - Slightly Significant - Completely Insignificant

Q12 How essential is customer feedback in improving AI interactions and services?	- Absolutely Essential - Essential - Fairly Essential - Moderately Essential - Slightly Essential - Not Essential at All
Q13 Please assess the importance of following ethical guidelines when implementing AI solutions.	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q14 How vital do you consider the transparency and understandability of AI system operations?	- Absolutely Vital - Vital - Fairly Vital - Moderately Vital - Slightly Vital - Not at All Vital
Q15 How important is it to have continuous learning opportunities for improving human-AI collaboration?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q16 Please rate the significance of having inclusive decision-making processes that consider diverse stakeholder perspectives when selecting and implementing AI applications.	- Highly Significant - Significant - Fairly Significant - Moderately Significant - Slightly Significant - Completely Insignificant
Q17 How significant is the contribution of AI to strategic decision-making in your organization?	- Highly Significant - Significant - Fairly Significant - Moderately Significant - Slightly Significant - Completely Insignificant
Q18 How critical is leadership's understanding of AI for its successful integration and organizational success?	- Absolutely Critical - Critical - Fairly Critical - Moderately Critical - Slightly Critical - Not Critical at All

Q19 How important is the clear communication of AI collaboration vision across all levels of your organization?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q20 To what extent is the integration of AI into strategic business planning essential for future readiness and competitive advantage?	- Absolutely Essential - Essential - Fairly Essential - Moderately Essential - Slightly Essential - Not Essential at All
Q21 How valuable are the training programs in preparing employees for effective human-AI collaboration?	- Extremely Valuable - Valuable - Fairly Valuable - Moderately Valuable - Slightly Valuable - Not Valuable at All
Q22 How vital is empowering employees to leverage AI effectively in their roles?	- Absolutely Vital - Vital - Fairly Vital - Moderately Vital - Slightly Vital - Not at All Vital
Q23 How important is it for your organization to adaptively reallocate human and AI resources in response to changing needs?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q24 How critical are upskilling programs for enhancing employees' ability to work with AI?	- Absolutely Critical - Critical - Fairly Critical - Moderately Critical - Slightly Critical - Not Critical at All
Q25 How essential is user-friendly AI design for effective collaboration and end-user satisfaction?	- Absolutely Essential - Essential - Fairly Essential - Moderately Essential - Slightly Essential - Not Essential at All

Q26 How important is the seamless integration of AI into the daily workflows of employees?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q27 How would you rate the importance of employee satisfaction with AI system interactions?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q28 How crucial is the quality of interaction between employees and AI systems for organizational effectiveness?	- Absolutely Crucial - Very Crucial - Moderately Crucial - Slightly Crucial - Not Very Crucial - Not Crucial at All
Q29 How beneficial is AI in improving the efficiency and productivity of organizational processes?	- Extremely Beneficial - Beneficial - Somewhat Beneficial - Slightly Beneficial - Not Very Beneficial - Not Beneficial at All
Q30 How important is human intervention in overseeing and enhancing AI-driven processes?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q31 How crucial is the smooth and effective transition of tasks between AI systems and human employees?	- Absolutely Crucial - Very Crucial - Moderately Crucial - Slightly Crucial - Not Very Crucial - Not Crucial at All
Q32 How significant is clear and efficient task allocation between humans and AI in achieving productivity?	- Highly Significant - Significant - Fairly Significant - Moderately Significant - Slightly Significant - Completely Insignificant

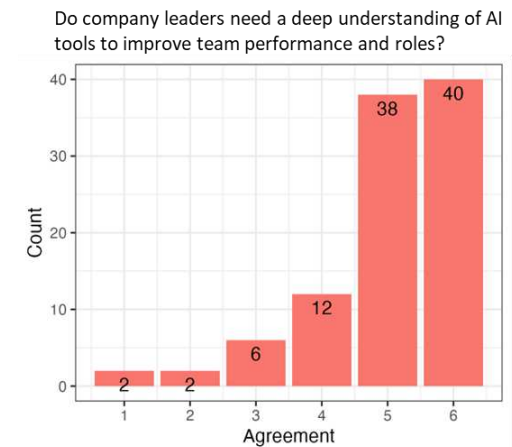
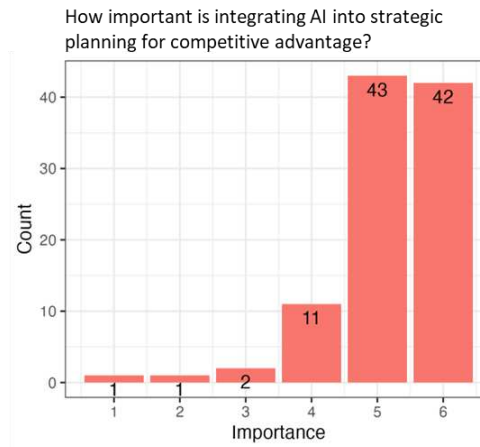
Q33 How significant is AI's role in enhancing customer interactions and satisfaction?	- Highly Significant - Significant - Fairly Significant - Moderately Significant - Slightly Significant - Completely Insignificant
Q34 How essential is customer feedback for improving AI-enhanced services and interactions?	- Absolutely Essential - Essential - Fairly Essential - Moderately Essential - Slightly Essential - Not Essential at All
Q35 How critical is efficient coordination between human and AI responses in customer service?	- Absolutely Critical - Critical - Fairly Critical - Moderately Critical - Slightly Critical - Not Critical at All
Q36 How important is AI in achieving successful resolutions in customer service?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q37 How vital is the regular assessment of AI usage against ethical guidelines in your organization?	- Absolutely Vital - Vital - Fairly Vital - Moderately Vital - Slightly Vital - Not at All Vital
Q38 How crucial is adherence to data governance and privacy standards in AI applications?	- Absolutely Crucial - Very Crucial - Moderately Crucial - Slightly Crucial - Not Very Crucial - Not Crucial at All
Q39 How essential is effective human oversight in managing and correcting AI outputs?	- Absolutely Essential - Essential - Fairly Essential - Moderately Essential - Slightly Essential - Not Essential at All

Q40 How important is the transparency of AI operations and their decision-making processes?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q41 How crucial is the representation of diverse data sets in AI training to avoid biases?	- Absolutely Crucial - Very Crucial - Moderately Crucial - Slightly Crucial - Not Very Crucial - Not Crucial at All
Q42 How significant has the impact of AI been on job roles and tasks within your organization?	- Highly Significant - Significant - Fairly Significant - Moderately Significant - Slightly Significant - Completely Insignificant
Q43 How essential are continuous learning opportunities for improving human-AI collaboration?	- Absolutely Essential - Essential - Fairly Essential - Moderately Essential - Slightly Essential - Not Essential at All
Q44 How important are inclusive decision-making processes that consider diverse stakeholder perspectives in AI applications?	- Extremely Important - Important - Fairly Important - Moderately Important - Slightly Important - Not at All Important
Q45 In an ideal scenario, AI integration would significantly impact my decision-making process or workflow.	- Strongly Agree - Agree - Somewhat Agree - Somewhat Disagree - Disagree - Strongly Disagree
Q46 If implemented, I believe my organization would effectively address challenges associated with AI technologies.	- Strongly Agree - Agree - Somewhat Agree - Somewhat Disagree - Disagree - Strongly Disagree

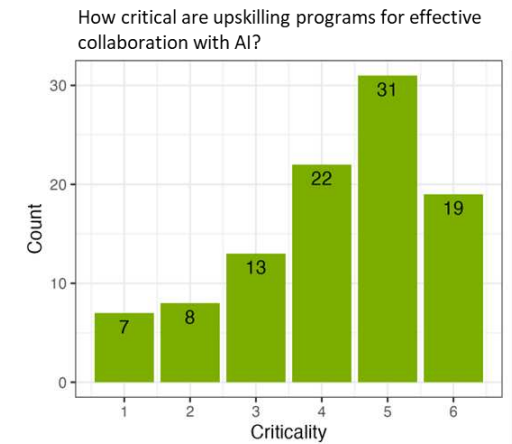
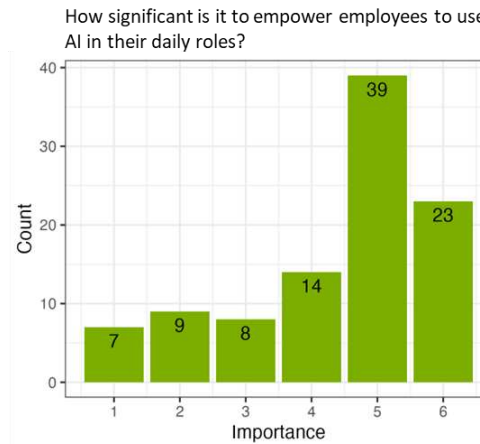
Q47 In an ideal AI implementation, I foresee the benefits significantly outweighing the challenges in my organization.	- Strongly Agree - Agree - Somewhat Agree - Somewhat Disagree - Disagree - Strongly Disagree
Q48 A successful AI integration, if it were to happen in my organization, would positively influence my views on AI's potential.	- Strongly Agree - Agree - Somewhat Agree - Somewhat Disagree - Disagree - Strongly Disagree

APPENDIX C: ONLINE SURVEY RESULTS CHARTS

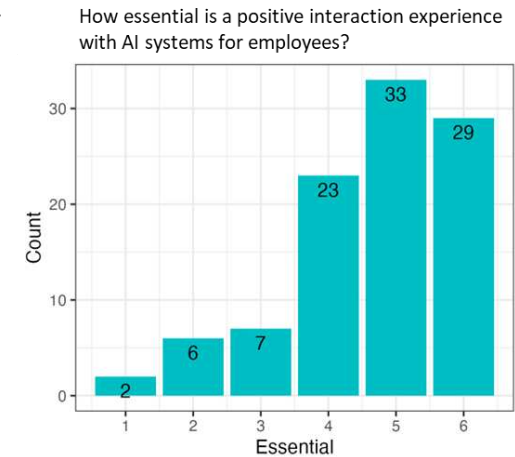
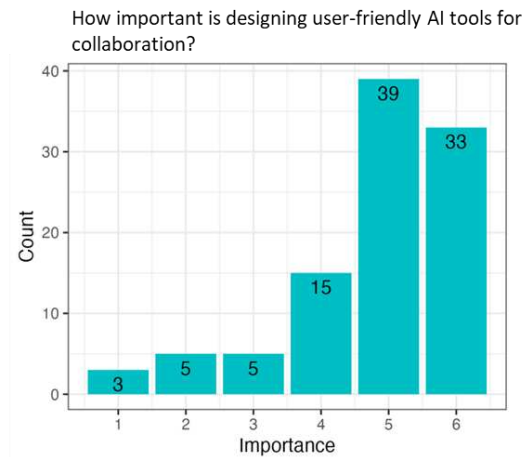
HAIC-MM Dimensions	
1	Collaborative Strategy and Leadership
2	Empowerment and Adaptive Culture
3	Integrated Technology and User Experience
4	Process Harmonization
5	Human-Centric Customer Engagement
6	Data Ethics and Human Oversight
7	Inclusive Governance and Continuous Learning



