Human-Machine Teaming in AI Driven Supply Chains

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ABSTRACT

Artificial Intelligence ("AI") in recent years has developed from a novel concept to practical applications throughout the global economy. AI increasingly performs cognitive tasks and has evolved into the role of a human's teammate. However, algorithms are not designed to facilitate a teaming process. Many firms do not adequately investigate the right combinations of the strengths of machines (computing power and memory storage) and humans (e.g. intuition and expertise) as well as the dynamics of their interactions, which undermines project performance.

To address the challenge of effective AI system design, MIT's Digital Transformation Research Group developed the human-machine teaming ("HMT") framework. It proposes that successful AI projects are enabled by appropriate configurations of HMT capabilities under the respective decision context of the AI project, which is characterized by the level of decision risk and AI's decision-making process. Building on these efforts, this paper provides three core results: 1) expansion and validation of the conceptual HMT capability framework and empirical assessment of AI projects; 2) recommendation of a quantitative assessment instrument for future research; 3) provision of recommendations to supply chain leadership for successful AI implementations.

The authors refined the conceptual HMT framework and propose that AI project success can be explained by the effectiveness of human-machine Mutual Learning, which is enabled by the HMT capabilities of Transparency, Authority Balance and Secure Interaction. The authors empirically validated the HMT capability conceptual framework via multiple case study research methodology, assessing 22 case studies of AI applications in supply chain management and conducting in-depth semi-structured interviews with two companies. Six academic propositions were derived from the results. For example, it was shown that seven foundational HMT capability indicator concepts are required for successful supply chain AI project implementation and that decision context is the determinant of HMT capability configurations. As AI projects evolve, they change position within the decision-context framework and require different capabilities as learning occurs. Related managerial recommendations were derived and an assessment tool for validation of the HMT capabilities' structural relationships was developed. The validated framework serves as a guideline for supply chain professionals in AI project implementations and assessments.

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-- From Christoph Friedrich Herrmann and Libin Huang

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CHAPTER 1: INTRODUCTION

1.1 Motivation and Relevance

Artificial Intelligence (AI) has in recent years moved from a novel concept to practical applications throughout the global economy. According to a study conducted by consulting firm McKinsey in 2018, 47% of firms surveyed have adopted AI into their business and 71% expect increased investment in AI in the short- to mid-term future. This dynamic is especially relevant in a supply chain context as 76% of respondents agree that supply chain management will benefit significantly from AI adoption (McKinsey, 2018) and as 50% of multinational corporations are expected to have implemented AI in supply chain operations by 2023 (Gartner, 2019b).

This development is mainly driven by firms' expectations to complement and augment human capabilities, thereby enhancing their success. However, according to a 2019 study by research firm IDC, at least 50% of AI projects fail for one in four companies surveyed (IDC, 2019). AI is significantly different from previous technologies (e.g. optimization methods, basic algorithms, etc.) in that it is highly dynamic and involves reciprocal learning from both the artificial intelligence and the human team member. However, algorithms are typically not designed to enhance this mutual learning interaction required. As a consequence, implementation of AI is frequently not as effective as anticipated because firms do not adequately appreciate the dynamics of human-machine teaming, and because they do not sufficiently investigate the right balance of the strengths of machines (computing power and memory storage) and humans (e.g. intuition and expertise).

In the past five years, research interest in AI has been growing, which is shown by significant contributions, for example, on AI strategy development (Kiron & Schrage, 2019), enhancement of business operations through AI (Tarafdar et al., 2019), and organizational decision-making structures in the age of AI (Shrestha et al., 2019). However, the field of AI management research is far from mature, and thus, significant gaps in the literature still exist. For instance, there is no consistent and practice-oriented framework to analyze the contingency factors enabling successful teaming between AI and the human beings.

Furthermore, significant anxiety exists among employees as AI is considered a threat to their employment. KMPG found in a 2019 study that 45% of executives considered building trust in AI systems either "challenging" or "very challenging" (Sokalski et al., 2019) despite Barron and Davenport's (2019) claim that fears of job-loss have in part subsided. Hence, economist David Autor's notion that people mostly focus on value creation of AI through replacement of humans and not the growth from "new goods, services and innovations" is valid for many in the workforce (Shook & Knickrehm, 2018).

As a consequence of these developments, only approximately 25% of executives believe their workforce is ready for AI adoption (Shook & Knickrehm, 2018).

1.2 Problem Statement

With recent advancements in AI, intelligence systems are becoming more sophisticated with increasing ability to conduct cognitive tasks in collaboration with users, which evolves the AI's role into that of a teammate. However, teams are not always effective. Facilitating effective human - machine teaming therefore becomes critical to AI project success – achieving the improvement outcomes expected. These observations raise the question which capabilities are required for the effective human-machine teaming.

1.3 Established Framework

To tackle the challenge of designing effective AI systems, the MIT Digital Supply Chain Research Group Saenz et al. (2020) has developed a framework for the successful implementation of AI projects. The research suggests that "the greatest potential from artificial intelligence will come from tapping into the opportunities for mutual learning between people and machines" (Saenz, Revilla, & Simón, 2020). The human-machine teaming (HMT) framework proposed that the success of AI implementation can be enabled by the appropriate configurations of four main teaming capabilities, namely Interoperability, Transparency, Authority balance and Mutual Learning, for different AI project type based on the decision context, which is determined by riskiness of the decision and openness of the AI decision making process.

1.4 Research Questions

Given the importance of AI in supply chain applications and the lack of academic research on a holistic review of the human-machine teaming capabilities requirements for supply chain AI project implementation, the authors arrive at the following research questions:

1) Which expanded HMT Capabilities dimension can be developed to better guide business professionals in the successful implementation of AI projects?
2) How can one empirically test the conceptual HMT capability framework?
3) Which insights from the results can be provided to organizations and supply chain leadership for handling AI implementation?
4) What assessment tool can be developed for future work to further validate the conceptual HMT framework?

1.5 Summary of Findings and Contributions

This Capstone project developed an expanded HMT capability conceptual framework which proposes that the AI project's success is explained by the effectiveness of human-machine **Mutual Learning**. The effective outcome of mutual learning is enabled by HMT capabilities in **Transparency, Authority Balance** and **Secure Interaction**. A sub-set of indicators for each HMT capabilities is also identified to measure the performance of the HMT capabilities. The authors tested the HMT capability conceptual framework via multiple case study research methodology, assessing a total of 22 actual supply chain AI projects.

The results validated the HMT capability framework, showed that seven foundational HMT capabilities indicator concepts are required for successful implementation of supply chain AI projects and suggested that the decision context is the determinant factor for HMT capability configurations. As AI projects evolve, they change their position within the decision-context framework and as a result, require different capabilities as learning takes place. The findings also offered insightful managerial recommendations which cover best practices in employee engagement, AI project scoping, design as well as project management. Companies' leadership and supply chain professionals can leverage these insights to develop AI more effective project design and implementation plans. The resulting assessment instrument can be applied to future validation of the structural relationship of the HMT capability framework and the development of AI project performance benchmark baselines.

The results of the study have both academic research and practical contributions. The validated framework and the derived managerial insights can serve as a guideline for supply chain professionals and company leadership for AI project implementations. Additionally, the framework also aids in the diagnostics of existing AI projects with ability to identify areas for improvement. Future research can further validate the framework and assist in the development of a benchmark baseline.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

To adequately assess how human machine teaming in artificial intelligence driven supply chains can be organized effectively, it is necessary to first provide an overview of the literature on the topic. Both business management in general and supply chain management in particular will be covered.

The authors will first provide an overview of the adoption and benefits of AI in the business world as well as potential field applications of AI. Thereafter, the challenges in the implementation of such AI initiatives will be outlined, which the research paper ultimately addresses.

Subsequently, the authors will briefly review the literature on theories and models of human machine teaming capabilities as well the management of knowledge workers' anxieties. To be able to validate the present model, different subdimensions, metrics, and measurement approaches for human machine teaming capabilities and knowledge workers' anxieties will be assessed.

After reviewing the research, the authors will identify the gap in the literature and present the research questions addressed in our capstone. Finally, the conceptual framework and develop several hypotheses will be introduced.

The literature review focuses predominantly on peer-reviewed academic journals but also includes several large-scale studies performed by leading management consulting firms, such as McKinsey and PwC, as well as select trade publications. Peer-reviewed academic journals come predominantly from the fields of management science, supply chain management, organizational theory but also cover fields such as economics, psychology, and computer science.

2.2 Adoption and Benefits of AI

In this section, an overview of the present literature on trends, motivation, and benefits of AI adoption will be provided. The authors will first summarize general developments, which are then applied specifically to the context of supply chain management.

2.2.1 General Adoption of AI

Several studies suggest a growing adoption rate of AI in daily business operations. According to a 2018 report, 47% of organizations have adopted AI applications in their business and 30% were running a pilot (McKinsey, 2018). This mirrors results by analytics firm RELX, which reported an adoption rate of 48% among US business for the same year (RELX, 2019). Similarly, Gartner (2019a) found an adoption rate of approximately 37%. In summary, several independent research firms currently estimate the adoption of AI applications at a level in the range of 35%-50% among businesses.

However, not just the absolute level of adoption should be investigated but also its dynamics. Across different studies, one can observe a fast growth in adoption over the past five years, which is projected to continue over the next decade. For example, McKinsey reported an increase in AI adoption of 27% between 2017 and 2018 (McKinsey, 2018). Similarly, Gartner (2019a), reported a 270% increase in AI adoption between 2014 and 2018 and RELX (2019) reported an increase by 30% between 2018 and 2019. This trajectory is expected to continue for the next decade, with professional services firm PwC estimating that US GDP will increase by 14% or USD 15.7 trillion by 2030 as a consequence of AI adoption (Rao & Verweij, 2017).

However, adoption and applications vary significantly by industry and function. For example, Bughin und Hazan (2017) reported levels of adoption varying between 19% and 41%. Technology sectors, such as telecommunications (42%), high tech (41%), energy (36%) have a significantly higher rate of AI adoption than more traditional sectors, such as construction (21%) and tourism (18%). However, these adoption rates also vary significantly by company function among these sectors. For example, within the service function of telecommunications firms, McKinsey (2018) reports a 75% adoption rate while in the same sector only 15% of strategy and corporate finance departments have adopted AI. Similarly, within the automotive and assembly sector, 49% of manufacturing functions have adopted AI whereas risk management only shows a 2% implementation rate. Therefore, significant variability exists among the different sectors as well as by company functions.

The variation of AI adoption rate in different industries and sectors led the authors to further explore the motivations and benefits driving these adoptions.

2.2.2 Motivation and Benefits to Adopt AI

The underlying reasons for adopting AI in businesses are thoroughly assessed in the literature. The most important factor with 84% approval is to "obtain or sustain a competitive advantage", followed by obtaining an opportunity to "move into new businesses" (75%) and "enter new markets" (75%), according to Ransbotham et al.

(2017). However, there are also more defensive motives such implementation due to incumbents using AI (69%), pressure to reduce cost (63%) and suppliers using AI (61%) are mentioned. This assessment was confirmed by Ramaswamy et al. (2008) who reported that 79% of participants in the study expected higher efficiency and lower costs. This research also confirmed potential for growth through AI in terms of higher revenue (74%) and the introduction of new products and businesses (73%). Deloitte (Budman et al., 2018) arrived at similar results as the above studies but also highlighted the importance of product enhancement (51%), operations optimization (36%), creating space for workers' creativity (36%), and application of scarce knowledge (25%).

According to PwC (Rao & Verweij, 2017), the dimension of "obtaining or sustaining competitive advantage" through AI can be analyzed even further. According to the professional services firm 70% of executives expect employees to concentrate on more meaningful work following AI introduction. Furthermore, 55% believe that the upsides of increased productivity – better informed strategy, and additional growth – will ultimately overcome employees' concerns. Finally, 54% reported that they had already created competitive advantage through improved productivity following AI implementation.

Consequently, one can conclude that the main draws of AI introduction are the creation of competitive advantage, the launch and improvement of new products, as well as cost reductions and operational improvements.