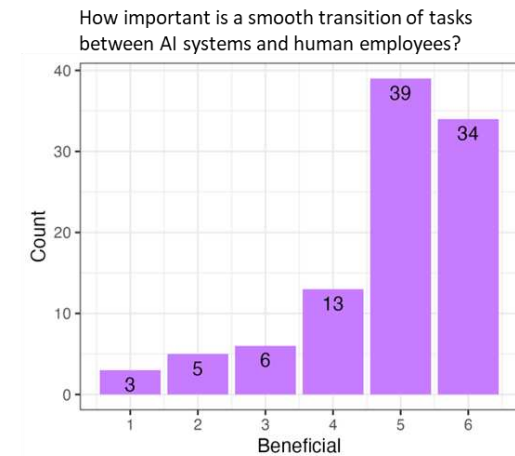
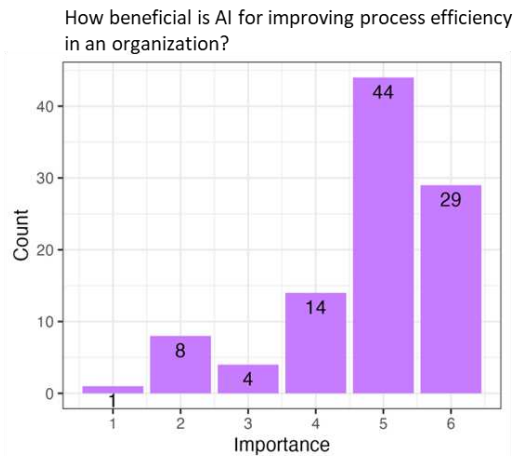
HAIC-MM Dimension	
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2	Empowerment and Adaptive Culture
3	Integrated Technology and User Experience
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5	Human-Centric Customer Engagement
6	Data Ethics and Human Oversight
7	Inclusive Governance and Continuous Learning



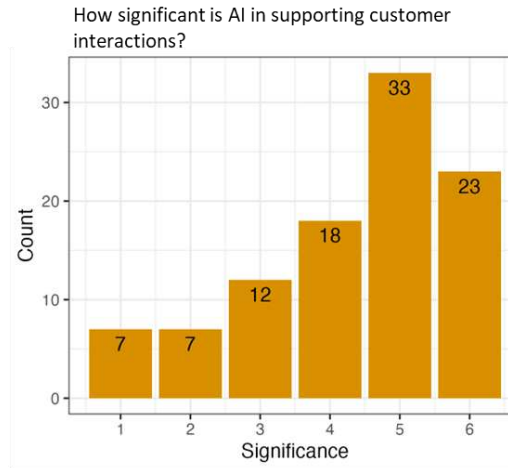
HAIC-MM Dimensions	
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2	Empowerment and Adaptive Culture
3	Integrated Technology and User Experience
4	Process Harmonization
5	Human-Centric Customer Engagement
6	Data Ethics and Human Oversight
7	Inclusive Governance and Continuous Learning



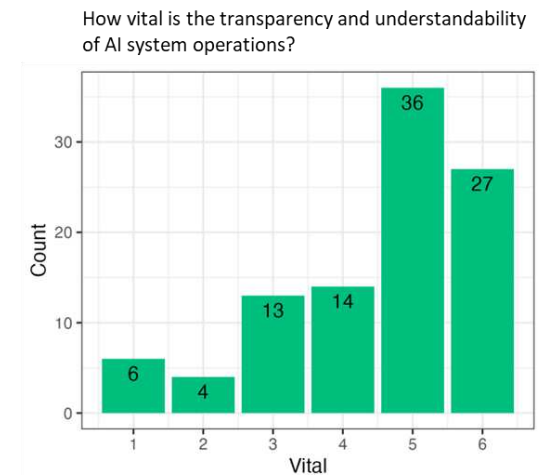
HAIC-MM Dimensions	
1	Collaborative Strategy and Leadership
2	Empowerment and Adaptive Culture
3	Integrated Technology and User Experience
4	Process Harmonization
5	Human-Centric Customer Engagement
6	Data Ethics and Human Oversight
7	Inclusive Governance and Continuous Learning



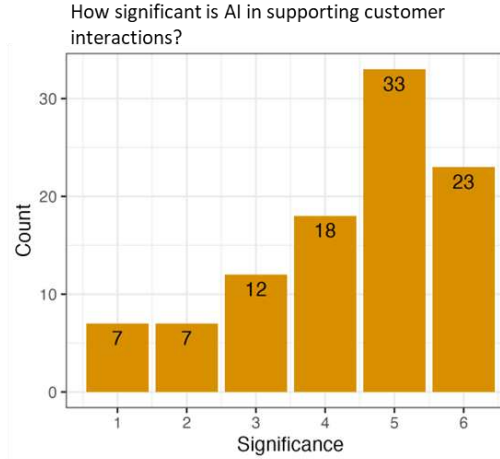
HAIC-MM Dimension	
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2	Empowerment and Adaptive Culture
3	Integrated Technology and User Experience
4	Process Harmonization
5	Human-Centric Customer Engagement
6	Data Ethics and Human Oversight
7	Inclusive Governance and Continuous Learning



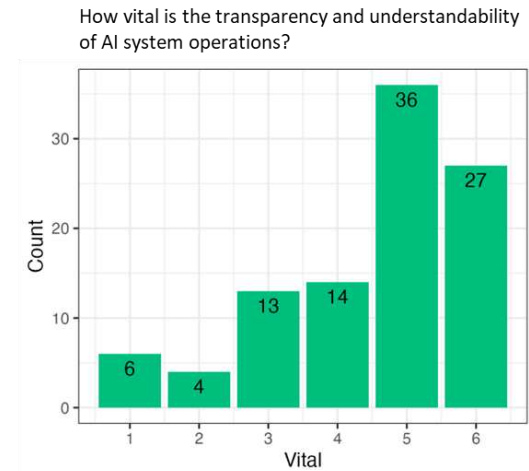
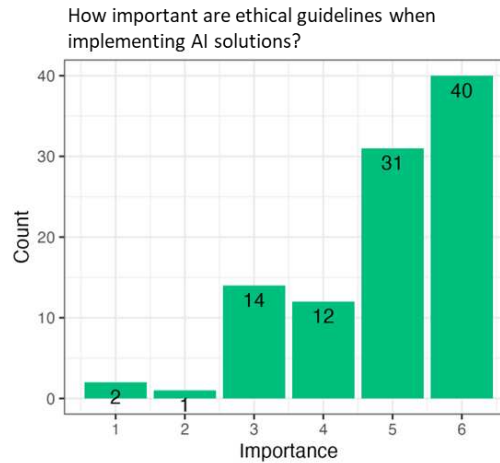
HAIC-MM Dimension	
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3	Integrated Technology and User Experience
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6	Data Ethics and Human Oversight
7	Inclusive Governance and Continuous Learning

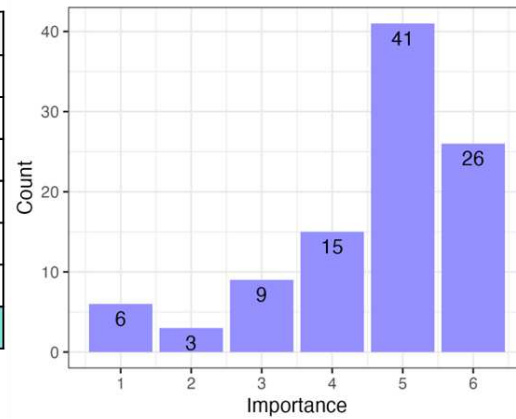


HAIC-MM Dimension	
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2	Empowerment and Adaptive Culture
3	Integrated Technology and User Experience
4	Process Harmonization
5	Human-Centric Customer Engagement
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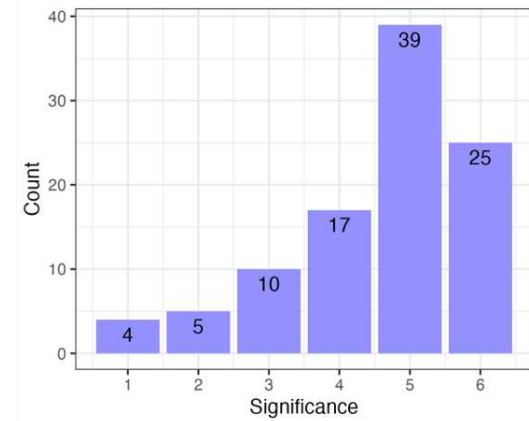


HAIC-MM Dimension	
1	Collaborative Strategy and Leadership
2	Empowerment and Adaptive Culture
3	Integrated Technology and User Experience
4	Process Harmonization
5	Human-Centric Customer Engagement
6	Data Ethics and Human Oversight
7	Inclusive Governance and Continuous Learning

How important are continuous learning opportunities for improving human-AI collaboration?



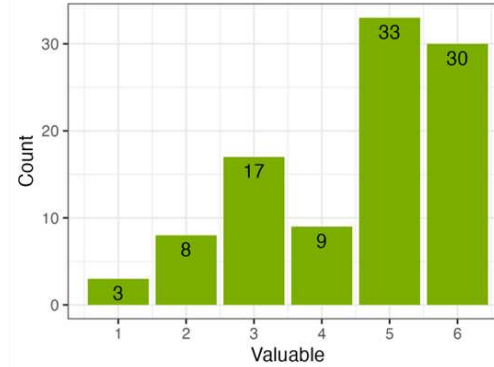
How significant are inclusive decision-making processes for AI implementation?



HAIC-MM Dimension	Capability
Collaborative Strategy and Leadership	AI-Enhanced Decision Making
	Leadership AI Literacy
	Collaborative Vision Communication
	AI Integration in Business Plans
Empowerment and Adaptive Culture	AI Collaboration Training
	Employee Empowerment Index
	Adaptive Workforce Dynamics
	Adaptive Workforce Development
Integrated Technology and User Experience	User-Centric AI Design
	Technology Integration Level
	Employee Technology Satisfaction
	Human-AI Interaction Quality
Process Harmonization	AI-Enabled Process Efficiency
	Human-Intervention Index
	Seamless Task Transition
	Human-AI Task Allocation
Human-Centric Customer Engagement	AI Augmented Customer Interactions
	Customer Feedback on AI Interactions
	Human-AI Response Coordination
	Human-AI Customer Resolution Success
Data Ethics and Human Oversight	Ethical AI Usage Monitoring
	Data Management Compliance
	Oversight Effectiveness
	Transparent AI Operations
Inclusive Governance and Continuous Learning	Diversity in AI Training Data
	AI Impact on Job Roles
	Continual Learning Opportunities
	Inclusive Decision-Making Processes

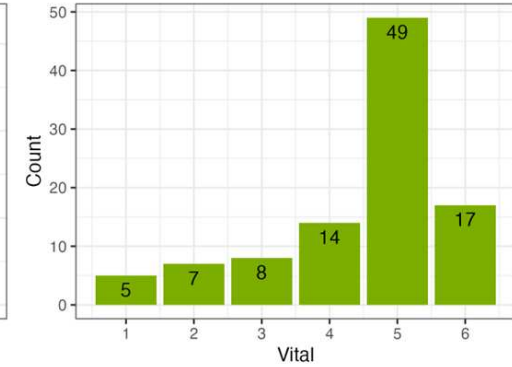
How valuable are training programs for effective human-AI collaboration?

AI Collaboration Training



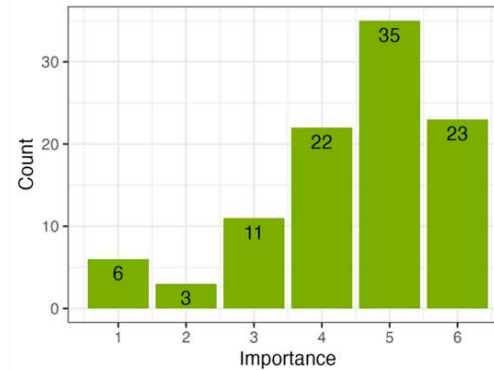
How vital is empowering employees to effectively use AI?

Employee Empowerment Index



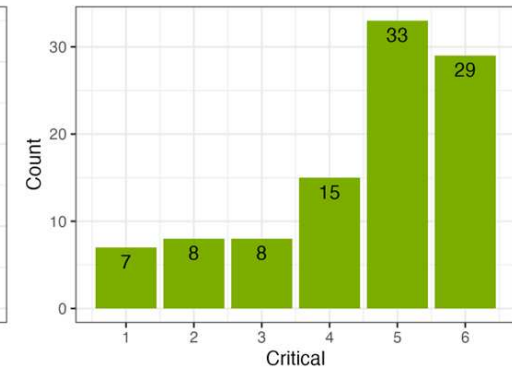
How important is adaptive reallocation of human and AI resources to changing needs?

Adaptive Workforce Dynamics



How critical are upskilling programs for employees' ability to work with AI?

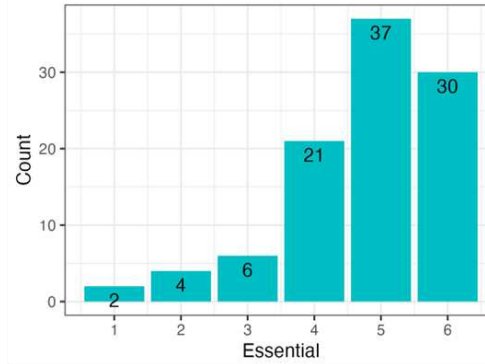
Adaptive Workforce Development



HAIC-MM Dimension	Capability
Collaborative Strategy and Leadership	AI-Enhanced Decision Making
	Leadership AI Literacy
	Collaborative Vision Communication
	AI Integration in Business Plans
Empowerment and Adaptive Culture	AI Collaboration Training
	Employee Empowerment Index
	Adaptive Workforce Dynamics
	Adaptive Workforce Development
Integrated Technology and User Experience	User-Centric AI Design
	Technology Integration Level
	Employee Technology Satisfaction
	Human-AI Interaction Quality
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	Oversight Effectiveness
	Transparent AI Operations
Inclusive Governance and Continuous Learning	Diversity in AI Training Data
	AI Impact on Job Roles
	Continual Learning Opportunities
	Inclusive Decision-Making Processes

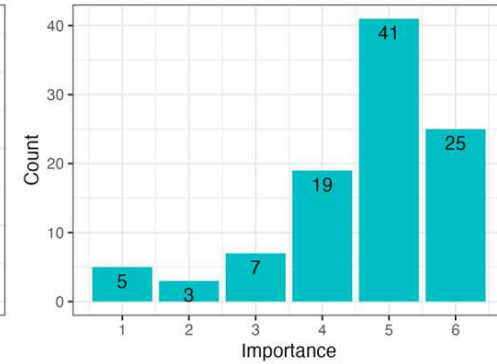
How essential is user-friendly AI design for collaboration and user satisfaction?

User-Centric AI Design



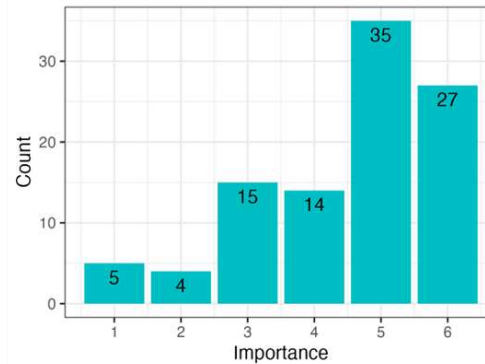
How important is seamless integration of AI into daily workflows?

Technology Integration Level



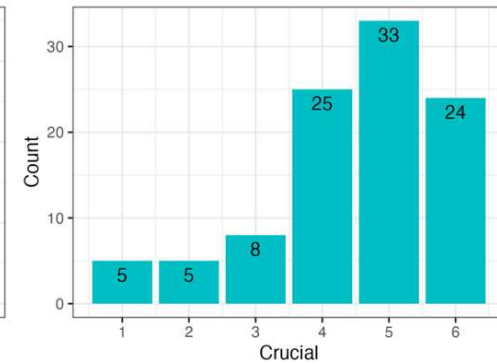
How important is employee satisfaction with AI system interactions?

Employee Technology Satisfaction



How crucial is the quality of interaction between employees and AI systems for effectiveness?

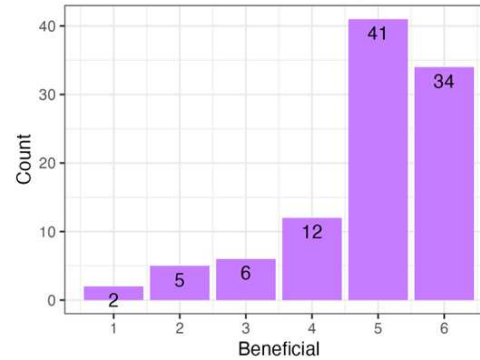
Human-AI Interaction Quality



HAIC-MM Dimension	Capability
Collaborative Strategy and Leadership	AI-Enhanced Decision Making
	Leadership AI Literacy
	Collaborative Vision Communication
	AI Integration in Business Plans
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	Inclusive Decision-Making Processes

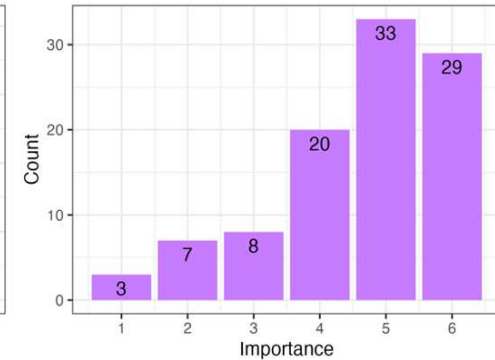
How beneficial is AI in improving efficiency and productivity?

AI-Enabled Process Efficiency



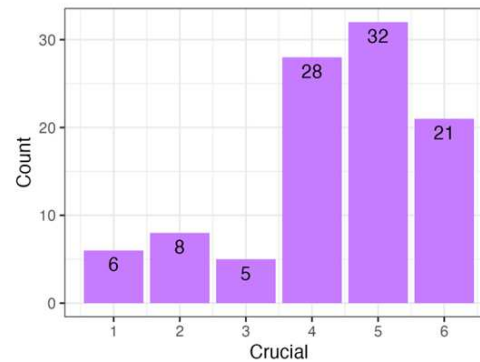
How important is human intervention in overseeing and enhancing AI processes?

Human-Intervention Index



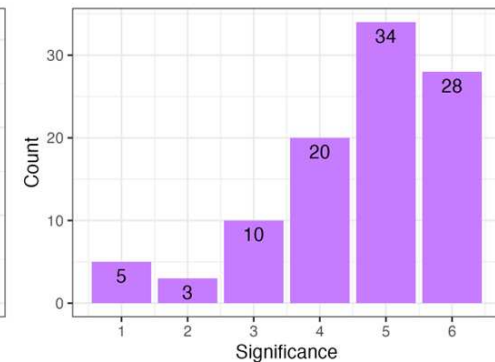
How crucial is the smooth and effective transition of tasks between AI and humans?

Seamless Task Transition



How significant is clear task allocation between humans and AI for productivity?

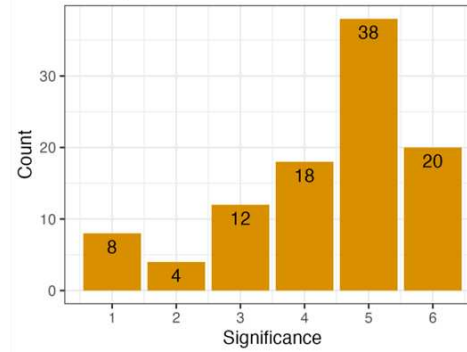
Human-AI Task Allocation



HAIC-MM Dimension	Capability
Collaborative Strategy and Leadership	AI-Enhanced Decision Making
	Leadership AI Literacy
	Collaborative Vision Communication
	AI Integration in Business Plans
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	Transparent AI Operations
Inclusive Governance and Continuous Learning	Diversity in AI Training Data
	AI Impact on Job Roles
	Continual Learning Opportunities
	Inclusive Decision-Making Processes

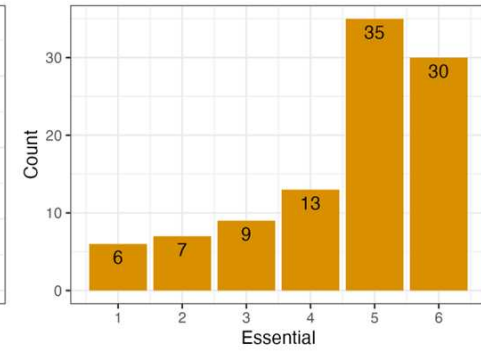
How significant is AI in enhancing customer interactions and satisfaction?

AI Augmented Customer Interactions



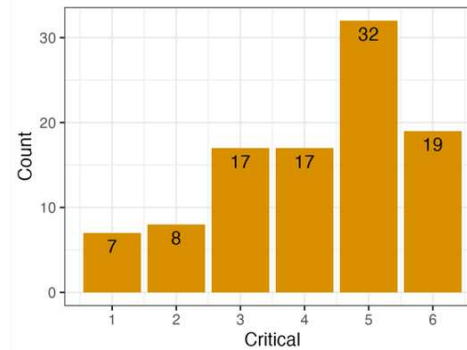
How essential is customer feedback for improving AI-enhanced services?

Customer Feedback on AI Interactions



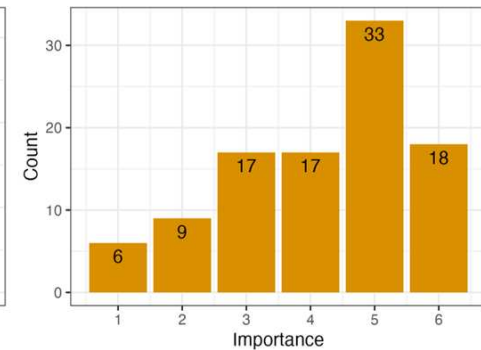
How critical is efficient coordination between human and AI responses in customer service?

Human-AI Response Coordination



How important is AI in achieving successful resolutions in customer service?