2.2.3 Adoption and Benefits of AI in the Field of Supply Chain Management

Generally, the fields of supply chain management, operations and transportation are considered especially apt for the introduction of artificial intelligence applications. For example, McKinsey reported in its 2017 study "Artificial Intelligence – The Next Digital Frontier" that transportation and logistics had both an above average current level of AI adoption as well as an above average future AI demand trajectory (Bughin et al., 2017). The latter aspect was confirmed by PwC (2017) which stressed that transportation and logistics had an above average potential to profit from AI by 2030, when the field is expected to approach maturity. Similarly, Capgemini (Patwardhan et al., 2018) reported that 63% of firms were experimenting with AI applications in the domain of supply chain and an additional 11% had implemented it into standard processes in at least one site.

Moreover, firms with a proactive AI strategy in the logistics sector reported a profit margin 9% higher than those who did not adopt AI (Manyika et al., 2017). Similarly, 80% of manufacturing functions and 76% of supply chain functions within companies reported having profited from AI by 2018 (McKinsey, 2018).

Supply Chain processes generate large amount of data. The recent e-commerce growth trend increases the complexity of supply chain planning and network design. The emergence of AI technologies can be leveraged to assist humans with prescriptive and predictive analytics to identify patterns and generate actionable insights in this field. Early adopters of AI driven data analytics in Supply Chain management outlined the key benefits in Figure 1.

*Figure 1: Benefits from Applying AI in Supply Chain ("*AI for Supply Chain"*, 2020)*

According to the above review, operations improvement, quality enhancements and advances in efficiency are common drivers of AI adoptions in supply chain management. Consequently, the type of AI applications and technologies enabling such benefits will be outlined in more detail.

2.3 AI Applications and Technologies

We will now provide an overview of the different ways in which AI can be applied to businesses both in general and specifically in a supply chain context.

2.3.1 General AI Applications and Technologies

According to McCarthy (2007) AI is "the science and engineering of making intelligent machines, especially intelligent computer programs" (p. 2). Most academics, such as Marr (1977), agree that this creation of intelligent machines may involve modeling or imitating human intelligence but this is not considered a necessity. Rather, research, such as Shanahan (1997), focuses on typologies of different AI, such as search, pattern recognition, representation, inference models, learning from experience (i.e. machine learning), planning, and heuristics.

These fields of research over the past four decades have in turn led to the emergence of technical fields of applications (McCarthy, 2007). These fields may vary significantly in their scope and cover areas such as speech recognition, natural language processing, computer vision, expert systems, advanced regression and heuristic classification.

In today's business world, these technological considerations lead to practical applications along the value chain from purchasing to operation, production, sales and distribution as well as overhead functions such as strategy, finance, and human resources (Porter, 1985). Similarly, McKinsey (2018) reports machine learning, virtual agents, natural-language text understanding, natural-language speech understanding, natural-language generation, robotic process automation, computer vision, physical robotics, and autonomous vehicles as the most common applications.

AI consultancy Axilo (Corea, 2018) built on this approach but separated the above categories into A.I. paradigms ("approaches used by AI researchers to solve specific AI-related problems") and introduced A.I. problem domains (types of problems to be solved, such as perception, reasoning, knowledge, planning and communication). From the resulting matrix (see Figure 2), six paradigms of AI applications (logic-based tools, knowledge-based tools, probabilistic, machine learning, embodied intelligence, and search and optimization) can be derived.

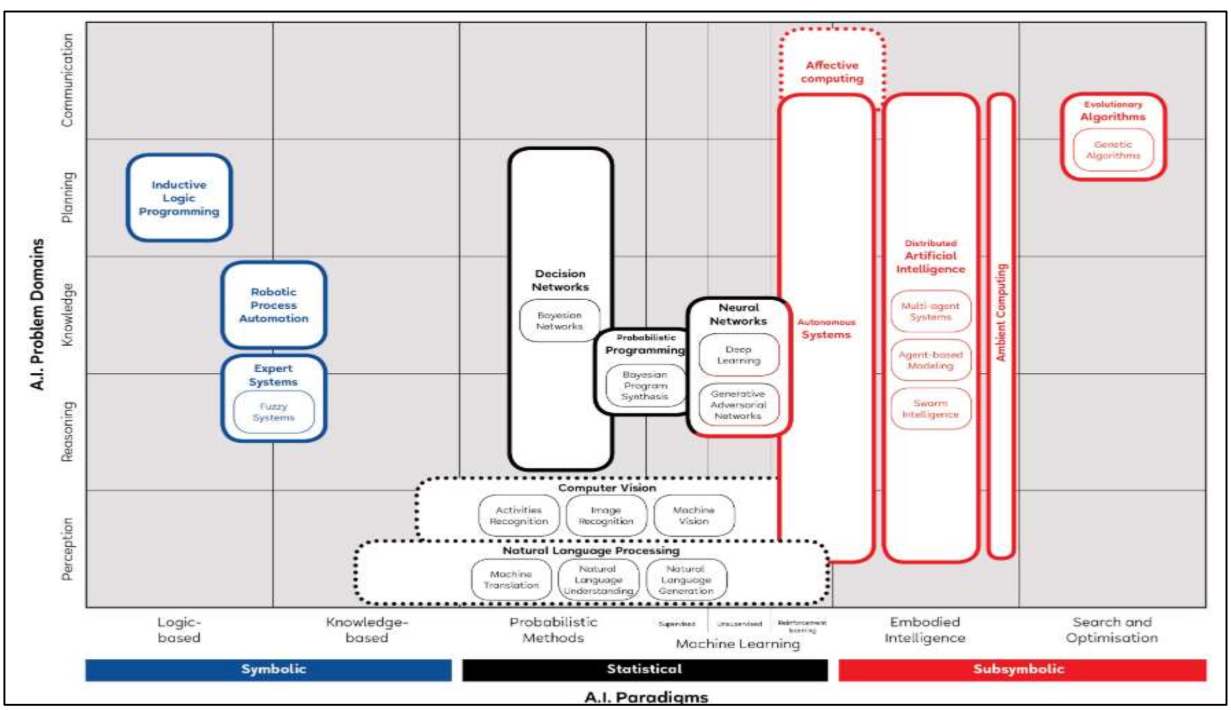


Figure 2: A.I. Domain and Paradigm Theory (Corea, 2018)

Finally, Deloitte (Budman et al., 2018) found that most AI use cases in practice are closely related to IT. For example, IT automation, quality control, cybersecurity, predictive analytics, customer services, sales optimization and decision support are considered the most prevalent practical applications.

2.3.2 AI Applications and Technologies in the Field of Supply Chain Management

Concerning the field of supply chain management, PwC (2017) pointed out a significant potential for several AI applications. For example, autonomous trucking can be enabled and diffused more quickly through AI. Moreover, warehouses can be managed more effectively through the diligent combination of AI, human intuition, and algorithms.

Academic research has focused predominantly on the usage of AI in supply chain management for risk management (Baryannis et al., 2019) and supplier relationships (Arnold et al., 2019). Min (2010) derived a typology of AI applications in supply chain management distinguishing between inventory control, transportation network design, purchasing and supply management, demand planning and forecasting, order-picking, customer relationship management, and information exchanged.

Accordingly, one can conclude that AI applications are adequate throughout the entire supply chain, with a focus on information exchange, risk mitigation, and process optimization.

2.4 Challenges in AI Implementation

In the following section, the literature review will highlight the practical challenges in the introduction of AI initiatives. Both general challenges and supply chain-specific challenges will be covered in the process to provide a holistic perspective.

2.4.1 General Challenges of AI Implementation

The introduction of artificial intelligence into organizations is not perceived as being without problems. Firms report significant problems in the introduction of AI applications due to lack of clear AI strategy (43%), lack of talent (42%), existence of functional silos (30%), lack of commitment (27%) as well as lack of technological infrastructure (25%) and data (24%) (McKinsey, 2018). On the other hand, Adixon (2019) argued that even today, many companies’ computing resources and capacities were not powerful enough for a majority of AI applications.

Additionally, Adixon (2019) considered lack of support for AI within organizations, a lack of trust, lack of data, data scarcity, and algorithm bias as challenges in adoption. Similarly, Ransbotham et al. (2017) found that unclear business applications, difficulties in talent attraction, competition from alternative investment opportunities, security concerns as well as lack of leadership support and technological capabilities, and cultural resistance to be the most important factors inhibiting the introduction of AI.

Another study (Budman et al., 2018) confirms the above findings but also points to the high importance of project implementation issues, and the integration of AI into a firm’s forms and functions.

The literature currently considers a lack of clear strategic focus, buy-in, and prioritization of AI, as well as difficulties in attracting talent the most important factors inhibiting successful AI introduction.

2.4.2 Problems and Challenges of AI Implementation in the Field of Supply Chain Management

Moreover, Duckworth (2019) identified barriers to successful AI adoption that are especially relevant for the supply chain space: the lack of sufficient amounts of quality data, compartmentalization of AI, inexplicability of AI’s results, short-sighted optimization, overly excited AI vendors, as well as lack of appropriate skills in the organization.

Similarly, Croom (2018) argued that firms have to secure sufficient resources and time in the supply chain management AI implementation process to maintain good results. Additionally, he argues that firms had to ensure that supply chain and project managers fully comprehend the complexities of the AI.

The challenges of AI implementation seem to be rooted in the interface between human and machine. As a consequence, implementation of AI is frequently not as effective as anticipated because firms do not adequately appreciate the dynamics of human-machine teaming, and because they do not sufficiently investigate the right balance of the strengths of machines (computing power and memory storage) and humans (e.g. intuition and expertise).

2.5 Human-Machine Teaming

In their recent book *Human + Machine,* Daugherty and Wilson described that currently the third wave of business transformation can be observed (Daugherty & Wilson, 2018).

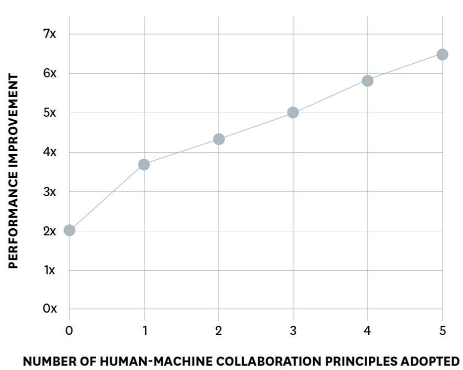
In the first wave, businesses benefited from significant productivity increase thanks to "standardized production processes." The second wave of transformation brought "automated processes" with broad adoption of computers, databases and software that enable automated tasks in data processing. For decades, these computer and automated technologies have been used to assist humans and transforming businesses, however, they are not considered a collaborative partner but merely tools that are programmed for specific tasks.

Now the third wave of business transformation is bringing "adaptive processes" that leverage AI technologies to learn from the large amount of unstructured data generated from the businesses and to continuously adapt to the optimal path. With this recent development of AI, the intelligence systems are becoming more sophisticated with increasing ability to conduct cognitive tasks in coordination with its users and their role evolving more as a human teammate.

In the following section, the authors will refer to all the AI enabled technologies and systems as "machines" to contrast the meaning of "humans."

It is believed that the intelligent technologies and human intuition could join force to create new value for businesses (Pitso, 2019). Human-machine teaming (HMT) is defined as the integration of human and machine into a team structure that maximizes respective strengths while complementing each other's limitations (Azad M. Madni & Carla C. Madni, 2018).

History has shown effective human teams can achieve great things, such as the Apollo moon landing. However, some researchers argued that, with AI evolution, the business transformation can achieve its full potential only through human-machine collaboration (Wilson & Daugherty, 2018). A research survey involving 1,500 companies suggests that firms achieve the most significant performance improvements when humans and machines work together, as illustrated in Figure 3.



"…Humans and machines collaborate to attain orders-of-magnitude increases in business performance, each augmenting the other and achieving far better outcomes than either could achieve alone…"

--- Human + Machine

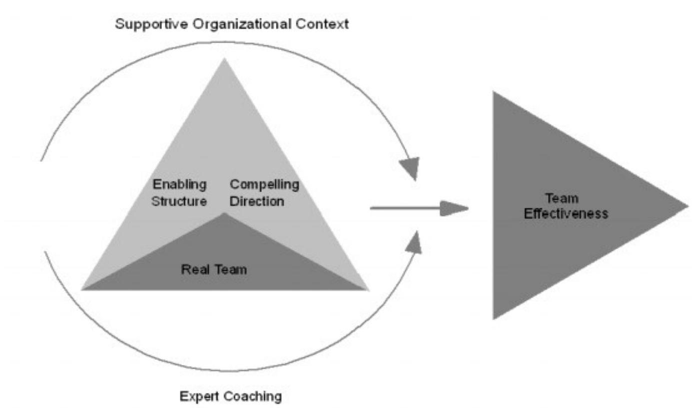
Figure 3: The Value of Collaboration (Wilson & Daugherty, 2018)

It seems that machine partners would have the potential to considerably enhance team collaboration. However, teams are not always effective, which leads to the question which capabilities might be required for the human-machine teams to enable effectiveness.