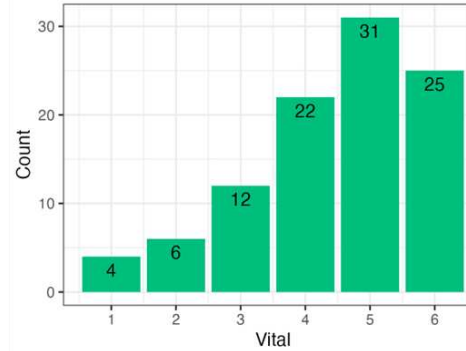
Human-AI Customer Resolution Success



HAIC-MM Dimension	Capability
Collaborative Strategy and Leadership	AI-Enhanced Decision Making
	Leadership AI Literacy
	Collaborative Vision Communication
	AI Integration in Business Plans
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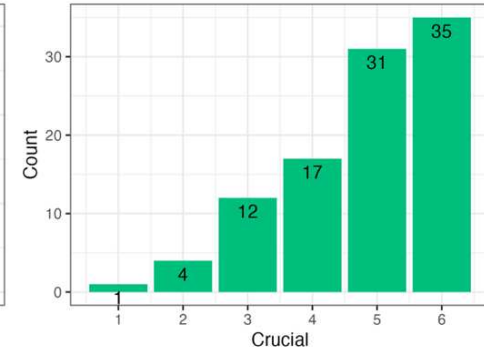
How vital is regular assessment of AI usage against ethical guidelines?

Ethical AI Usage Monitoring



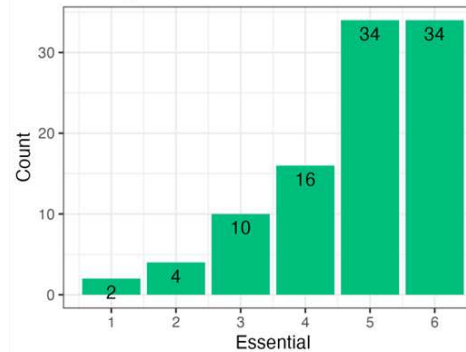
How crucial is adherence to data governance and privacy standards in AI?

Data Management Compliance



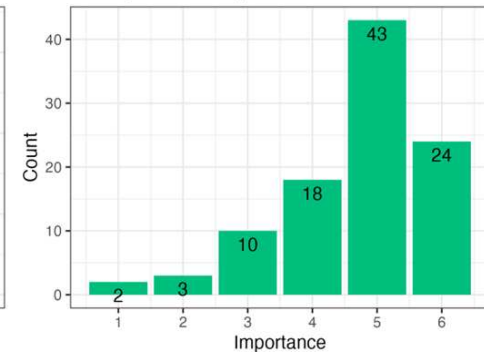
How essential is human oversight in managing and correcting AI outputs?

Oversight Effectiveness



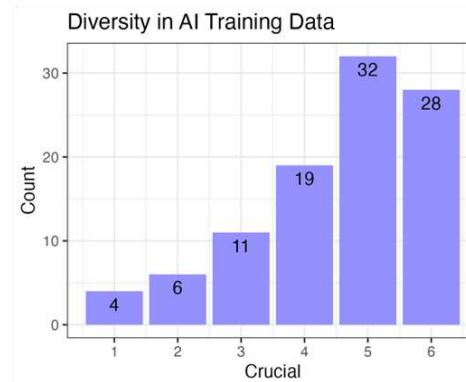
How important is the transparency of AI operations and decision-making processes?

Transparent AI Operations



HAIC-MM Dimension	Capability
Collaborative Strategy and Leadership	AI-Enhanced Decision Making
	Leadership AI Literacy
	Collaborative Vision Communication
	AI Integration in Business Plans
Empowerment and Adaptive Culture	AI Collaboration Training
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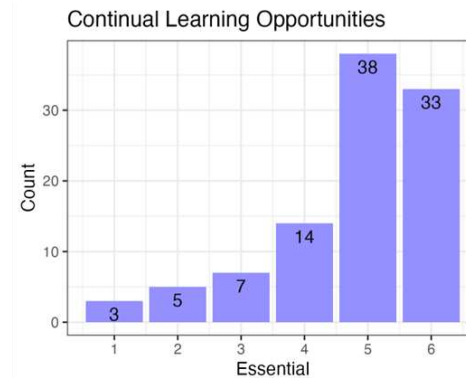
How crucial is diverse data representation in AI training to avoid biases?



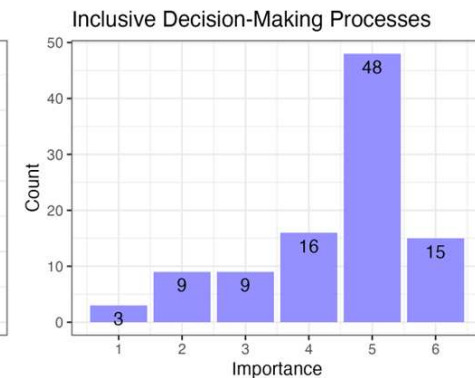
How significant has AI's impact been on job roles and tasks in your organization?



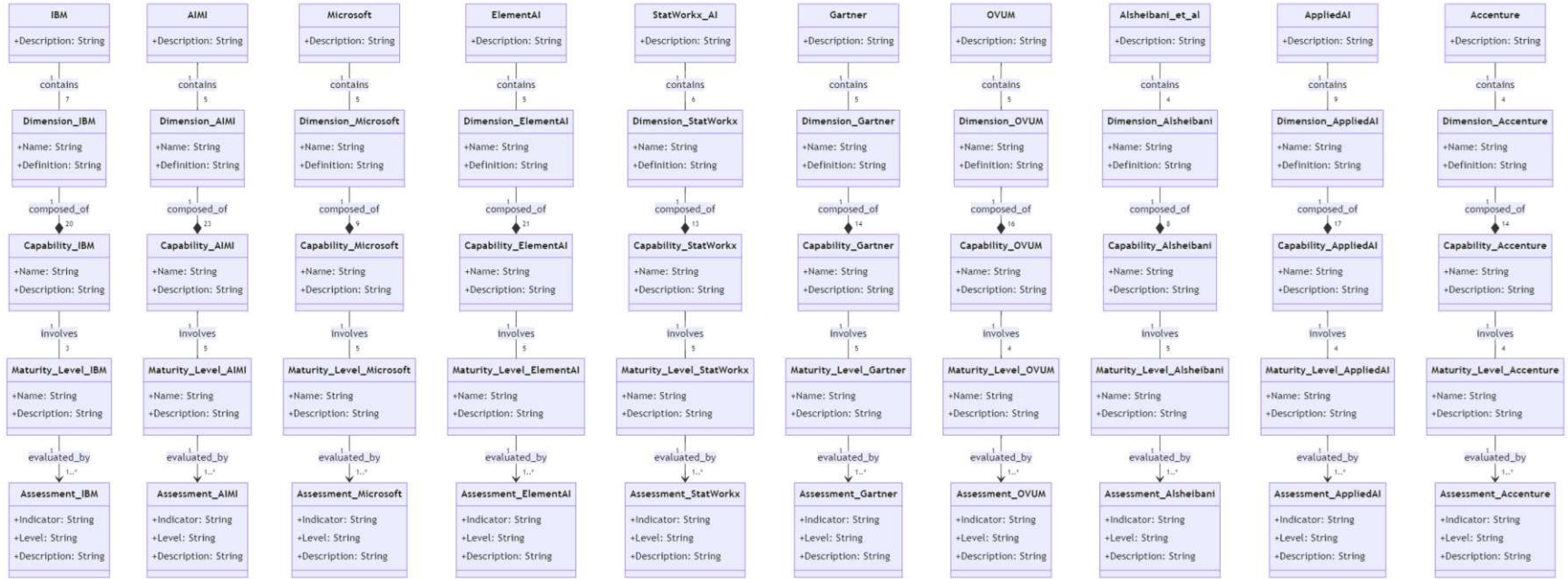
How essential are continuous learning opportunities for human-AI collaboration?



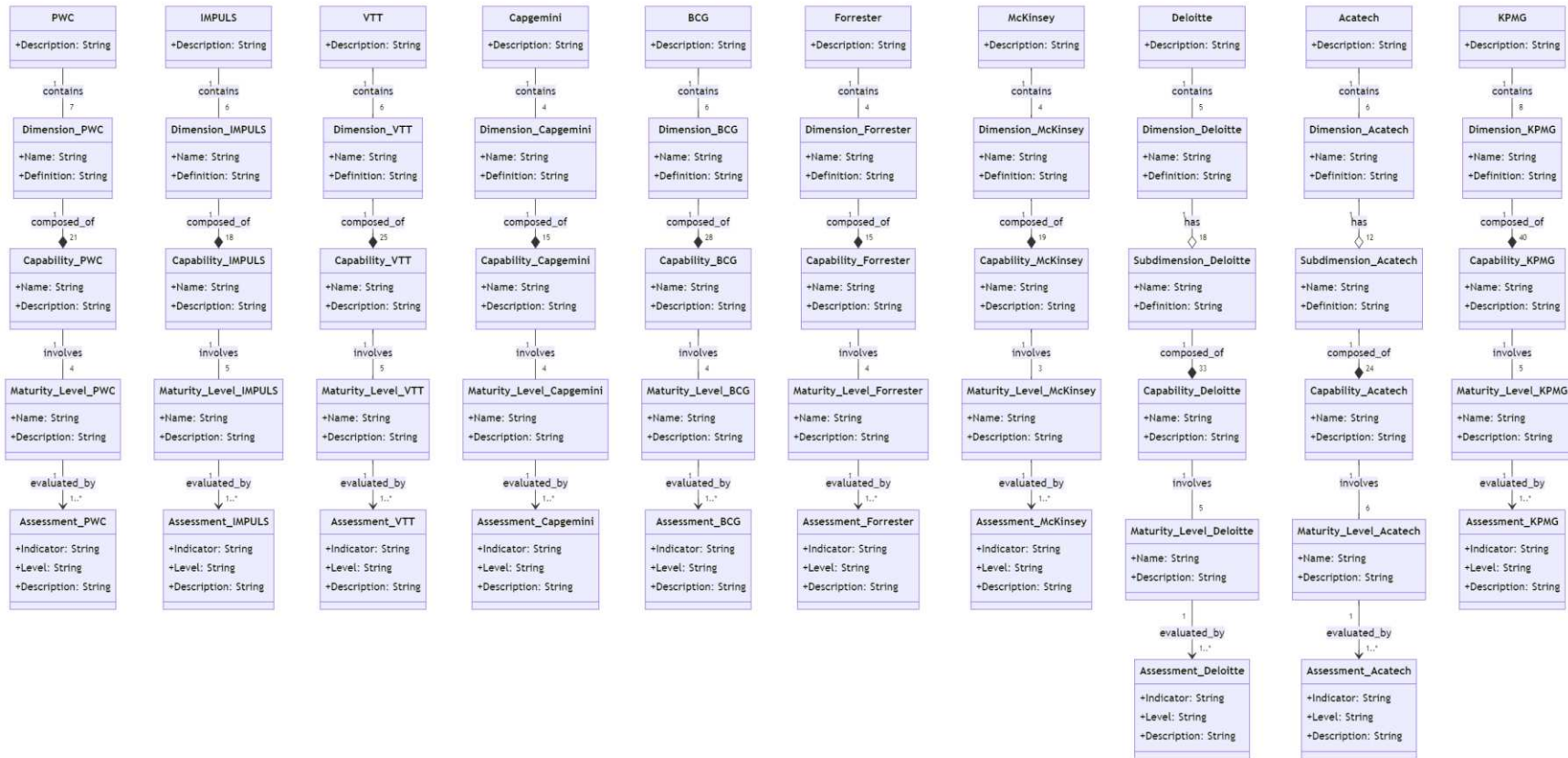
How important are inclusive decision-making processes in AI applications?



APPENDIX D: METAMODELS FOR THE SELECTED AI MATURITY MODELS



APPENDIX E: METAMODELS FOR THE SELECTED DT MATURITY MODELS



APPENDIX F: HMT FRAMEWORKS – CONCEPT MATRIX AND APPLICABILITY TO SMES

HMT Principle	CIQ	CMF	TSAC	HAT	HMHR	FAHMT	TST	MUHMT	MAHMT	R-HMT	Contributions	Limitations	Focus Areas	Key Techniques & Concepts	Applicability to SMEs
Common Ground	Y	N	Y	Y	N	Y	Y	Y	Y	Y	Varied focus on team alignment and shared goals.	Some frameworks do not explicitly address AI-human collaboration.	Varies by framework	Varies by framework	Varies by framework
Observability	Y	Y	Y	Y	N	Y	N	N	N	Y	Emphasis on clarity of actions and progress in teams.	Limited discussion on the clarity of AI actions in some frameworks.	Collaborative Dynamics, Teamwork Characteristics, Empirical Literature	Communication techniques, situational awareness models, autonomy spectrum	Moderate to High
Predictability	N	N	N	N	N	Y	N	N	Y	N	Few frameworks address the anticipation of future actions in HMT.	Most frameworks lack a focus on predictability.	-	-	-
Directability	N	Y	N	Y	N	N	N	N	Y	Y	Some frameworks allow for human control over AI systems.	Often overlooked in favor of other HMT aspects.	Trust, Directability, Modeling	Trust building models, human-AI trust factors, task delegation frameworks	High

Directing Attention	Y	N	N	N	Y	N	Y	N	N	N	Attention management between team members highlighted.	Not widely considered across frameworks.	Human-Robot Collaboration, Human-Autonomy Teaming	Human-robot interaction models, synthetic teammate design, role assignment optimization	Moderate
Exploring the Solution Space	N	N	N	N	Y	Y	N	N	Y	Y	Encourages diverse problem-solving approaches.	Many frameworks do not emphasize exploration.	Adaptive Teaming	Automation, AI, machine learning techniques	High
Adaptability	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Adaptability to dynamic conditions is well-represented.	Some frameworks may be too complex for SMEs.	Adaptive Teaming, Teamwork Characteristics	Adaptive behavior, human-machine observability, autonomy spectrum	High
Calibrated Trust	N	Y	Y	Y	Y	N	Y	Y	Y	Y	Trust as a critical aspect of HMT is extensively covered.	Some frameworks may overemphasize trust.	Mutual Understanding, Trust	Explainable AI (XAI) techniques, transparency frameworks, trust calibration	High
Information Presentation	Y	Y	N	Y	N	N	N	Y	N	Y	Information presentation is recognized for effective teamwork.	Not all frameworks provide guidance on information design.	Collaborative Dynamics, Resilience	Information presentation strategies, communication frameworks, presentation strategies	Moderate to High
Design Process	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Design process considerations are prominent in some frameworks.	Technical specifics on design may be lacking.	Design Process	Design considerations, task delegation frameworks	High

APPENDIX G: FULL HUMAN-AI COLLABORATION MATURITY MODEL (HAIC-MM)

This appendix presents the full HAIC-MM model structure in one place. It supplements the Chapter 4 overview by listing the model constructs, maturity levels, dimensions, capabilities, focus areas, and state descriptions used in the final model.

This table gives the reader a high-level map of the model. It shows how the maturity levels, dimensions, capabilities, focus areas, advancement practices, and state descriptions fit together.

Table G1: HAIC-MM Construct Hierarchy

Construct	Count/Scope	Purpose
Maturity model	HAIC-MM	The overall assessment framework for evaluating human-AI collaboration maturity in SMEs.
Maturity levels	5	The staged progression from AI Exploration to Symbiotic Partnership.
Dimensions	7	Broad assessment domains that organize the model.
Capabilities	32	Specific organizational abilities assessed within the dimensions.
Focus areas	5 per capability	The lenses used to examine each capability from organizational, socio-technical, interaction, systems, and trust perspectives.
Advancement practices	4 per focus area	Action-oriented improvement guidance for moving from diagnosis to practice.
State descriptions	Level-specific	Narrative descriptions explaining what each level means for every dimension and capability.

This table defines the five maturity levels used by HAIC-MM. These levels describe the progression from early AI exploration to a mature human-AI partnership.

Table G2: HAIC-MM Maturity Levels

Level	Final Label	Score Range	Final Description
L1	AI Exploration	0.00-1.99	The SME is trying AI in a few isolated ways, usually through small pilots or ready-made tools. Use is limited, data is not well connected, and most people are still figuring out where AI may help.
L2	AI-Enabled	2.00-2.99	The SME is using AI in some specific workflows and seeing early results in selected teams. Adoption is still uneven, systems are only partly connected, and most efforts stay within departments.
L3	AI-Embedded	3.00-3.79	AI is now part of several core processes in the SME, with clearer operational benefits. Employees are more comfortable using it, data practices are improving, and teams are starting to rely on AI more regularly in daily work.
L4	AI-Aligned	3.80-4.49	The SME is using AI with clearer purpose and stronger connection to business priorities. AI supports both day-to-day operations and broader goals, backed by better data practices, governance, and employee confidence.
L5	Symbiotic Partnership	4.50-5.00	AI and humans work in complete harmony. AI is seamlessly integrated at all levels, and decision-making naturally combines AI insights with human judgment while supporting continuous innovation.

This table lists the seven dimensions of HAIC-MM. The dimensions are the broad areas of assessment that organize the more detailed capabilities.

Table G3: HAIC-MM Dimensions

Dimension ID	Dimension	Dimension Weight	Description
D1	AI-Enhanced Leadership and Strategy	1.4	How leadership integrates AI into strategic planning and decision-making.
D2	Adaptive AI Culture and Empowerment	1.2	How the organization's culture embraces and adapts to AI.
D3	Harmonizing AI and Human Processes	1.2	How well human and AI processes are integrated.
D4	Human-Centric AI Integration and Experience	1.0	How AI is designed with human users in mind.
D5	Human-Centered AI Customer Engagement	1.2	How AI enhances customer interactions.
D6	AI Ethics and Human Oversight	1.4	How ethical considerations and human oversight are implemented.
D7	Inclusive AI Governance and Learning	1.0	How diverse perspectives inform AI governance and continuous learning.

This table lists the 32 capabilities in the model. It also shows each capability's dimension, weight, classification, dependency relationships, and short description.

Table G4: HAIC-MM Capabilities, Weights, Classifications, and Dependencies

Capability ID	Dimension ID	Dimension	Capability	Capability Weight	Classification	Required Capabilities	Brief Description
CAP1	D1	AI-Enhanced Leadership and Strategy	Augmented Decision Making	1.00	Supporting	2 (medium), 13 (medium)	Use AI and data analytics to enhance leaders' decision-making with data-driven insights.
CAP2	D1	AI-Enhanced Leadership and Strategy	Leadership AI Literacy	1.40	Strategic	4 (low)	Equip leaders with deep understanding of AI to champion initiatives and manage risks.
CAP3	D1	AI-Enhanced Leadership and Strategy	Inclusive AI Vision Communication	1.00	Supporting	14 (high)	Communicate the AI vision clearly across all levels, aligning with organizational goals.
CAP4	D1	AI-Enhanced Leadership and Strategy	AI Strategy Alignment	1.20	Core	5 (high), 7 (high)	Align AI initiatives with business objectives to maximize competitive advantage.
CAP5	D1	AI-Enhanced Leadership and Strategy	AI Adoption Readiness Assessment	1.00	Supporting	--	Assess readiness for AI by evaluating infrastructure, skills, and resources.
CAP6	D2	Adaptive AI Culture and Empowerment	Comprehensive AI Training and Development	1.20	Core	3 (high)	Build AI-focused training programs to enhance collaboration and adaptability.
CAP7	D2	Adaptive AI Culture and Empowerment	AI Partnership Index	1.00	Supporting	6 (medium), 13 (medium)	Develop metrics to assess the quality and effectiveness of human-AI collaboration.
CAP8	D2	Adaptive AI Culture and Empowerment	Workforce AI Adaptability	1.20	Core	5 (high), 6 (low)	Enhance adaptability to AI-driven changes through targeted training and support.

Capability ID	Dimension ID	Dimension	Capability	Capability Weight	Classification	Required Capabilities	Brief Description
CAP9	D2	Adaptive AI Culture and Empowerment	Psychological Safety in AI Collaboration	1.00	Supporting	--	Create a safe environment for employees to interact openly with AI.
CAP10	D4	Human-Centric AI Integration and Experience	Human-Centered AI Design	1.20	Core	15 (high), 16 (high)	Design AI systems that prioritize user needs, ensuring usability and accessibility.
CAP11	D4	Human-Centric AI Integration and Experience	AI Integration Effectiveness	1.00	Supporting	10 (high), 15 (high)	Ensure smooth AI integration into workflows, minimizing disruptions.
CAP12	D4	Human-Centric AI Integration and Experience	Employee Experience with AI Tools	1.00	Supporting	9 (high), 11 (medium)	Improve user interaction with AI through feedback-driven interface adjustments.
CAP13	D4	Human-Centric AI Integration and Experience	Human-AI Collaboration Quality	1.20	Core	11 (high), 12 (high)	Measure collaboration productivity by evaluating communication, task completion, and outcomes.
CAP14	D4	Human-Centric AI Integration and Experience	Human Trust in AI Assessment	1.00	Supporting	12 (high), 13 (medium)	Assess and foster trust in AI through transparency, reliability, and employee involvement.
CAP15	D3	Harmonizing AI and Human Processes	AI-Driven Process Optimization	1.20	Core	5 (high), 9 (high)	Use AI to optimize processes, increase efficiency, and reduce redundancies.
CAP16	D3	Harmonizing AI and Human Processes	Human-AI Collaboration Index	1.00	Supporting	15 (medium)	Create metrics to quantify collaboration effectiveness between humans and AI.
CAP17	D3	Harmonizing AI and Human Processes	Human-AI Task Flow	1.00	Supporting	15 (high), 16 (high)	Design workflows that distribute tasks effectively between humans and AI.
CAP18	D3	Harmonizing AI and Human Processes	Adaptive Task Allocation	1.00	Supporting	17 (high)	Use real-time assessments to dynamically assign tasks to humans or AI.

Capability ID	Dimension ID	Dimension	Capability	Capability Weight	Classification	Required Capabilities	Brief Description
CAP19	D5	Human-Centered AI Customer Engagement	AI-Enhanced Customer Engagement	1.20	Core	10 (high), 17 (high)	Personalize customer interactions with AI, improving experience and satisfaction.
CAP20	D5	Human-Centered AI Customer Engagement	Customer Insights on AI Experiences	1.00	Supporting	15 (medium), 19 (high)	Collect feedback on AI interactions to refine customer-facing AI tools.
CAP21	D5	Human-Centered AI Customer Engagement	Human-AI Response Integration	1.00	Supporting	17 (medium), 20 (high)	Enable seamless coordination between humans and AI in customer service.
CAP22	D5	Human-Centered AI Customer Engagement	Human-AI Collaborative Resolution Rate	1.00	Supporting	13 (medium), 21 (high)	Measure resolution success in issues solved through human-AI collaboration.
CAP23	D6	AI Ethics and Human Oversight	AI Ethical Oversight	1.40	Strategic	31 (high)	Establish governance structures to oversee ethical AI deployment.
CAP24	D6	AI Ethics and Human Oversight	AI Data Compliance	1.40	Strategic	--	Ensure AI operations comply with data protection laws and standards.
CAP25	D6	AI Ethics and Human Oversight	AI Governance Effectiveness	1.00	Supporting	24 (high)	Assess and strengthen AI governance for policy enforcement and risk management.
CAP26	D6	AI Ethics and Human Oversight	AI Operational Transparency	1.00	Supporting	14 (medium), 25 (high)	Maintain transparent communication about AI operations to foster trust.
CAP27	D6	AI Ethics and Human Oversight	Responsible AI Practices	1.20	Core	25 (high), 26 (high)	Adopt best practices to ensure ethical, fair, and accountable AI usage.