2.5.1 Present Theories and Models on Human-Machine Teaming

In human teams, teammates typically perform complementary functions. Teammates are defined as free individuals, with bounded autonomy, acting within the confine of social structures and situational constraints, and join together for a specific activity or endeavor. Teammates share their knowledge, understand each other's capabilities and limitations, and as such, they learn and adapt from each other. Teammates typically developed trust over positive engagement history, and their collective experiences will lead to mutual capability growth and further the team's goals (Brill et al., 2018).

The research on human teams has a long history and has generated many mature models to develop and diagnose effective teamwork. One of the most influential models is proposed by Wageman, Hackman and Lehman (2005) in "Five Conditions That Foster Team Effectiveness" (see Figure 4). They suggest that the effective teamwork requires not only the capabilities to drive effective team interactions but also enabling company organizational context to support a learning culture and co-creating solutions.



"I have no question that when you have a team, the possibility exists that will generate magic, producing something extraordinary, a collective creation of previously unimagined quality or beauty. But don't count on it. "

--- J. Richard Hackman

Figure 4: The Five Conditions That Foster Team Effectiveness (Hackman, 2005)

From human teaming research, one can suggest that to form an effective human-machine team it will require facilitation of trust through mutual learning to enable collaboration and goal attainment. But what capabilities are needed to support this facilitation?

2.5.2 Human-Machine Decision Context Framework

As discussed in Wageman, Hackman and Lehman's "effective team framework" in Figure 4, a "compelling direction" – or, leadership – is critical for a team's success (Wageman et al., 2005). In modern societies, leaders can make timely and informed decisions with support of information and communication systems (Daggett & Hurley, 2019). With the advancement of AI technologies, the decisions are often influenced by, or in some circumstances can be made entirely by, machines. AI can replace, support and complement the human decision-making process (Jarrahi, 2018). Jarrahi believes that a partnership between the rationality of machines and the intuition of humans is the best combination to make a decision.

However, this leads to the question how human and machine should partner in decision-making. Moreover, it should be investigated which decisions can be delegated to the machine, and which decisions need to be retained by the human.

To tackle the challenge of designing effective AI systems, the MIT Digital Supply Chain Transformation researcher Dr. Saenz and team have developed a framework to align the human-machine roles under different decision-making context (Saenz, Revilla, & Simón, 2020).

According to the framework, before designing any AI system, the decision-making context in which the AI will be implemented must be properly assessed. Two main characteristics can help the manager in this assessment:

- Whether the AI system is designed as "closed" or "open" by defining the boundaries and sources of variability. "Closed system" means a well-established decision parameter structure is already defined within the AI algorithm. "Open system" refers to an AI algorithm that is capable to discover the underlying structure of the contextual information without reference to known or labeled parameters.
- The level of risk ("weak" to "severe") of the decision making in which the AI system is involved. The types of risks could pertain to flawed decisions that lead to physical damage to humans, company facilities, reputational damage, or financial loss.

The assessment of the decision-making context will dictate the design of the AI system in terms of the machine and human collaboration in order to successfully implement the AI system and maximize learning (Saenz, Revilla, & Simón, 2020). Dr. Saenz's work proposed that human and machine can play different roles in the different decision-making and AI design contexts. The above discussed decision context and human-machine role configurations for successful AI project implementation are summarized and illustrated in Figure 5.

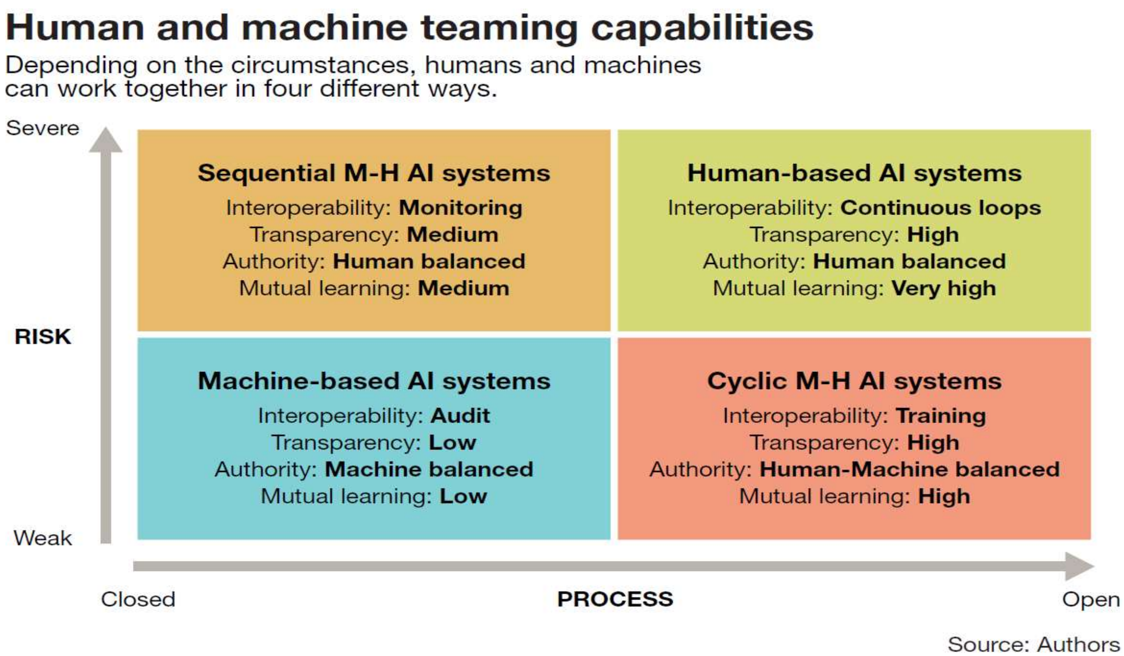


Figure 5: HMT in Decision Contextual Framework (Saenz, Revilla, & Simon, 2020)

Dr. Saenz's HMT framework provided a pioneer view on the critical HMT capabilities required between human and machine, namely Transparency, Interoperability, Authority Balance and Mutual Learning to drive successful AI implementations. Building on her work, the authors addressed the previously mentioned research questions of which sub-dimensions of the HMT capabilities can be expanded for the established framework, and how the HMT framework can be empirically tested and validated.

In the following literature reviews, the authors continued to explore the detailed meaning of these proposed capabilities, other potential additions and the measurable sub-dimensions of the HMT capabilities to address the research questions holistically.

2.5.3 HMT Capabilities

Human teams have been the subject of extensive studies in the psychological research literatures, however there has been little research found in teaming between human and AI driven cognitive machine partners.

The first key theme the authors observed is an emphasis on a "human centric" approach for human-machine relationships. "The growth of sophistication in machine capabilities must go hand in hand with the growth of sophistication in human-machine interaction capabilities", stated John & Vera (2019, p.18). They continue: "Teaming itself is not an isolatable, unitary capability that needs to be developed as an add-on to systems. Rather, it should be viewed as an approach to what AI capabilities should be built to enable intelligent systems with teaming competence" (Johnson & Vera, 2019, p. 18).

In the earlier years of HMT research, a lot of focus were placed on "Controllability". Urlings and Jain (2002) described the human-machine team as a "pilot" and "co-pilot" relationship, where the team will still be led by the human with the machine as a subordinate associate or assistant, sharing the responsibility, authority and autonomy over tasks. Therefore, the AI systems should be controllable, useful and usable (Urlings & Jain, 2002).

In response to the concerns over AI threats to human lives, Stanford University, UC Berkeley, and MIT have teamed up on Human-centered AI (HAI) research. Their HAI research strategies emphasize on the humanistic and ethical aspect of AI that AI is to enhance humans rather than replace them (Stanford, 2013).

Xu (2019) argued that besides not replacing the human, the AI design should maintain fairness. He continued to argue that AI technology is in need of continued development to fully mimic human intelligence and that AI solutions should be explainable (Xu, 2019).

Another major theme in the recent HMT research is "transparency" which enables trust to be built between humans and machines. McDermott (2017) discussed that as the autonomy technology evolves and no longer required constant human supervision, machines needs to behave in a way to earn human's trust. Therefore, the HMT requires transparency in machine operations, bi-directional human-machine interaction, situational awareness to understand changes in conditions. Human needs to have the ability to intervene at different levels in ongoing machine operations to reallocate resources or revise goals. (McDermott, 2017).

Similarly, Smith (2019) emphasized that Human-machine teams are strongest when human users can trust AI systems to behave as expected, safely, securely, and understandably (Smith, 2019). Cruz (2019) proposed that maximally accurate, countering algorithmic bias, and creating explainable and transparent intelligent systems is the key to garner trust from human (Cruz, 2019).

Focusing on the interaction capabilities of the AI systems design, Azad et al. (2018) proposed that HMT should be adaptive. The important factors that need to be addressed in adaptive HMT include: human-machine joint performance, task allocation based on human cognitive load balance, knowledge sharing, interoperability, shared decision making, and protect human-machine teaming processes (Azad M. Madni & Carla C. Madni, 2018).

Table 1 summarizes the capabilities and their definitions discussed in various studies mentioned above.

Table 1: HMT Capabilities Literature Review Summary

Capabilities	Authors	Definition/Key Concepts
Directability, Controllability, Accountability	Urlings et al, 2002 McDermott et al. 2017 Azad et al. 2018 Smith 2019	• Humans should be able to control the system and allocate authority between human and machine based on situations • Allow humans to intervene at the right level in ongoing machine processes to successfully address situations that fall outside the human-machine system's designed performance envelope • Humans having the ability to redirect resources, re-allocate tasks, modify workflow parameters, or adjust task sequences & priorities
Explanation	Smith 2019 Cruz, 2019 Xu, 2019	• Machine learning must be "interpretable by design" • Humans recognize when and why AI is taking action including making decisions. • Enable users to understand the algorithm and parameters used
Observability, Directing Attention, Predictability	Urlings et al, 2002 McDermott et al. 2017 Smith 2019	• Provide information about the states or parameters of the system and its environment • People should be able to verify what the AI system is doing, and why, in a timely manner • Human-machine team members can direct each other's attention to critical issues or warnings • Human-machine team can recognize and understand each other's future intentions. • Machine's ability to anticipate changes in the situation to aid the user in projecting future states • Information are presented in a way that supports simplicity and understandability
Ethical, Honest	Smith 2019 Xu, 2019	• Humans can recognize that they are interacting with AI not humans
Learning	McDermott et al. 2017 Smith 2019	• Human-machine teams can recognize and adapt seamlessly to unexpected situations • Machine is able to improve itself regularly to meet human needs and technical standards

Capabilities	Authors	Definition/Key Concepts
Shared Decision Making	McDermott et al. 2017 Azad et al. 2018	• Shared human-machine decision making and assures elimination of human oversight slips and reduction in human error • Human-machine partners can leverage multiple views, knowledge, and solutions to jointly understand the problem space
Transparency	Azad et al. 2018 Cruz, 2019	• Awareness of the errors and biases from the machine learning models and ability to correct them • Evidence for the decision-making are presented for humans
Shared Knowledge of State; Shared Context; Common Ground	McDermott et al. 2017 Azad et al. 2018	• Shared knowledge and awareness: human stay apprised of the information that the machine uses to perform tasks, and the machine is aware of human cognitive, physical and emotional state • Relevant beliefs and assumptions are shared among team members • Team members maintain a constantly updated shared picture of what is happening and the status of the overall plan
Usable, Useful	Smith 2019 Xu, 2019	• AI solution provides the functions required to meet users' needs in the valid usage scenarios
Cognitive Load Balance	Azad et al. 2018	• Assure a manageable human workload by balancing workload distribution between human and machine with changing contexts
Interoperability	Azad et al. 2018	• Ability to connect the human-machine team into broader systems
Security	Smith 2019	• AI system provides understandable security methods, and is robust, valid and reliable • Protect HMT processes, mechanisms, physical elements, data, and services from unintended/unauthorized access and use, as well as damage and destruction

The HMT capabilities discussed above seem to have a lot of similarities with capabilities in effective human teams. As authors discovered in section 2.5.1, mutual learning is a key to drive positive engagement among human team members. Hence, the question arises how humans and machines optimize mutual learning.