Capability ID	Dimension ID	Dimension	Capability	Capability Weight	Classification	Required Capabilities	Brief Description
CAP28	D6	AI Ethics and Human Oversight	Equity and Fairness Assessment	1.00	Supporting	27 (high)	Promote fairness in AI systems with inclusive policies and bias mitigation.
CAP29	D7	Inclusive AI Governance and Learning	Achieving Diversity in AI Training Data	1.00	Supporting	24 (high), 28 (high)	Ensure diverse and representative data in AI training to reduce biases.
CAP30	D7	Inclusive AI Governance and Learning	Assessing AI Impact on Workforce Roles	1.20	Core	8 (high)	Analyze how AI impacts job roles and plan reskilling as needed.
CAP31	D7	Inclusive AI Governance and Learning	Implementing Inclusive AI Decision-Making	1.00	Supporting	13 (medium), 29 (high)	Involve diverse perspectives in AI-related decisions to promote fairness.
CAP32	D7	Inclusive AI Governance and Learning	Adaptive AI Workforce Upskilling	1.20	Core	6 (high), 30 (high)	Provide ongoing AI skill development to maintain a proficient workforce.

This table explains what each maturity level looks like at the dimension level. It provides the broad state descriptions for all seven dimensions from Level 1 through Level 5.

Table G5: Dimension State Descriptions

Dimension ID	Dimension	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
D1	AI-Enhanced Leadership and Strategy	Leadership gives limited attention to AI, and most planning still follows traditional business habits. AI may come up in conversation, but there are few concrete plans, little structure, and no clear approach for connecting AI to business priorities. Decisions are still made mostly through experience, basic reporting, and individual judgment.	Leaders begin exploring where AI might help the business, often through a few targeted pilots or departmental initiatives. Some managers use basic AI tools for analysis or routine decisions, but use is still uneven and depends on individual interest. The SME starts to build simple ways of discussing where AI fits, even though execution remains inconsistent.	AI becomes part of planning and decision-making in more areas of the business. Leaders are more intentional about where AI supports growth, service, or efficiency, and teams begin using AI with clearer purpose. The SME is moving beyond experimentation and starting to treat AI as something that can support regular business decisions.	AI is now tied more clearly to business priorities and longer-term direction. Leaders use AI with greater confidence in planning, prioritization, and performance improvement, while still relying on human judgment where needed. AI is no longer treated as a side initiative, but as a practical business capability that supports results.	AI is fully built into how the SME plans, decides, and grows. Leaders and teams use AI in a steady and disciplined way, balancing data-driven support with human experience and accountability. The business sees AI as part of how it runs and evolves, not as a separate experiment.
D2	Adaptive AI Culture and Empowerment	The culture is still cautious about AI. Employees may be curious, but there is also hesitation, uncertainty, or resistance, especially when the value of AI is not yet clear. Support is limited, and AI is not seen as a normal part of work.	Interest in AI starts to grow as some employees test basic tools and see small benefits in daily tasks. Early training or awareness efforts appear, but support is still uneven and often depends on certain teams or managers. The culture is	AI becomes more accepted in day-to-day work, and more employees use it with growing confidence. Learning opportunities improve, and experimentation becomes more common in practical tasks rather than	The culture is more open to AI, ongoing learning, and trying new ways of working. Employees are more willing to use AI in their roles and more likely to share ideas, test approaches, and improve how work gets done. AI adoption is becoming part of how	People and AI work together with confidence and trust across the business. Learning, adaptation, and practical experimentation are part of normal work, and employees feel supported as tools and expectations continue to evolve. The culture

Dimension ID	Dimension	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
			beginning to shift, though adoption is still fragile.	staying at the awareness stage. The workplace begins to see AI as something useful, not just something new.	the SME builds capability.	treats AI as part of continuous improvement, not as a separate initiative.
D3	Harmonizing AI and Human Processes	Human work and AI-supported work are mostly separate. Processes are still largely manual, and where AI appears, it is often added without much thought to how it fits the workflow. Task ownership, handoffs, and coordination remain unclear.	AI begins to support selected processes, usually in narrow areas where the business sees quick value. Some workflows now include both human and AI steps, but coordination is still basic and often depends on local workarounds rather than clear design.	AI is brought into workflows more intentionally, and task sharing becomes clearer. People and AI start contributing to the same process in ways that improve flow, reduce repetitive effort, and make responsibilities easier to understand. The SME is beginning to redesign work rather than just layer AI on top of it.	Processes are designed with both human and AI strengths in mind. The business is better at deciding which work should stay with people, which can be supported by AI, and how handoffs should happen. This leads to smoother workflows, better use of time, and more reliable execution.	Human and AI processes are closely integrated across the SME. Work moves more smoothly, responsibilities are clearer, and both human judgment and AI capability are used where they add the most value. The result is not only better efficiency, but also better control and follow-through.
D4	Human-Centric AI Integration and Experience	AI tools are introduced with limited attention to usability, workflow fit, or employee needs. They may feel awkward, hard to trust, or disconnected from how work is actually done. Employees often have little influence over how the tools are selected or introduced.	The organization starts paying more attention to how AI affects employees and how tools fit daily work. Some feedback is gathered, and basic improvements are made, but technology choices are still driven more by availability than by user experience.	AI tools fit more naturally into regular work, and employee input begins to shape improvements more directly. Usability, support, and workflow fit matter more than before, and teams are more likely to see AI as helpful rather than disruptive.	AI integration is clearly shaped around employee experience and the way work really happens. Tools are easier to use, support is stronger, and people are more comfortable relying on AI in practical ways. The business recognizes that adoption improves when tools actually fit the work.	AI is designed and integrated around how people actually work in the SME. The experience feels intuitive, useful, and well supported, and teams can focus more on results than on working around the technology. Human needs and system capability are closely aligned.

Dimension ID	Dimension	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
D5	Human-Centered AI Customer Engagement	Customer engagement is still mainly human-led, and AI has little practical role in customer-facing work. Service remains manual, personalization is limited, and AI adds little beyond isolated trials or simple automation.	AI begins helping with selected customer interactions, usually in routine or lower-complexity cases. It may support faster responses or basic automation, but the experience is still uneven and depends heavily on human follow-up.	AI takes on a more regular role in customer engagement, helping with consistency, responsiveness, and some personalization. Human staff still play the central role in more sensitive or nuanced interactions, but the business is learning how AI can improve service delivery.	Customer engagement reflects a stronger mix of AI support and human involvement. AI helps improve response quality, follow-up, and customer understanding, while employees focus more on cases where empathy, judgment, or relationship management matter.	Customers experience a mature partnership between human care and AI support. The SME delivers better responsiveness, more relevant interactions, and stronger personalization, while still preserving trust, empathy, and the human side of service.
D6	AI Ethics and Human Oversight	Formal oversight is limited, and ethical concerns are usually addressed only when a problem becomes visible. The SME may lack clear guidelines for responsible use, accountability, transparency, or review of higher-risk AI decisions.	Basic ethical guidelines and review practices begin to appear, though they are still early, uneven, and often limited to obvious risk areas. The business starts to recognize that AI use needs clearer guardrails, especially where people, data, or decisions may be affected.	The organization develops clearer governance and stronger oversight of AI use. Compliance, transparency, and responsible practice receive more consistent attention, and leaders begin taking a more active role in monitoring how AI is used in the business.	Ethical use of AI is managed more formally, with clearer accountability, stronger review processes, and more consistent follow-through. The SME is better able to balance innovation with caution and to make deliberate choices about where human involvement is still necessary.	Ethics and human oversight are built into how AI is managed across the business. Innovation and responsibility stay in balance, and the SME has a more mature way of reviewing AI use, handling risk, and maintaining trust with employees, customers, and leadership.
D7	Inclusive AI Governance and Learning	Governance is limited, learning is informal, and different perspectives are rarely included in AI-related decisions. Knowledge sharing happens only occasionally, and AI	The organization begins building basic governance and offering more learning opportunities, though both are still developing. A wider range of voices starts	Governance and learning become more structured. More stakeholders are involved in AI discussions, and employee development is more regular and easier to	AI governance is more inclusive, and learning is ongoing rather than occasional. Broader input helps shape decisions, and the SME becomes better at spreading knowledge, building skills, and	Inclusive governance and continuous learning are part of normal operations. Diverse perspectives help shape better decisions, and ongoing development helps the SME keep improving as AI tools,

Dimension ID	Dimension	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
		capability tends to grow unevenly across the business.	to be heard, and the SME begins to see that adoption improves when more people are included.	support across teams. Knowledge sharing starts becoming part of how the business learns from AI use.	improving adoption through shared understanding.	business needs, and workforce expectations continue to change.

This table provides the capability-level state descriptions for AI-Enhanced Leadership and Strategy. It shows how each capability in this dimension changes from Level 1 through Level 5.

Table G6A: AI-Enhanced Leadership and Strategy Capability State Descriptions

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP1	Augmented Decision Making	Most decisions still rely on manager experience, spreadsheets, and basic reporting. AI may be discussed, but it rarely plays a real role in setting priorities, approving investments, or guiding day-to-day choices.	Some leaders begin testing AI for routine analysis, forecasting, or reporting in selected areas. It helps in narrow cases, but decision-making is still mostly manual and depends heavily on the judgment of a few individuals.	AI starts informing recurring business and operational decisions in several functions. Leaders and teams use it alongside judgment, and the SME begins to see where AI-supported decisions improve speed, consistency, or visibility.	AI is used more deliberately in planning, prioritization, and resource decisions. Leaders understand where AI adds value, where human review is still needed, and how decision support connects to business goals.	AI-supported decision-making is built into how the SME plans and runs the business. People use AI and experience together in a disciplined way, and decision quality improves without weakening ownership or accountability.
CAP2	Leadership AI Literacy	Leaders have limited understanding of AI and are often unsure where it fits. Teams receive little guidance on practical use, likely risks, or how AI relates to the business.	Leaders gain basic awareness through introductory learning, vendor demos, and early use cases. They start asking better questions, but confidence is still modest and varies widely across the leadership team.	Leaders understand common AI opportunities and constraints well enough to guide implementation in their own areas. They can connect AI use more clearly to cost, service, efficiency, and operational risk.	Leaders use AI knowledge more confidently when shaping priorities, investments, and business tradeoffs. They do not need to be technical experts, but they understand enough to sponsor adoption responsibly.	Leadership shows strong practical understanding of AI and uses it to guide growth, change, and value creation. AI literacy is now part of how leaders assess options, support teams, and make strategic choices.
CAP3	Inclusive AI Vision Communication	AI plans are not clearly shared across the SME. Communication is limited, irregular, and mostly top-down, while employee questions and	Leaders begin sharing an early AI direction and explain some of the reasons behind it. Staff hear more about upcoming changes, but communication is still basic and not yet	AI plans are discussed more openly and with better structure. Employees have clearer ways to ask questions, raise concerns, and contribute ideas about	AI communication is more consistent across the business. Teams understand the direction better, and employee feedback plays a more visible role in how the	The AI vision is broadly shared and understood across the SME. Dialogue moves in both directions, and staff at different levels help shape how AI

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
		concerns are often left unanswered.	consistent across teams.	how AI may affect their work.	AI vision is explained and carried out.	supports the business over time.
CAP4	AI Strategy Alignment	AI projects are started without a strong link to business priorities. Teams make tool choices with limited strategic direction, little follow-up, and no clear way to judge business value.	The SME begins linking some AI initiatives to business goals such as efficiency, service, or cost reduction. Simple criteria help guide decisions, though alignment is still uneven and usually limited to certain departments.	AI efforts are chosen with clearer business purpose. Teams are more intentional about where AI supports growth, service delivery, productivity, or internal operations, and leaders begin reviewing business fit more seriously.	AI work is tied more closely to strategic goals, budgets, and operating priorities. Leaders track business impact more consistently and make better choices about where AI should, and should not, be used.	AI is fully aligned with business direction and investment choices. It supports both current priorities and longer-term growth in ways that are visible, practical, and better coordinated across the SME.
CAP5	AI Adoption Readiness Assessment	The SME introduces AI without first checking whether people, systems, processes, or data are ready. Gaps in workflow, skills, or infrastructure tend to surface late and create avoidable friction.	Basic readiness checks begin, usually focused on tools, infrastructure, and immediate implementation needs. Some effort is made to prepare teams, but planning still tends to be narrow and technical.	Readiness is assessed more systematically before broader AI efforts move ahead. The SME reviews people, process, data, and system needs with more care, leading to fewer surprises during rollout.	The business uses readiness reviews to guide sequencing, planning, and rollout decisions. Change impact, training needs, process fit, and operational risk are now considered more deliberately.	Readiness assessment becomes part of normal planning and investment discipline. The SME uses it to support smoother adoption, better timing, and more reliable results from AI initiatives.

This table provides the capability-level state descriptions for Adaptive AI Culture and Empowerment. It shows how each capability in this dimension changes from Level 1 through Level 5.

Table G6B: Adaptive AI Culture and Empowerment Capability State Descriptions

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP6	Comprehensive AI Training and Development	AI training is minimal and informal. Employees mostly learn on their own, often after tools are already introduced, and there is little structure to build capability across the business.	Basic training appears through simple programs, internal demos, shared resources, or vendor materials. Learning is still uneven and depends heavily on manager support and individual initiative.	Training becomes more structured and more relevant to different roles. Employees build practical skills they can apply in daily work, rather than only receiving general awareness content.	Development paths are clearer, and teams receive more consistent support to deepen their AI capability. Training is more intentional, more role-based, and better matched to business needs.	Learning is ongoing and well organized. The SME builds AI skills as part of normal workforce development and uses training to support adoption, performance, and future growth.
CAP7	AI Partnership Index	The business does not formally measure how well people and AI work together. Any signs of value are anecdotal, inconsistent, and difficult to compare across teams.	Simple indicators begin to show whether AI is helping employees in practice. These may include usage rates, task support, output quality, or general feedback from staff.	The SME starts tracking human-AI collaboration using practical measures such as usage, satisfaction, time saved, or help with decision support and execution.	Measurement becomes more useful in showing where AI partnership is working, where it is weak, and where better workflows, training, or tool choices are needed.	The SME has a solid way to evaluate and improve how people and AI work together across different functions, use cases, and operating conditions.
CAP8	Workforce AI Adaptability	Employees are hesitant about AI, and change support is weak or missing. Teams often stay with familiar work methods even when AI tools are available.	Some teams show openness to AI and begin testing new ways of working. Adaptation is still uneven and depends heavily on local leadership, confidence, and tool quality.	Employees adjust more steadily to AI tools, with better support and more practical experience. New work habits are beginning to form, and resistance is less pronounced.	Teams adapt more confidently as AI use expands. Change is managed with more structure, and employees are better able to shift roles, routines, and workflows when needed.	Adapting to new AI tools and work methods becomes part of how the SME operates and learns. The workforce is more resilient as business needs and technology continue to change.

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP9	Psychological Safety in AI Collaboration	Employees worry about getting things wrong with AI and often avoid experimenting. Concerns about judgment, mistakes, and job impact make adoption slower and more guarded.	People begin raising questions and concerns, though caution remains high. Support is emerging, but not all teams feel equally safe trying new tools or changing established routines.	Employees feel more comfortable trying AI, sharing concerns, and learning from mistakes. Support is more visible, and teams begin treating experimentation as part of practical learning.	Teams are more open in discussing what works and what does not. Managers and peers provide stronger backing, making experimentation feel less risky and more useful.	The SME has a strong culture of safe experimentation, where people can question, test, learn, and improve without fear of blame when working with AI.

This table provides the capability-level state descriptions for Harmonizing AI and Human Processes. It shows how each capability in this dimension changes from Level 1 through Level 5.

Table G6C: Harmonizing AI and Human Processes Capability State Descriptions

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP15	AI-Driven Process Optimization	Most work stays manual, and AI is rarely used to improve processes. Bottlenecks, repetitive effort, and automation opportunities are not yet clearly identified.	AI begins helping with selected process improvements, often in narrow use cases with modest gains in speed, consistency, or effort reduction.	The SME uses AI more deliberately to identify delays, reduce manual work, and improve key workflows where business value is becoming easier to see.	Process improvement becomes more structured, and AI helps drive stronger gains in efficiency, consistency, throughput, and operational visibility across more teams.	AI and people work together to improve processes on an ongoing basis, helping the business run better, faster, and with fewer avoidable inefficiencies.
CAP16	Human-AI Collaboration Index	There is no structured way to measure collaboration between people and AI. Teams rely on informal impressions rather than meaningful evidence.	The SME begins using simple indicators to understand whether collaboration is helping or not. Measures are still basic, local, and often inconsistent.	Structured measures are used more regularly to track results and identify gaps in how people and AI work together across functions.	Collaboration data is used more effectively to improve workflows, training, tool use, and adoption decisions across the business.	The SME has a mature, practical way to track and improve human-AI collaboration over time, based on recurring business use and observable results.
CAP17	Human-AI Task Flow	Task flow between people and AI is unclear. Work handoffs are inconsistent, responsibilities are assumed rather than defined, and delays or duplication are common.	Basic rules begin to guide which tasks AI handles and which remain with people. Some handoffs improve, though not yet in a reliable or repeatable way.	Task flow is more organized. Handoffs are clearer, and workflows run more smoothly with fewer interruptions, missed steps, or duplicated effort.	Work is distributed more thoughtfully between people and AI, improving flow, timing, ownership, and coordination across departments.	Human-AI task flow is smooth and dependable, with clearer roles, fewer breakdowns, and better use of both human judgment and system capability.
CAP18	Adaptive Task Allocation	Work is assigned in fixed ways, with little flexibility when needs	The SME starts adjusting tasks more flexibly based on	Task allocation becomes more responsive to context,	The business shifts work more effectively between people and	Task allocation is dynamic and well managed, helping the

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
		change. AI use does not yet shift much based on workload, urgency, or task complexity.	basic needs, workload, staffing, or process demands. AI support is still fairly simple.	team capacity, and performance. AI support is adjusted more intentionally as work patterns become clearer.	AI as priorities, demand, and task complexity change. Allocation becomes more deliberate and better informed.	SME make better use of both people and AI as conditions change across the business.

This table provides the capability-level state descriptions for Human-Centric AI Integration and Experience. It shows how each capability in this dimension changes from Level 1 through Level 5.

Table G6D: Human-Centric AI Integration and Experience Capability State Descriptions

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP10	Human-Centered AI Design	AI tools are introduced with little attention to usability. People often struggle to work with them, and feedback is either not collected or not used in a meaningful way.	Basic user input starts shaping design choices. Early efforts improve usability, but design changes are still limited, reactive, and driven more by complaints than by a clear method.	Design is more clearly shaped by how people actually work. Feedback leads to practical improvements in screens, workflow, task support, and ease of use.	AI tools are designed with stronger attention to workflow, ease of use, and employee needs. Design choices are more deliberate and better connected to real work patterns.	The design of AI tools fits naturally into work. People can use them easily, with less friction, stronger confidence, and better alignment between system design and daily tasks.
CAP11	AI Integration Effectiveness	AI tools are added in isolated ways, and results are limited or unclear. Teams often struggle to make them fit daily work or existing systems.	Initial integrations start to improve selected workflows, though adoption is still patchy and outcomes vary from one function to another.	AI is integrated more effectively into key processes, with clearer operational benefits and fewer workarounds in day-to-day use.	Integration is stronger across the SME, and the business sees more consistent value from AI-enabled work in multiple teams and business functions.	AI is well integrated into how the business runs. It supports daily operations in a stable, useful, and increasingly dependable way across the SME.
CAP12	Employee Experience with AI Tools	Employees often find AI tools frustrating, unclear, or hard to use. Help is limited, and confidence drops when tools interrupt rather than support the work.	The experience improves in some areas as support and usability begin to get attention. Some teams still struggle more than others, especially where tools are poorly matched to workflows.	Most users report a better day-to-day experience with AI tools, though quality still varies by role, process, or department. Friction is lower, and support is improving.	AI tools are easier to use, better supported, and more clearly helpful in daily work. Employees see more value and spend less time working around system limitations.	Employees experience AI tools as reliable, practical, and well matched to their work. Support, usability, and confidence are no longer major barriers to use.
CAP13	Human-AI Collaboration Quality	Collaboration with AI is weak and inconsistent. There is little clarity on what good collaboration looks like, and teams often use AI in	Basic quality measures begin to guide how teams use AI. Early improvements can be seen, though results still depend a lot on local	Teams are working with AI in more effective ways, and the value of that collaboration is easier to see in task quality, speed,	Collaboration is stronger across more workflows, with better task quality, clearer shared roles, and more dependable	The SME shows strong, dependable human-AI collaboration across its main activities, with visible benefits to both

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
		disconnected or ineffective ways.	habits, leadership, and tool fit.	consistency, and follow-through.	human-AI interaction in daily operations.	employees and business outcomes.
CAP14	Human Trust in AI Assessment	Trust in AI is low or not formally assessed. Skepticism is common, especially when outputs are unclear, inconsistent, or difficult to verify.	The SME starts checking trust through basic feedback, usage patterns, or confidence measures. Trust is still fragile and often depends on the task or department.	Trust is reviewed more regularly through performance, transparency, and user experience. Teams begin relying on AI more comfortably in routine work where results are stronger.	The business uses clearer signals to strengthen trust where AI is proving reliable, understandable, and useful in practice. Trust-building becomes more intentional.	Trust in AI is well understood and actively maintained through steady performance, transparency, and clear communication about when AI is dependable and when human review still matters.

This table provides the capability-level state descriptions for Human-Centered AI Customer Engagement. It shows how each capability in this dimension changes from Level 1 through Level 5.