2.5.4 Human-Machine Mutual Learning

In the context of HMT, the paradigm of learning in a traditional didactical format will shift. Not only will the human's capability be augmented through the assistance of the machine, but the machine's capabilities will be also continuously improved via the interaction with humans. In this section, we will review how humans and machines learn, and the benefits of mutual learning.

Human Learning

According to the most popular human learning theories (Figure 6), humans learn most effectively through experiences and interactions. Constructivist theory has established the “foundation for the majority of teaching methods that have taken hold in recent years (for example, problem-based learning, authentic instruction, computer-supported collaborative learning)” (Ansari et al., 2018).

Figure 6: Reproduced based on Instruction for Youth in School and Public Libraries (Rawson, 2018)

Machine Learning

Machine learning (“ML”) is a subset of AI, the computational algorithms that automate the analytical model building. One can classify ML algorithms’ learning approaches into 1) supervised learning, 2) unsupervised learning, 3) reinforced learning (Table 2).

Table 2: Machine Learning Types (Oladipupo, 2010)

Learning Approach	Description
Supervised learning	The algorithm generates a function that maps inputs to desired outputs
Unsupervised learning	Models a set of inputs: labeled examples are not available
Reinforcement Learning	The algorithm learns a policy of how to act given an observation of the world

Implementing ML alone does not lead to AI. Figure 7 illustrates the difference and relationships between ML and AI. In order to mimic human cognition and arrive at accurate predictions, the ML algorithms need to be trained continuously and dynamically with an intentional learning process.

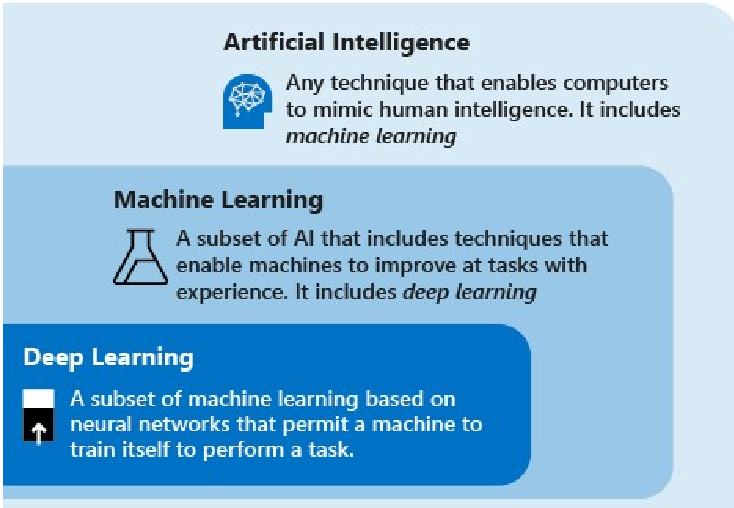


Figure 7: Machine Learning and AI (Francesca, 2020)

In the HMT context, mutual learning is defined as "a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration, which results in creating new meaning or concept, enriching the existing ones or improving skills and abilities in association with each group of learners" (Ansari et al., 2018).

It is broadly acknowledged by leading businesses that creating a learning organization is essential to compete in a changing environment (Aly, 2016). By the same token, the human-machine mutual learning is just the new form of organizational learning capabilities in today's AI business transformation stage that attribute to a company's competitive advantages. However, it is unclear in an AI project development and deployment context, what role the different members of the project team should play in terms of facilitating the mutual learning process. Hence, special attention will be dedicated to the different roles played by employees from varying hierarchical levels and functions within the mutual learning and feedback process.

To better understand the effect of HMT capabilities on AI project success, the authors continue to explore how performance should be measured and what potential metrics can be used for the performance measurement.

2.6 Understanding the Performance Measurements

Metrics serve as an evaluation platform for assessing the performance and the verification and validation of a system. The range of metrics used to measure performance can be summarized into two categories: subjective and objective measurements. Subjective metrics are used to measure abstract qualities based on human perception, such as self-feedback, evaluation, or ratings. Objective metrics are task-specific tools, functions, and formulas to measure task performance quantitatively.

2.6.1 Common HMT Metrics

Accurately and effectively measuring performance of a human-machine team is crucial for benchmarking and improving the design of the AI systems. After an extensive survey of publications, Damacharla et al. (2018) synthesized and proposed 10 common metrics to evaluate HMT performance as can be seen in table 3. He suggested the measuring of these proposed Human, Machine and Team metrics can derive an empirical value to allow comparison with another Human-machine team systems (Damacharla et al., 2018).

Table 3: Common Metrics for HMT (Damacharla et al., 2018)

Metric	*Agent*	*Selection criteria*	*Description*
Judgement	Human	Objective, non-real-time, user studied, reviews, and correlation with team performance	Measures human judgement skills and trust levels, can be measured at design or application stage
Attention allocation	Human	Objective, real-time, user studies, reviews, and correlation with human performance	Proven measurement techniques will measure human attention allocation efficiency that can be related to human performance
Mental computation	Human	Objective and/or subjective, user studies, reviews and correlation with HMT design	Using EEG techniques, we can create human mental models that will be useful in HMT design and development
Human Error	Human	Objective, real-time, published results, relation with task execution	Real-time mode error measurement will help HMT execute its tasks with precision
RAD	Machine	Objective, real-time, published results, characteristic graphs and relation with machines performance	RAD monitoring will provide significant results that can be used to measure machine performance
State	Machine	Objective, real-time, published results, characteristic graphs and relation with machines performance	Machine state can be used by human to understand the machine, and help improve machine and team performance
Errors	Machine	Objective, real-time, published results, characteristic graphs and relation with machines performance	Being a generalized metric that gives all machine errors as a quantitative value and can be used in performance evaluation
Productive time	Team	Objective, real-time, published results, characteristic graphs and relation with team performance	Being a time metric, it can be used to significantly identify team success
Cohesion	Team	Objective, real-time, published results, characteristic graphs and relation with team performance	An observer metric and helps in identifying HMT teaming nature quantitatively
Interventions	Team	Objective, real-time, published results, characteristic graphs and relation with team performance	Can be positive or negative in performance score formula and plays a crucial role in understanding team

2.6.2 Measurement of Mutual Learning

As discussed in section 2.5.4, Mutual Learning is a key outcome of the HMT, which attributes to a company's competitive advantages. Based on the work of Roger Schwartz (2013) on effective teams, the key outcomes of mutual learning are as follows:

- Improved efficiency
- Increased trust

- Increased commitment
- Higher quality decisions
- Increased learning
- Increased working relationships
- Greater personal satisfaction and well-being

Measuring the subjective and objective value of the above expected outcomes can provide an understanding of the effectiveness level of mutual learning.

2.6.3 Performance Metrics

As described in section 2.1.2, the main motivation of adopting AI is to augment human capabilities and enhance company success. To determine the success of an AI program, users need to consider corporate objectives, business process optimization and user satisfaction.

The Balanced Scorecard was first introduced in Harvard Business Review article (Kaplan & Norton, 1992), and later adopted by tens of thousands of companies around the world as a popular management tool to describe, communicate and monitor company strategy and execution performance. As can be seen in table 4, the balanced scorecard (BSC) monitors 4 key areas of performance: Financial, Customer, Internal Process and Organizational Capacity. Under each of the areas, there are many leading and lagging metrics that can be deployed to monitor performance.

Table 4: Adopted from Balanced Scorecard Perspectives & KPIs (Balanced Scorecard Institute)

Areas	Measurement	Metrics Examples
Financial or Stewardship	Financial Performance	• Sales growth • Profit • Return on investment
Customer & Stakeholder	Customer satisfaction	• Net Promoter Score (NPS)
Internal Process	Efficiency & Quality	• Forecast accuracy • Operating Efficiency • Machine downtime • First pass yield
Organizational Capacity **or Learning & Growth**	Sustainability (Human Capital, Infrastructure & Technology, Culture)	• Retention & Turnover • Employee Engagement

To evaluate AI Project Performance, company would select metrics based on the process where the AI project is implemented. Based on the above literature review on the various potential metrics for performance measurement, the authors investigate which type of assessment tool can be developed to evaluate HMT capability performance.

2.7 Identification of the gap in literature

The literature review show that the current literatures are mostly narrowly focused – some mainly focused on the application of AI in specific industry or process, some on the system design requirements for HMT, and the others on how company should establish proper organizational structure to manage AI. Few researchers have focused on the interdependency relationships of AI technology and HMT capabilities in the context of company adoption.

The capstone study contributes insights to this lack of research within the field of AI and implementation within organizations. The Capstone's objective is to tackle the challenge of designing effective AI systems and organizational management strategies for the successful implementation of AI projects.

2.8 Consolidated research questions

Based on questions posed along the literature review process, the authors consolidated the research questions for the Capstone project as below:

1) Which expanded HMT Capabilities dimension can be developed to better guide business professionals in the successful implementation of AI projects?
2) How can one empirically test the conceptual HMT capability framework?
3) What insights from the results can be provided to organizations and supply chain leadership for handling AI implementation?
4) What assessment tool can be developed for future work to further validate the conceptual HMT framework?

2.9 Summary

This chapter reviewed the overall perspective of AI technology, business adoption trends, specific AI applications in the context of supply chain, and challenges in AI implementations based on a systematic literature review of prior research and industry reports. Examining the critical factors associated with HMT contributed to finding appropriate structural relationships between the factors.

The systematic literature review also helped identify the current gaps in research: lack of a holistic framework that provides guidance on how to integrate capabilities in system design considerations and organizational enabling strategies. In this study, the authors contributed insights to this research gap and propose an integrated framework that addresses the challenge of designing effective AI systems for the successful implementation of AI projects.

In the following chapters, the authors will conduct an empirical evaluation on AI projects to validate the conceptual framework and hypothesis developed. The corresponding research methodology adopted for this capstone project is discussed in the next chapter.

CHAPTER 3: METHODOLOGY

This chapter outlines the approach to establish a conceptual framework that addresses the challenge of designing effective AI systems for the successful implementation of AI projects and the methodology to validate the framework with empirical AI projects. Figure 8 summarizes the methodology's high-level process steps.

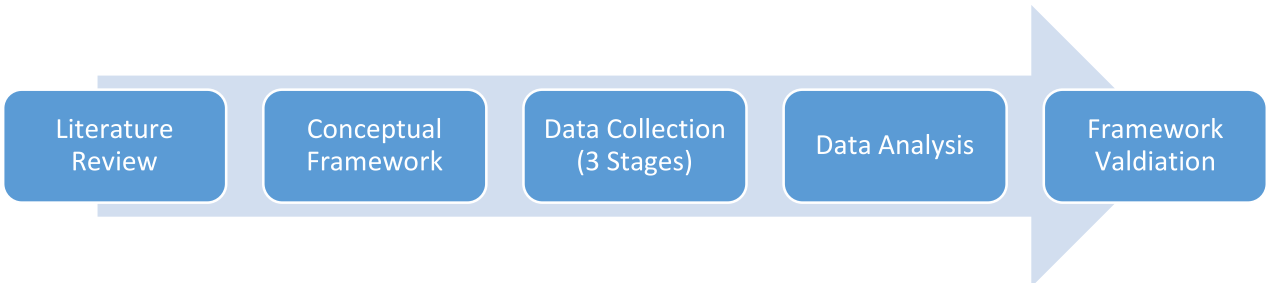


Figure 8: High-level Methodology Process Steps

To answer the first research question – "Which expanded HMT Capabilities dimension can be developed to better guide business professionals in the successful implementation of AI projects?" – an extended literature review was conducted in Chapter 2. The information was synthesized to be used as the basis to formulate the constructs of conceptual HMT framework for successful AI project implementation.

3.1 Conceptual Framework

HMT Capabilities

A number of HMT-related theoretical approaches were analyzed in our literature review. The identified critical capabilities for our conceptual HMT framework development are illustrated in Figure 9.