Table G6E: Human-Centered AI Customer Engagement Capability State Descriptions

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP19	AI-Enhanced Customer Engagement	Customer engagement is still mostly manual, with little or no AI support. Personalization, speed, and consistency remain limited in many interactions.	AI begins supporting simple customer interactions and routine service tasks. Some efficiency gains appear, but impact is still narrow and uneven.	AI is used more regularly to support customer service, consistency, and some personalization across key touchpoints and service channels.	Human and AI support work together more effectively, improving customer experience, response quality, and service reliability in a wider set of situations.	The SME delivers a strong mix of human care and AI support that improves responsiveness, personalization, and overall customer experience without losing the human touch.
CAP20	Customer Insights on AI Experiences	The SME gathers little useful feedback about how customers experience AI-supported service. Decisions are made with limited evidence and narrow visibility.	Basic feedback is collected and begins shaping simple improvements. Insight is still limited and not always analyzed in a structured way.	Customer experience data is reviewed more regularly and used to adjust AI-supported service in practical, visible ways.	The business uses better insight to improve how AI affects customer satisfaction, service quality, and the design of customer interactions.	The SME has a strong understanding of customer AI experiences and uses it to improve service continuously across channels, use cases, and customer segments.
CAP21	Human-AI Response Integration	Human and AI response channels are disconnected. Handoffs are weak, unclear, or frustrating for both staff and customers.	The SME begins using simple handoff rules between AI and staff in selected cases, especially for routine inquiries and service requests.	Responses are coordinated more consistently, and transitions between AI and people improve across common customer workflows.	Human and AI responses work together more smoothly across service channels, reducing confusion and improving continuity, speed, and response quality.	The customer experiences a more unified response model, with AI and people working together behind the scenes in a more natural and coordinated way.
CAP22	Human-AI Collaborative Resolution Rate	AI contributes little to issue resolution, and results are inconsistent or slow. Success is not	AI begins helping with straightforward issues, and resolution improves in some cases, though the	Teams combine AI and human support more effectively, leading to better resolution outcomes	Collaborative resolution becomes faster and more reliable across service areas, with better	The SME shows strong performance in solving issues through a balanced mix of human and AI support, with

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
		measured well, so learning is limited.	overall effect is still fairly limited.	for a broader set of customer issues.	tracking, stronger coordination, and higher staff confidence.	better speed, consistency, and customer follow-through.

This table provides the capability-level state descriptions for AI Ethics and Human Oversight. It shows how each capability in this dimension changes from Level 1 through Level 5.

Table G6F: AI Ethics and Human Oversight Capability State Descriptions

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP23	AI Ethical Oversight	Ethical oversight is weak or missing. AI use is guided mostly by immediate business needs rather than clear standards, review, or accountability.	Basic ethical guidelines begin to appear, though they are still limited, uneven, and not always applied consistently in real decisions.	The SME has clearer oversight of AI use and stronger attention to responsible practice, especially in processes that affect customers, employees, or sensitive data.	Ethical review, accountability, and governance are more formal and more consistent across systems, use cases, and implementation decisions.	Ethical oversight is built into how the business manages AI, balancing growth, practicality, and responsibility in a steady and workable way.
CAP24	AI Data Compliance	Data compliance for AI use is poorly defined or mostly ignored. Protection measures are limited, inconsistent, or dependent on individual teams.	Basic controls begin guiding how AI-related data is handled. Awareness of compliance needs is improving, but practices remain early and not yet dependable.	The SME has clearer rules and stronger practices for protecting, storing, and managing AI-related data in day-to-day operations.	Data compliance is managed more consistently across AI use cases, with stronger safeguards, clearer ownership, and better operational follow-through.	AI data compliance is well established and supports secure, responsible use across the business, including more sensitive workflows and regulated activities.
CAP25	AI Governance Effectiveness	AI governance is weak, reactive, or absent. Tool use and implementation decisions happen with limited oversight or coordination.	Basic governance structures begin to appear, but they remain narrow and still depend on local initiative rather than business-wide discipline.	The SME has clearer governance and uses it to guide implementation more effectively across a growing set of AI use cases.	Governance is stronger, more consistent, and better able to support broader AI use without losing accountability, risk control, or decision clarity.	AI governance is mature, practical, and well integrated into how the business manages change, risk, and emerging opportunities tied to AI.
CAP26	AI Operational Transparency	AI systems operate with little visibility. Employees and users have limited understanding of how they work, what they	Basic explanations and documentation begin making AI use more visible. Transparency is still limited and	Transparency improves through better communication, clearer process visibility, and stronger documentation	The business provides clearer understanding of how AI operates, where it is used, and what role it plays in	Operational transparency is strong enough to support trust, oversight, and more confident use of AI by

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
		influence, or where they are used.	inconsistent across teams and workflows.	of AI-supported work and decisions.	workflows, service, or decision support.	staff, leaders, and other stakeholders.
CAP27	Responsible AI Practices	Responsible AI is not clearly defined or applied. Decisions are made with limited attention to broader ethical, legal, or operational consequences.	Early practices begin to appear through simple policies and basic awareness of acceptable use, risk, and control needs.	Responsible AI is more clearly built into implementation, review, and day-to-day management of systems, tools, and business processes.	The SME applies responsible AI practices more consistently across teams and systems, with clearer expectations, checks, and practical follow-through.	Responsible AI is part of how the business works, not just a separate policy area. It shapes how AI is chosen, used, and monitored.
CAP28	Equity and Fairness Assessment	Fairness is rarely checked, and bias risks are poorly understood. There is little structure for reviewing how AI may affect different groups.	Basic fairness checks begin in selected areas, often where risk is easier to see or where customer impact is more direct.	The SME reviews fairness more regularly and takes clearer steps to address issues that affect employees, customers, or business decisions.	Fairness assessment is more structured and supports better monitoring, mitigation, and follow-up across different AI-supported processes.	Equity and fairness are managed in a mature way as part of responsible AI use, especially where outcomes matter most to people.

This table provides the capability-level state descriptions for Inclusive AI Governance and Learning. It shows how each capability in this dimension changes from Level 1 through Level 5.

Table G6G: Inclusive AI Governance and Learning Capability State Descriptions

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
CAP29	Achieving Diversity in AI Training Data	The SME pays little attention to whether training data is balanced or representative. Bias risks remain largely unmanaged and often unnoticed.	Early efforts begin to improve variety in data, though gaps remain and coverage is still inconsistent across use cases.	Data diversity is reviewed more systematically, with better sourcing, stronger awareness of bias, and more deliberate checks on representation.	The SME actively works to improve representation in training data and reduce avoidable bias in outputs, models, and downstream decisions.	Data diversity is managed in a disciplined way that supports more trustworthy AI outputs and a better fit with real business use.
CAP30	Assessing AI Impact on Workforce Roles	The SME does not formally assess how AI affects jobs, roles, or career paths. Changes happen reactively and often create confusion or uncertainty.	Early reviews begin through informal discussions, manager input, and basic HR tracking of role changes, concerns, or skill gaps.	The business assesses workforce impact more regularly and starts planning for role changes, training needs, and employee support in a more structured way.	Workforce impact is reviewed proactively, with clearer role design, skills planning, and more deliberate support for transitions tied to AI adoption.	The SME manages role evolution in a deliberate way, helping people adapt as AI changes work, team structure, capability needs, and growth opportunities.
CAP31	Implementing Inclusive AI Decision-Making	AI-related decisions are made by a small group, with little wider input from employees, managers, or affected teams.	The SME starts inviting feedback from more teams, though inclusion is still informal, selective, and often inconsistent.	Cross-functional input is more structured, and different perspectives are considered more regularly in AI planning, rollout, and review.	Inclusive decision-making becomes a more regular part of AI planning, governance, and implementation across the business.	The business shows strong inclusive practice in how it makes AI decisions and adjusts them over time based on broader and more visible input.
CAP32	Adaptive AI Workforce Upskilling	AI upskilling is minimal and reactive. Employees mostly learn on their own, often after tools are already introduced into the workflow.	Basic training opportunities begin through workshops, shared resources, or simple learning plans that support early	The SME builds more structured upskilling programs, with clearer role-based learning, stronger support, and better progress tracking.	Learning becomes more targeted and continuous, helping employees grow as AI use expands and roles begin to change more noticeably.	The SME has a strong upskilling approach that keeps pace with changing tools, business needs, and the changing shape of

Capability ID	Capability	L1: AI Exploration	L2: AI-Enabled	L3: AI-Embedded	L4: AI-Aligned	L5: Symbiotic Partnership
			adoption and awareness.			work across the business.

This table defines the five focus areas used across the capabilities. These focus areas act as lenses for examining each capability from organizational, technical, interaction, systems, and trust perspectives.

Table G7: HAIC-MM Focus Areas

Focus Area ID	Focus Area	General Description
FA1	Organizational Readiness & Adaptation	This Focus Area builds a practical pathway for small businesses to embrace AI effectively, combining leadership support, team development, and measured progress tracking. It creates an environment where AI tools enhance daily operations while nurturing employee growth, ensuring the organization adapts smoothly to AI-driven improvements through clear goals and regular evaluation.
FA2	Socio-Technical Integration	This Focus Area aligns people, processes, and AI systems to create a productive workplace where technology enhances daily operations. It builds a strong technical foundation, streamlines workflows, and optimizes service delivery while ensuring smooth collaboration between staff and AI tools to support better decision-making and operational efficiency.
FA3	Human-AI Interaction Design	This Focus Area shapes how teams interact with AI tools through intuitive design and practical skill development. It creates smooth, user-friendly workflows that build confidence and trust in AI systems, while enabling teams to customize solutions for their specific needs. The result is more effective decision-making and improved productivity across the organization.
FA4	Systems Engineering Support	This Focus Area builds a reliable technical foundation for AI adoption by combining proven methods with flexible approaches. It streamlines system integration, strengthens operational processes, and adapts infrastructure to support data-driven leadership decisions, while ensuring AI tools blend naturally into daily workflows for sustainable business growth.
FA5	Human-AI Trust Dynamics	This Focus Area builds lasting confidence in AI systems through clear performance tracking, ethical oversight, and transparent decision-making processes. It helps teams understand and trust AI outcomes by ensuring fairness, addressing concerns promptly, and maintaining strong standards that make AI a reliable partner in daily operations.

This table summarizes how advancement practices are organized in the model. Each capability is examined through the five focus areas, and each focus area contains four advancement practices with level-specific guidance.

Table G8: Advancement Practice Structure

Focus Area	Number of Distinct Advancement Practices	Advancement Practices
Human-AI Interaction Design	4	AI Solution Adaptation Skills; AI Tool Proficiency Development; Digital Interaction Advancement; Human-AI Partnership Growth
Human-AI Trust Dynamics	4	AI Equity and Bias Mitigation; AI Transparency Management; Ethical AI Governance; Human-AI Trust Index
Organizational Readiness & Adaptation	4	AI Adoption & Workforce Evolution; AI Change Management & Leadership Engagement; AI Readiness & Transformation; Human-AI Collaboration Development
Socio-Technical Integration	4	AI-Enhanced Service Delivery; Digital Capability Advancement; Human-AI Workflow Intelligence; Process & Task Optimization
Systems Engineering Support	4	Digital Engineering Enablement; Human-AI Systems Integration; Systems Engineering Practices; Technology & Infrastructure Evolution