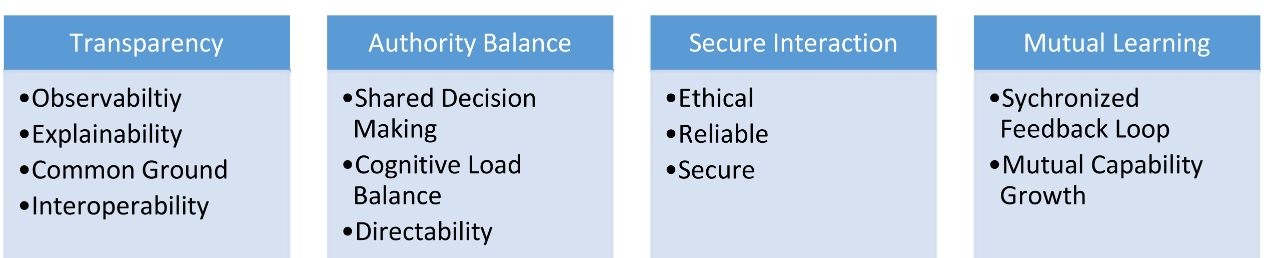


Figure 9: Conceptual HMT Capability Framework Thematic Dimensions

Through the literature review, the authors learned that an effective human-team is facilitated by a strong mutual learning culture. Therefore, as shown in Figure 10, our proposed HMT framework hypothesizes that the AI project's success can be explained by the effectiveness of human-machine mutual learning. Effective mutual learning is determined by the AI system's capabilities in Transparency, Authority Balance and Secure Interaction.

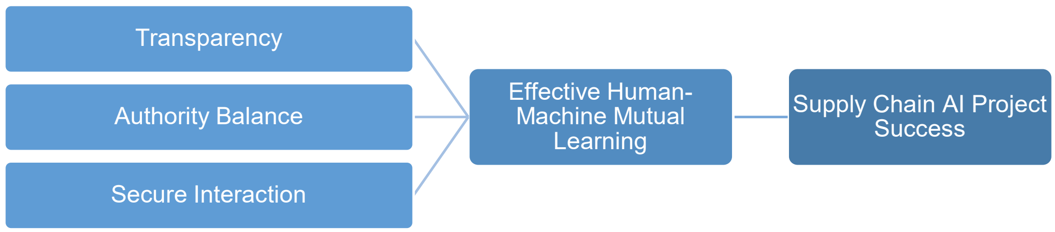


Figure 10: Conceptual HMT Framework developed

The effectiveness of these capabilities can be inferred by the measurement of their respective indicators (as illustrated in Figure 11). The indicators of each of the capabilities were identified and synthesized through the literature review. The presence of these capabilities is further tested in Chapter 4 via empirical examination of actual AI projects across various companies.

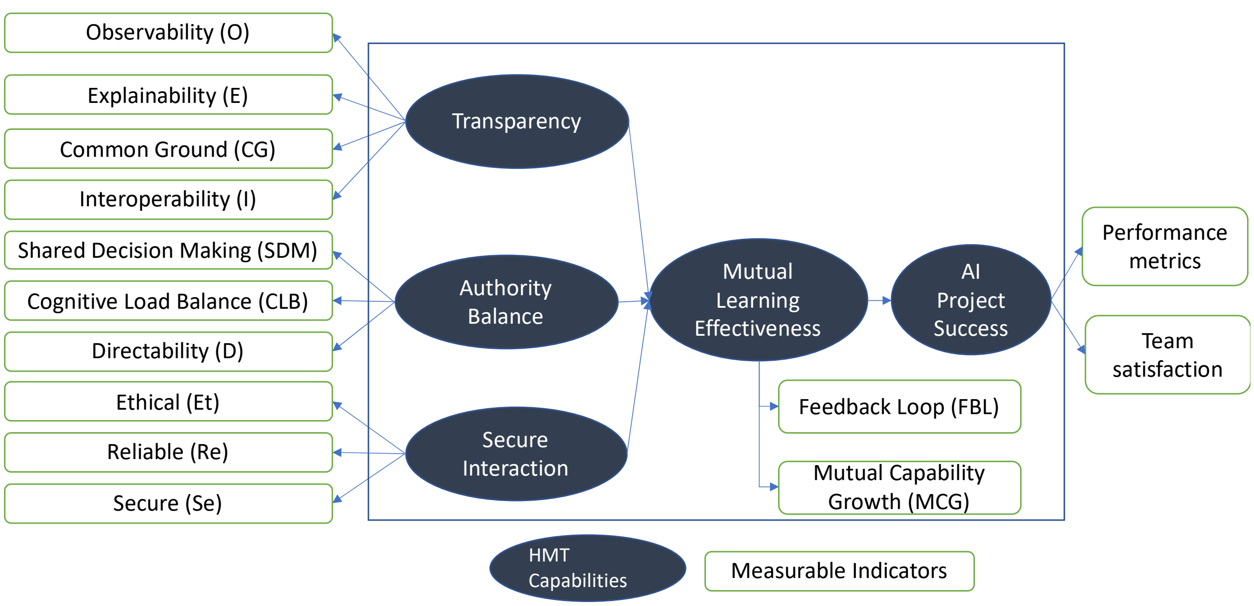


Figure 11: Measurement Model of HMT Capabilities

3.2 Research Design

Solutions for the second research question -- “How can one empirically test the conceptual HMT capability framework? “-- can be found by empirical examination of actual AI projects across various companies, applying the multiple case study method. Case studies as a research method are typically used in the exploratory stage of a research project to inform the “more structured” studies (Rowley, 2002). Single case study, which as its name indicated – research study of a single case -- has often been met with criticism regarding its stability to arrive at a generalized conclusion (Zainal, 2007). However, the robustness of a theory can be claimed if similar patterns are found in multiple cases (Yin, 2002).

Sources of a case study typically include direct observations, interviews and documents (Rowley, 2002). In this capstone project, the researchers used two types of case study sources: semi-structured interviews and literature reviews. Empirical investigation in this study considers a single AI project case as the unit of analysis. A company may have multiple AI projects.

The authors conducted the data collection and analysis in three stages (see Figure 12). In stage one, the authors assessed the publicly published case studies. The generated initial insights from stage 1 data analysis were tested and assessed in stage two (semi-structured company interviews). The consolidated and refined HMT framework were presented and confirmed in company webinars during stage three.

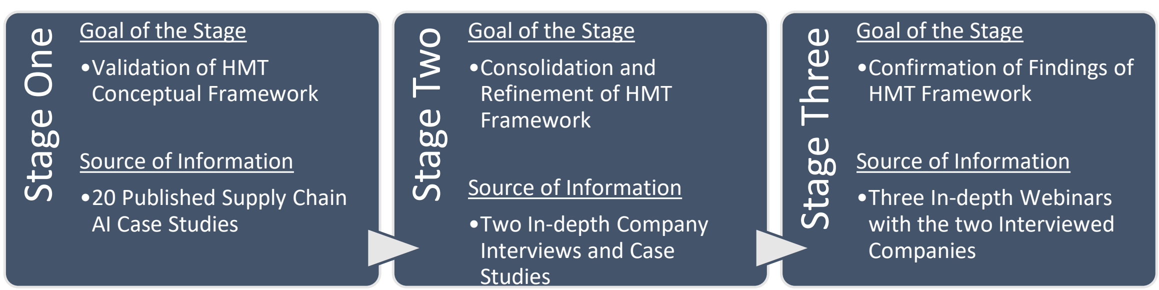


Figure 12: Data Collection & Analysis Stages

3.3 Stage One: Case Studies Assessment

Case Selection

The authors employed the following criteria for case selections and the detailed rationale are further discussed in the subsequent paragraphs.

- AI-driven technologies
- Strong interaction between human and the machine
- Supply chain application
- Sufficient history of implementation
- Relevant interviewee profiles

To adequately assess the Human-Machine Teaming framework, the right cases needed to be selected, taking into account both types of AI projects selected as well as interview partners chosen. One selection determinant was that the specific initiative should be a clear implementation of AI. While many AI projects did have some overlap with adjacent technologies (e.g. Internet of Things, Machine Learning, Augmented Reality), it was necessary to select projects that are predominantly AI-driven (i.e. where adjacent technologies play at most an auxiliary role) to assess this technology's impact and to limit potential "noise" from other applications.

Moreover, projects selected had to have a strong interaction between the human and the artificial intelligence concerning both the frequency and the depth of the interaction. Projects in which AI was independently applied without affecting the workflow of the employees in the organization are not the focus of this project. Additionally, the interaction between the human and the AI should involve continuous and intense learning between both parties, encompassing both the human and the machine interpreting each other's actions and adjusting their behavior accordingly, thereby improving process results.

As has been touched upon, projects also needed to have been implemented for several months prior to the investigation. In this way, the authors were able to ensure clearly measuring differences in the organization's behavior and the corresponding performance prior and after the project implementation. Startups, for example, were therefore not the best options for analysis.

Finally, another determinant for project selection was that the AI initiative should pertain to the area of supply chain management. Therefore, the project researched stem from the sectors of transportation or manufacturing, or from the functional areas of operations, logistics, procurement, or distribution. While such sector affiliation did not have to be exclusively the case, the core of each project must be within these topic areas.

3.4 Stage Two: Semi-structured Company Interviews

Company Selection
Project participating companies were also selected based on the same criteria as discussed in section 3.3. A list of more than 40 potential companies to contact for inquiry of their AI project was compiled using personal and professional networks, alumni

directories, and desk research. The low response rate was mainly due to low maturity of AI projects in many firms as well as the demands of daily operations. To counteract the difficult acquisition of company partners, twenty case studies were analyzed to derive additional insights on the interplay of project configuration, HMT capabilities, and project outcome.

Interviewee Profiles

With regard to the roles of employees included in the assessment of the projects, a differentiated approach was used. First, in the introductory interview the manager responsible for AI projects within the company was chosen. This way, comprehension of the project's details and its organizational context was assured. Moreover, support from senior managers in the organizations researched contributes to buy-in from other employees' part of the research project.

The second group of employees interviewed are those cooperating with the AI closely or being involved in its design, such as process owners (e.g. purchasing director), project manager, system developer (e.g. data scientist) and users (e.g. buyers). They are exposed to the exact situations in which the human-machine teaming process takes place and are therefore vital to share their perspective. Where appropriate, this panel was supplemented by employees from departments and process adjacent to the AI project itself to better assess the larger organizational impact. During the interviews, the different roles played by each of the project team members are inquired and discussed in order to understand the roles they played in terms of facilitating the human-machine mutual learning process.

Interview Process

Introductory interviews were conducted with managers responsible for artificial intelligence projects within the firms chosen. These interviews provided a better comprehension of the AI project investigated in the context of the individual company. Through this approach, the following data collection methods were calibrated for the individual organizational context. For example, the approach allowed for identification of the correct interview partners in the subsequent structured interviews, to potentially adjust the correct performance metrics for the scorecard assessment, understand the motivation behind the introduction of the project, and to discuss the logistics of the data collection process. Finally, it also served to build a relationship with senior staff within the firm, which facilitated all subsequent steps of the research process.

Next, semi-structured interviews were conducted with the actual users of the artificial intelligence. Depending on the availability of interview partners, approximately one to three interviews of one to two hours held through a web meeting or on-site visit. Within these interviews, the interactions between the employees and the AI as well as the resulting mutual learnings were the focus of investigation. More specifically, a structured questionnaire enabled us to identify how the human being was receiving input from the

AI, how user was responding to it, and the consequences of this interaction. Hence, this semi-structured interview involved both procedural and behavioral aspects as well as questions regarding how the employee was perceiving his or her work environment. Similar to the subsequent scorecard development, the structured interview involved assessing the work environment both before and after the AI introduction. Moreover, operational, financial, and strategic performance indicators were collected to facilitate the assessment of the AI project implementation's success.

3.5 Stage Three: Company Webinars

In the third stage of the research, the authors organized in-depth webinars with participating companies for project findings review and assessment results of their respective AI projects using the HMT framework. In each of the webinars, the following agenda was followed. Company feedback were collected to aid in the refinement of the final research outputs.

Webinar Agenda:

- Research motivation
- Established HMT framework
- Research questions
- Research hypothesis
- Research methodology
- Results findings & initial conclusions
- Managerial recommendations
- Company specific AI project HMT framework assessment result
- Recommendation for company specific AI project future improvement
- Questions & answers
- Company Feedback

In summary, with each step of the collection process, the data gathered became richer and more specific. This approach enabled a comprehensive understanding and evaluation of the developed framework.

3.6 Data Analysis Methodology

Based on the established conceptual framework, the authors developed a qualitative evaluation tool to enable the categorization of the AI project into the riskiness and openness dimensions as well as facilitated the assessment of each sub-dimension of the HMT capabilities.

Grouping

The AI projects are grouped into 4 quadrants based on the decision contextual framework discussed in section 2.5.2.

Table 5 depicts the measurement items for project groupings.

Table 5: Grouping Criteria and Assessment Items

Grouping Criteria	Description of Measurement Items
AI Design Openness	• Existence of pre-defined rules and actions • Freedom of options selection
Decision Risk Level	• Level of severity of consequence if error • Level of probability of occurrence • Level of detectability of occurrence

Indicators assessment

This study examines the critical capabilities affecting AI project implementation success through determining the likeliness of presence of the capability within each of the case studies. As observed in the conceptual framework, this research contains multiple HMT capabilities (unobserved variables) and Indicators (observed variables). The investigation of the relationships between these variables is necessary to answer the research questions.

The HMT Capabilities identified in the conceptual framework are the following:

- Transparency
- Authority Balance
- Secure Interaction
- Mutual Learning

A series of indicators and their potential concepts, identified through the literature review, were used to evaluate the level of presence of the HMT capabilities. A 5-point Likert scale was used to assess each of the indicators. 1 means the authors consider the level of presence is weak, while 5 indicates the authors considers the level of presence of the indicator is strong within the AI project.

Table 6 depicts the concepts included in the qualitative assessment tool.

Table 6: Measurement Items for HMT capabilities

HMT Capabilities	Indicators	Code	Description of concepts
Transparency	Observability	O1	Visibility on state parameters, capabilities of the system
		O2	Users visibility of AI system's intentions
		O3	Ability to anticipate mutual changes
	Explainability	E1	User Interface simplicity and understandability of information presented
		E2	Ease of discerning how AI system's decisions are made
		E3	Ease of understanding of algorithms
	Common Ground	CG1	High level of human-machine mutual awareness
		CG2	High level of information sharing
	Interoperability	I1	Ability of making coherent connections for inputs from various sources
		I2	Ease of interoperability with other systems and stay connected
Authority Balance	Directability	D1	Ability to control and override
		D2	Ability to allocate decision authority based on situation
		D3	Ability to redirect, re-allocate tasks
	Shared Decision Making	SDM1	Presence of simultaneous or sequential decision making
		SDM2	Ability to assist human to eliminate oversight slips and errors
		SDM3	Ability to understand the problem and develop solutions jointly leveraging each other's knowledge and viewpoints
	Cognitive Load Balance	CLB	Ability to assure a manageable human workload by balancing workload distribution between human and machine
Secure Interaction	Ethical	Et	Accordance to acceptable social conduct principles
	Reliable	Re	High level of system robustness and reliability
	Secure	Se	Validated method to protect interaction processes and prevent unintended access

HMT Capabilities	Indicators	Code	Description of concepts
Mutual Learning	Feedback loop	FBL1	Human-machine is able to provide synchronized feedback loop
		FBL2	Ease of incorporating user explanations into learning algorithms
	Mutual Capability Growth	MCG1	Help users broaden their view of the situation and help users revise solutions
		MCG2	Solution enables human team member to work more effectively with AI and shorten learning curve.

Measurement of AI Project Success

Table 7 provides a list of indicators, identified through the literature review, which will be used to measure the level of success in AI project implementations.

Table 7: Measurement Items for AI Project Success

Indicators	Detailed Description of Measurements
Performance Improvement	• Level of improvements in target performance metrics • Level of satisfactions working with AI systems

3.7 Data Validation

To check for the validity of the qualitative assessment results, the authors performed a cross-validation exercise to examine the consistency of the analysis. Each of the researchers used the qualitative assessment tool to rate all twenty case studies independently. The rating results were compared to check for agreement of the interpretation of the concepts and consistency of the assessment.

3.8 Conclusion

The project takes a holistic methodological approach, covering several aspects of the research methodology from the end-to-end view of the conceptual framework, the broad range of parameters included, the different methodologies including well-rounded case selection method, case studies evaluation and company interviews. This way, a scientific methodology based on an extensive literature review ensures that practical takeaways are based on sound academic methods. In the next two chapters, the data analysis results and their contribution to the research questions will be reviewed.

CHAPTER 4: RESULTS

The capstone project has three key expected outputs:

1) developing a valid conceptual framework of HMT capabilities that contributes to successful AI project implementations
2) recommending an assessment instrument for further validation of this framework
3) providing recommendations to organization and supply chain leadership for handling AI implementation

The conceptual HMT capability framework was developed based on the literature review. The underlying concepts of the HMT capabilities were assessed by analyzing carefully selected empirical AI projects. High rated indicator concepts are considered to have a strong presence in the framework, while low rated concepts are considered to have a weak presence. Detailed assessment results are outlined in this chapter.

The capstone project conducted qualitative research on two stages. First, 20 case studies were selected based on a set of defined criteria. Second, two companies were selected for a series of in-depth semi-structured interviews.

4.1 Stage One: Case Studies Analysis Results

4.1.1 Case Profiles Overview

1) Company: Univired

Project: Procurement Chatbot

Industry: Procurement

AI-Application: IT

Description:

Univired Chatbot facilitated the process of gathering procurement related information within organizations. Being connected to data sources (e.g. ERP systems) within a company and its suppliers, AI assists procurement professionals by issuing alert actions that need to be taken and by delivering information using chat bot functionality. Only when a request exceeds the capabilities of the chatbot is the demand being passed on to a service agent who further supports the procurement professional (Bharadwaj, 2019; "Chyme SAP Sales Assistant", 2017).

2) Company: Big River Steel

Project: Smart Steel Plant

Industry: Steel Industries

AI-Application: Production Efficiency

Description:

Big River Steel in cooperation with Noodle Analytics developed an AI-powered steel plant in Osceola, Arkansas, which leveraged data for optimized end-to-end processes. Collecting data from accounting, sales, and production sensors, the AI and human team members work together to make better decisions. For example, the Demand Signal AI assists in steering the ideal production capacity, Asset Health AI implements predictive maintenance, Energy Conservation AI facilitates self-learning to reduce energy consumption, whereas Product Quality AI prevents the occurrence of production and product anomalies ("*Big River Steel Case Study"*, 2020; Murawski, 2019).

3) Company: IBM

Project: IBM QRadar Advisor

Industry: IT

AI-Application: Security & Safety

Description:

IBM QRadar Advisor is a cloud-based solution for security professionals to facilitate the management of security information and incidents. The QRadar Advisor analyzes internal data (e.g. from firewalls) and compares it to external threat intelligence collected from the web, using NLP and a knowledge graph. Potential threats are then assessed by the human security analyst who has the final say on whether proposed interventions are implemented, which in turn is used as an input for additional learning of the AI (Rogers, 2019).

4) Company: GM/Autodesk

Project: "Dreamcatcher"

Industry: Automotive

AI-Application: Prototyping

Description: Autodesk's Dreamcatcher procedurally (i.e. creating data algorithmically) generates dozens of plausible designs of a given part based on a series of inputs such as required weight, strength, size, material, cost, or other performance requirements. These plausible designs can be sent directly to machining to generate test parts. Real performance data of the parts can be fed back into Dreamcatcher to optimize the program's understanding of the performance implications of its design choices. What would normally take a designer several days to create a single design, can now be done in hours with multiple viable alternatives. The more parts that are designed and analyzed with dreamcatcher, the larger its knowledge base of performance outcomes – allowing it to cross-leverage knowledge from multiple different classes of parts ("GM and Machine Learning", 2018; Keane, 2018; Kvernvik, 2018).

5) Company: Kone / IBM

Project: Preventive Elevator Maintenance and Optimization

Industry: Industrial Goods / Real Estate

AI-Application: Predictive Maintenance

Description:

Using IBM's Watson and Bluemix IoT and cloud platforms, Kone has established predictive maintenance systems, which are supporting field technicians to identify and fix malfunctions before they occur. In many of the more than 400,000 elevators and escalators Kone has in operation, it is collecting information on equipment behavior based on more than 200 input parameters. This information is paired with additional data, such as weather reports, to optimize service delivery. The engineer is provided with information about what to fix and potential solutions. Decisions and outcomes may be fed back into the system as it keeps on learning iteratively ("How KONE Is Using Watson IoT", 2019; Khizhniak et al., 2018; SCMP, 2019).

6) Company: Senseye / Nissan

Project: Predictive Maintenance

Industry: Automotive

AI-Application: Predictive Maintenance

Description:

Using the Senseye predictive maintenance platform, Nissan is reducing the downtime of more than 9,000 machines in its production park for the Qashqai, X-Trail, Leaf and Infinity models. This encompasses the collection and analysis of data from more than 30 different types of machines, such as robots, conveyor belts, pumps, and press machines. Senseye's AI then derives recommendations for preventive maintenance measures based on patterns in the data collected, which may be implemented by a service engineer. Through an app, engineers can then provide feedback that is fed back into the algorithm. Senseye reports a 50% reduction in production downtime and a 85% improvement in maintenance accuracy for its solution (Kampa, 2018; "Senseye Predictive Maintenance", 2020; "Senseye Whitepapers & Resources", 2020).

7) Company: Steward Healthcare Systems

Project: DataRobot

Industry: Healthcare

AI-Application: Job Scheduling

Description:

Healthcare provider Steward Healthcare Systems uses the DataRobot machine learning platform to derive and test models on day- and shift-specific patient volume and staff demands. Utilizing historic data on the number of patients, illnesses and treatment needs, the AI incorporates recommendations for eight hospitals in Steward's network. Staff planners have the option to intervene. With every iteration and day implemented, the solution continues to learn and improve. Results included USD 2 million in cost savings and a 95% accuracy of patient volume prediction ("Datarobot: Steward-Healthcare Case Study", 2018; Goh, 2018).

8) Company: BMW

Project: Artificial Intelligence in Quality Assurance

Industry: Automotive

AI-Application: Quality Assurance

Description:

Using AI, BMW is assisting quality assurance employees in the final checks of the production process to ensure a car has been assembled as indicated. The AI compares vehicle order data with a live image of the model designation as well as additional identification aspects (e.g. "xDrive" logo) of the manufactured car. If the AI recognizes a mismatch between the order data and the image from the production line, it notifies the quality assurance employees who then needs to verify whether an error has been made and provides feedback ("BMW Factory – Integration of A.I. in the Production Line", 2019; Bouchaala, 2020; "Fast, Efficient, Reliable", 2019).

9) Company: BMW

Project: Artificial Intelligence in Flat Metal Sheet Pressing

Industry: Automotive

AI-Application: Quality Assurance

Description:

BMW is using AI in detecting potential micro-cracks that occur in the manufacturing of high-precision components using flat metal sheet pressing. Using image recognition, a neural network assesses approximately 100 real images and 100 images of a "perfect" part and determines whether a defect is present. Potentially defect parts are sorted out for further investigation by technicians, who will determine whether the defect was present or not. BMW obtained efficiency gains due to higher degree of automation and fewer cases of false positives than in the previously manual process ("BMW Factory –

Integration of A.I. in the Production Line", 2019; Bouchaala, 2020; "Fast, Efficient, Reliable", 2019).

10) Company: DHL

Project: Resilience360 Supply Chain Risk Monitoring

Industry: Logistics

AI-Application: Supply Chain Risk Management

Description:

DHL Resilience360's cloud-based offering enables companies to monitor and manage disruption risks. The solution maps supply networks from an end-to-end perspective, assesses risks and identifies vulnerabilities as the basis for mitigation strategies. Resilience360 uses machine learning and natural language processing to analyze company profiles as well as articles from news sources and social media. These assessments are further enriched with the insights from human risk analysts and provided to clients who can access risk notifications as well as dashboards and have the option to participate in several feedback loops to improve the system further ("10 Reasons to Invest in Resilience", 2014; "DHL Resilience 360 - Customer Solutions & Innovation", 2020; DHL Resilience360, 2020).

11) Company: Bosch Rexroth / Hägglunds

Project: Predictive Maintenance

Industry: Industrial Goods

AI-Application: Predictive Maintenance

Description:

Bosch's Hägglunds CMp leverages AI to create an accurate health index for the manufacturer's drive system during normal operating procedures. The health index is then continually monitored for difference from the ideal state. When a discrepancy is observed, Bosch Rexroth analysts identify the cause using the AI outputs and suggest counteractive measures to technical engineers on the ground. When a divergence from the index is spotted, Bosch Rexroth experts interpret the cause and recommend actions to keep the system running to clients. Iterations then help the AI to become more apt at predicting future machine failure (Herzlieb, 2017; Wallin, 2018).

12) Company: Reyes Holdings

Project: AI-supported Demand Planning

Industry: Wholesale

AI-Application: Demand Planning

Description:

Reyes Holdings is using AI and machine learning to improve demand forecasting in the market of beer distribution. Both demand planners and analysts were involved in the preparation of the data and development of the correct models. The AI now delivers recommendations which show a decision space for purchasing coordinators. Accuracy continually improved over time and through interventions from the data science team (e.g. feedback collection). The solution reduced forecast error from approx. 38.6% to 19.6%, which again resulted in significant financial gains (Olazabal & Caballero, 2019).

13) Company: Jabil / Microsoft

Project: Manufacturing Quality Assurance with AI

Industry: Electronics

AI-Application: Quality Assurance

Description:

Jabil uses artificial intelligence to reduce overhead cost and improve product quality by checking electronic products when they are manufactured. In “Project Brainwave,” Jabil utilized IoT sensors to combine production processes with machine learning to optimize its optical inspection procedure. Based on Microsoft’s cloud platform, Jabil developed a predictive deep learning model identifying defect products along its production system. Once the AI identifies a part as defect it is sorted out for human inspection, whose result is being fed back into the system for the purpose of retraining and improvement of accuracy (Behringer, 2018; Novet, 2018)

14) Company: Starbucks

Project: Deep Brew

Industry: Food & Drink

AI-Application: Job Scheduling / Demand Planning / Predictive Maintenance

Description:

In its Deep Brew project, Starbucks uses AI in the realms of predictive maintenance, job scheduling, and demand planning. For example, data from espresso machines is analyzed for patterns indicating future defects. Similarly, (transaction) data is being analyzed by AI using the Azure Sphere platform for the optimization of shift scheduling and demand prediction. As more data is collected and merged with feedback from staff, the AI becomes more competent at its dedicated tasks (Sozzi, 2020; "Starbucks Deep Brew”, 2019).

15) Company: Ochsner Healthcare System

Project: Patient Risk Prediction

Industry: Healthcare

AI-Application: Job Scheduling

Description:

Ochsner, an operator of hospitals in the United States, uses AI to improve patient monitoring. A patient's vital signs are constantly monitored and applied to historical data which is able to identify patterns in the vital signs that could indicate future implications. Such patients subsequently receive timely individual attention, are analyzed for underlying reasons of the alert, and the AI further improves from the results (Adriamen, 2018; Arndt, 2018).

16) Company: Nauto

Project: AI-based Transportation Safety Management

Industry: Logistics

AI-Application: Safety and Security

Description:

Nauto provides an opportunity for fleet managers to improve the safety of drivers and vehicles in their fleet. An AI application analyses data from cameras inside and outside the driver's cockpit, from sensors, and additional sources and issues warnings to the driver when he behaves in a risky way. Fleet managers receive safety scores for the different drivers and can implement counteractive measures. (Benzinga, 2019; Lu, 2019; "Nauto Atlas-Driver+Safety Report", 2018; "Nauto Product Overview Brochure", 2018; "Reducing Distracted Driving", 2019).

17) Company: Covarian / Knapp

Project: AI-based Transportation Safety Management

Industry: Logistics

AI-Application: Production Efficiency

Description:

Covarian has developed an AI powered robot able to perform component-sorting in order picking. In the development, the robot mimics the behavior of a human worker in identifying and picking of different objects. In a recent application, the robot can now pick and sort more than 10,000 products with an accuracy of 99% (Hao, 2020; Satariano & Metz, 2020).

18) Company: TechnologyCo

Project: Quality Advisor

Industry: Electronics / IT

AI-Application: Quality Assurance / Procurement

Description:

TechnologyCo uses AI to monitor the quality of products of different suppliers delivered to its manufacturing supply chain. It applies deep learning techniques to data collected internally and externally along the supply chain. Quality assurance engineers have the opportunity to deliver feedback along the process. The initiative has allowed TC to proactively improve component performance thereby improving end product reliability, which it considers a critical competitive advantage (TechnologyCo personal communication, March 3, 2020).

19) Company: TechnologyCo

Project: Test Advisor

Industry: Electronics / IT

AI-Application: Quality Assurance

Description:

TechnologyCo utilizes AI in manufacturing decision support, enabling a system debut operator to repair the machine. The traditionally slow debugging and testing process is significantly accelerated through the new approach. Test personnel can request help from the Test Advisor throughout a platform interface, which the AI then processes based on a data lake and returns ranked recommendations for debugging and repair. In the process, NLP is utilized to facilitate interactions (TechnologyCo personal communication, March 11, 2020).

20) Company: Fujitsu / Siemens Gamesa

Project: Wind-Turbine Blade Quality Checks

Industry: Industrial Goods

AI-Application: Quality Assurance

Description:

Fujitsu and Siemens Gamesa worked together to improve and accelerate post-manufacturing quality assurance of wind turbine blades through AI and deep learning. Utilizing image pattern recognition, potential defects, such as wrinkles in the fiberglass used, can be identified without compromising the product surface. In case of identifying a potential defect, quality engineers can further investigate whether a production issue has occurred, take counteractive measures, and further improve the capabilities of the AI. Through this effort, inspection time was reduced by 80% ("Artificial Intelligence Solution from Fujitsu Helps Siemens Gamesa", 2017; Garrett, 2017; Rouz, 2018).

4.1.2 Cross-Validation Result

The researchers conducted cross-validation exercise as discussed in section 3.6 on the 20 cases to validate the consensus on definitions and consistency of the findings. The results indicate that there are no major inconsistencies, which indicates that the researchers have the same interpretation of the HMT capability indicator concepts, as well as how they are exhibited in each of the case studies.

4.1.3 Case Studies Findings

Case Profile Summary

The authors grouped the 20 cases using two different classification methods: decision context group and application type. Decision context grouping method is outlined in section 3.6. Application type grouping method is based on the supply chain process where the AI application is applied. The detailed application type information is described in section 4.1. Figure 13 summarizes the number of cases under each of the two different grouping approaches.

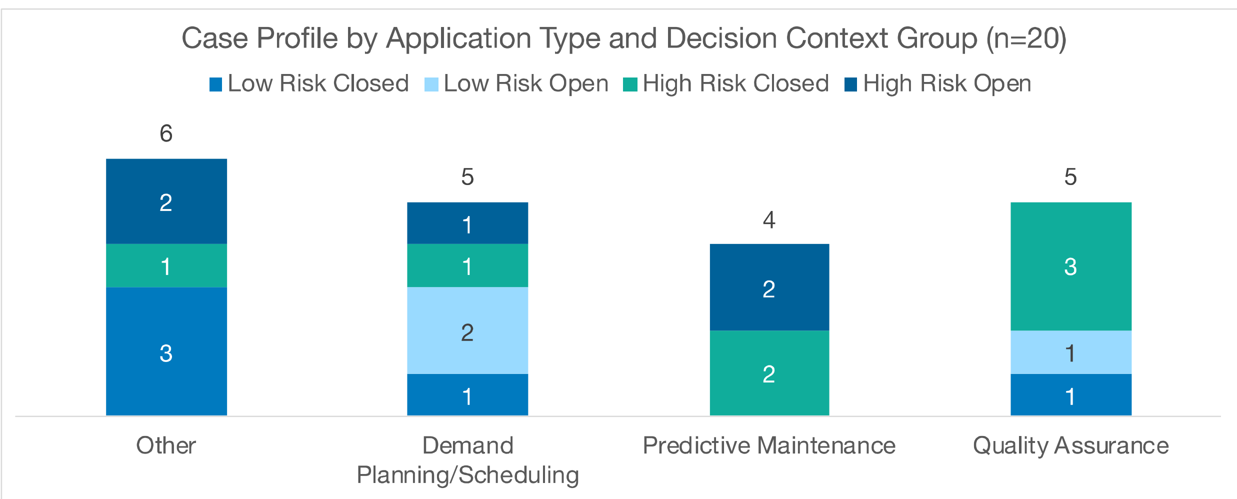


Figure 13: Case Profile by Application Type and Decision Context Group

Overall Assessment of HMT Capability Framework

The consolidated rating of the HMT capabilities is shown in Figure 14. The overall rating is calculated as the median of the scores, which indicates the level of presence of the HMT capability among the cases studied. The authors consider that a rating level greater than 4 indicates a strong level of presence while a rating level less than 1.5 indicate a weak level. According to the result, all 4 HMT capabilities have shown strong presence which confirmed the strong presence of these HMT capabilities in a successful AI implementation. These results confirm the validity of the conceptual framework set forth in section 3.2.

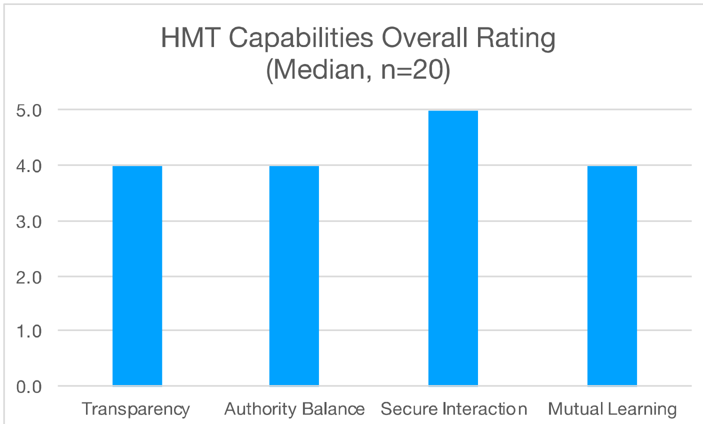


Figure 14: HMT Capabilities Overall Rating

The authors further evaluated the results at the HMT capability indicators level to understand which indicator concepts are more and less pronounced. This analysis is based on the rating level and the rating spreads. The median score greater than 4 indicates a strong presence and a score greater than 3 and less than or equal to 4 indicates a relative strong presence. A median score less than 1.5 indicates a weak presence and a score greater or equal to 1.5 and less than 2 indicates a relatively weak presence.

The rating spread is defined as range of the scoring distribution between the maximum score and the minimum score, which indicates the distribution pattern of the presence of the HMT capability indicators among the cases studied. The spread of less than 1 indicates a strong consistency while a spread less of than 2 but greater than 1 is considered as relative consistent. The indicator level and spread analysis result is summarized in the Figure 15.

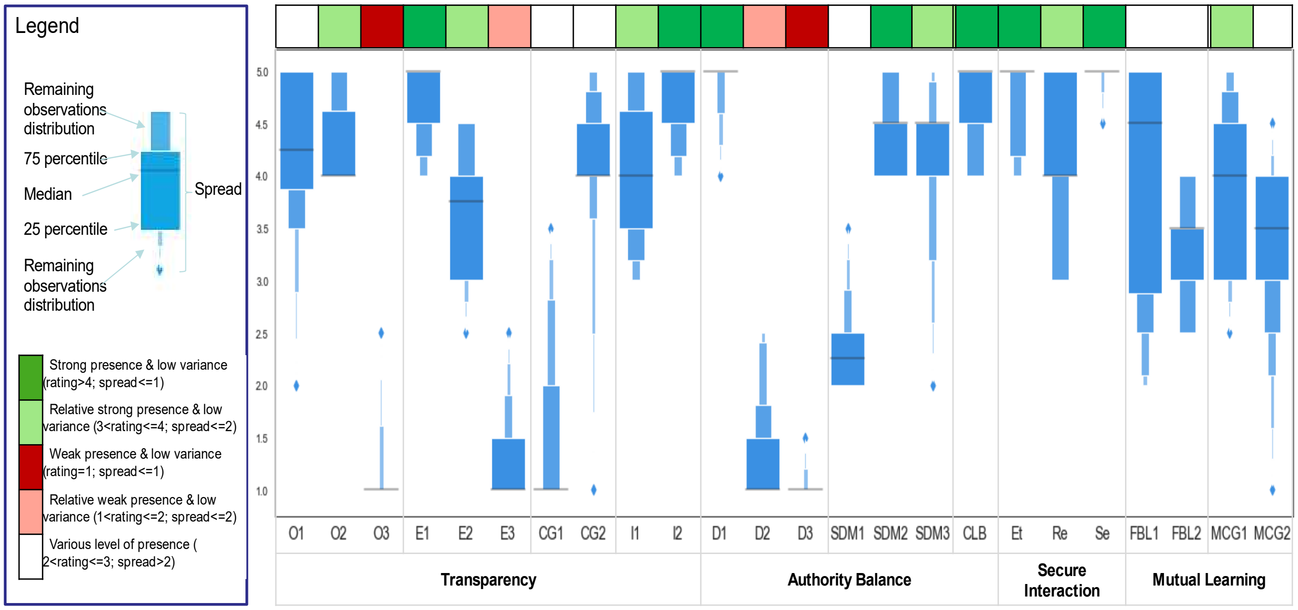


Figure 15: Enhanced Boxplot of HMT Capability Indicators

Based on the analysis, the consistently strong and relatively strong capabilities are summarized in Table 8.

Table 8: Consistently Strong HMT Capability Indicators

HMT Capability	Indicator	Indicator Concept (S=Strong; RS=Relatively Strong)		
Transparency	Observability	O2	RS	User's visibility of AI system's intentions
	Explainability	E1	S	User interface simplicity and understandability of information present
		E2	RS	Ease of discerning how AI system's decisions are made
	Interoperability	I1	RS	Ability of making coherent connections for inputs from various sources
		I2	S	Ease of interoperability with other systems and stay connected
	Directability	D1	S	Ability to control and override

HMT Capability	Indicator	Indicator Concept (S=Strong; RS=Relatively Strong)		
Authority Balance	Shared Decision Making	SD2	S	Ability to assist human to eliminate oversight slips and errors
	Cognitive Load Balance	CLB	S	Ability to assure a manageable human workload by balancing workload distribution between human and machine
Secure Interaction	Ethical	Et	S	Accordance to acceptable social conduct principals
	Reliable	Re	RS	High level of system robustness and reliability
	Secure	Se	S	Validated method to protect interaction processes and prevent unintended access
Mutual Learning	Mutual Capability Growth	MCG1	RS	Help users broaden their view of the situation and help users revise solutions

The consistently weak and relatively weak capabilities are summarized in Table 9.

Table 9: Consistently Weak HMT Capability Indicators

HMT Capability	Indicator	Indicator Concept (W=Weak; RW=Relatively Weak)		
Transparency	Observability	O3	W	Ability to anticipate of mutual changes
	Explainability	E3	RW	Ease of understanding of algorithms
Authority Balance	Directability	D2	RW	Ability to allocate decision authority based on situation
	Directability	D3	W	Ability to redirect, re-allocate tasks

Decision Contexts Group Assessment

To further understand how the decision context may influence the HMT capability configuration, the authors further analyzed the results by different decision context groups. Figure 16 summarizes the similarities and differences in the level of presence of HMT capability indicator by decision contexts group.

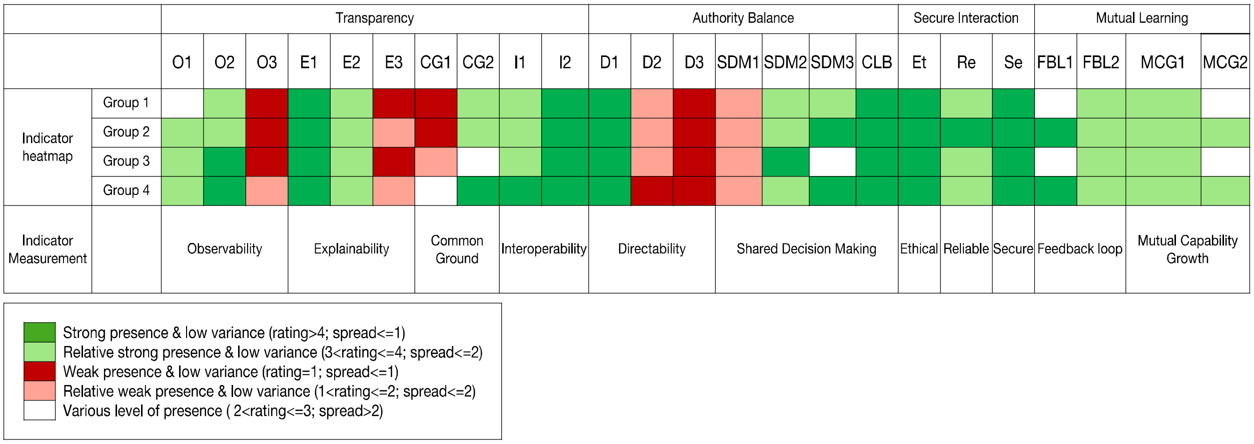


Figure 16: HMT Capability Similarity and Differences by Decision Context (n=20)

Based on the analysis illustrated in Figure 16, the differences in HMT capability indicator level of presence among the 4 decision context groups are summarized in Table 10. The table outlines the different capabilities between two different groups. For example, between group 1 and 2, 6 of 24 HMT capability indicators are configured differently, while between group 3 & 4, 10 of 24 HMT capability indicators are configured differently.

Table 10: HMT Capability Indicator Differences among 4 Decision Context Groups

	Group 1	Group 2	Group 3
Group 2	O1, E3, SDM2, Re, FBL, MCG2		
Group 3	O1, O2, CG1, CG2, SDM2, SDM3	O2, E3, CG1, CG2, SDM2, Re, FBL1, MCG2	
Group 4	O2, O3, CG1, CG2, D2, SDM3, FBL1, MCG2	O2, O3, CG1, CG2, D2, Re	O3, E3, CG1, CG2, I1, D2, SDM2, SDM3, FBL1, MCG2

Application Group Assessment

To evaluate whether the type of applications also plays a role in influencing the HMT capability configuration, the authors further analyzed the results by different application groups. Figure 17 summarizes the similarities and differences in the level of presence of HMT capability indicator by application type.

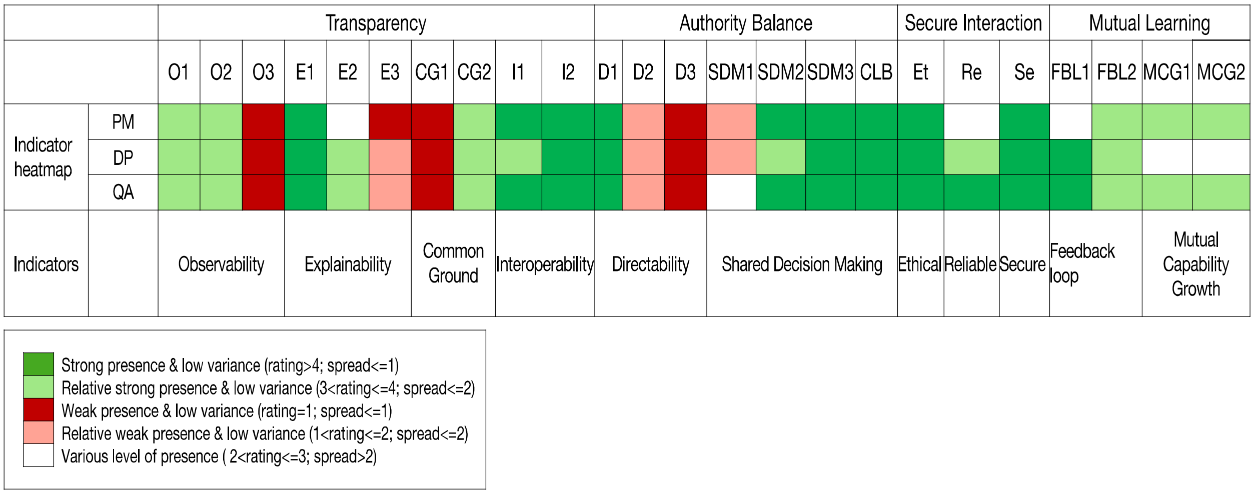


Figure 17: HMT Capability Similarity and Differences by Application Types (n=20)

Table 11 summarizes the differences in HMT capability indicator level of presence among the 3 application groups. For example, the result indicates that between PM and DP applications, 8 of 24 capabilities are configured differently, while only 5 of 24 capabilities are configured differently between PM and QA applications.

Table 11: HMT Capability Indicator Differences among Different Application Groups

	PM	
DP	E2, E3, I1, SDM2, Re, FBL1, MCG1, MCG2	**DP**
QA	E2, E3, SDM1, Re, FBL1	I1, SDM1, SDM2, Re, MCG1, MCG2

4.2 Stage Two: Company Semi-Structured Interview Analysis Results

4.2.1 Case Profiles Overview

The authors conducted extensive semi-structured interviews with two companies. Company names are anonymized due to confidentiality. The company's profiles are provided in Table 12.

Table 12: Overview of the interviewed companies

Company	Business Overview	SC spend (USD bn.)	SC AI Application	Interviewee Profile
TechnologyCo	Leading software, service & cloud computing company	$40B+	Supply Chain Advisor	• Senior Managers of Digital Supply Chain Transformation • Transformation Lead • User of the application
Manufacturing Co	Global manufacturing service company	$20B+	Inventory Optimization	• Supply Chain Sr. Director • Operations Director • Data Scientist

The authors further validated the conceptual framework via semi-structured interviews with two selected companies. In the next two sections each of the company's AI project context, performance and the HMT capabilities configurations are reviewed and assessed in detail.

4.2.2 ManufacturingCo – Inventory Optimization AI

1) Company Overview

ManufacturingCo (MC) is one of the world's largest manufacturing solution providers. It operates a business-to-business (B2B) model that requires extremely complex manufacturing work for a wide variety of industries, including consumer products, defense & aerospace, healthcare, automotive, energy, industrial & building, networking and telecommunications.

In the preparation of this paper, interviews with three representatives of MC were conducted, including Senior Director of Supply Chain, Director of Manufacturing Systems, and Data Scientist of the AI project.

2) AI Project Overview

MC desires to reduce the cost burden induced by excessive inventory of high-value parts, thereby freeing up cash for company to invest in other growth areas. Currently, experts of MC's operations can figure out causes for high inventory by reviewing historical snapshots of ERP transaction data, but this is a slow and labor-intensive process.

MC’s existing ERP system generates exception messages based on rules set up in the system. When demand increases, the system may send exception message to alert the buyer that a new purchase order needs to be placed to meet the demand. There is an approval process to go through to react to exception. Knowing whether to accept or reject the exception message is not straight-forward. More experienced users will tend to know which exception message needs to be followed and which ones should be ignored. Typically, the excess inventory situation is caused by buyers reacting to all exception message from ERP.

The Inventory Optimization AI project aims to automate the cause analysis for over-inventory in a faster and more efficient way to allow process improvements in the buyer operations within MC. Another objective of this AI application is to provide buyers with predictive analysis on what actions he/she should take regarding ERP exception messages and what related outcome may result in.

This project is envisioned to be carried out in three phases:

- Phase 1: Proof-of-concept (PoC)
- Phase 2: Deployment/Scale-up
- Phase 3: Predictive insight and MRP workflow integration

Currently, MC has just completed phase 1 (PoC) and is planning phase 2 (deployment/scale-up).

3) Decision Context Assessment

The decisions expected to be made from this AI application is to fine-tune the governance rules around material planning and purchasing to prevent loopholes that drive bad purchasing behaviors. One day of inventory addition will significantly impact the company’s working capital and its ability to fund other capital expenditure needs. The project team believes that fine-tuning the governance rules for bad behaviors will drive positive impact, so the decision risk is low for the current application. Current AI design is supervised learning with defined features and labels, therefore is “closed”.

4) HMT Capability Framework Analysis

From the Senior Supply Chain Director’s (process owner) perspectives, the most important elements for the success of the project are: 1) executive sponsor support; 2) selecting the right business case; 3) setting the right expectation upfront on project scope and demonstrating success; 4) motivated team by building **trust** in the application.

The project manager, Director of Manufacturing System, further expanded that the “trust” element is enabled by data **Interoperability**, **Explainability** capabilities and the AI’s human centric positioning.

Transparency: Observability, Explainability, Common Ground and Interoperability

The AI application is currently using a subset of existing data for training and testing purposes. Even with a mature enterprise data lake, the team discovered that significant efforts were needed in data cleaning & processing. A separate project team is working on developing the automated data processing tool to clean the data in the background to enable seamless **Interoperability**. Establishing credibility with users is considered paramount by the project leaders, which is enabled by having the intuitive **Explanation** - developing useful visuals by showing the underlying evidence of the impact correlating to the actions taken by the users. **Observability** and **Common Ground** indicators are not present in the PoC due to its pilot stage.

Authority Balance: Directability, Shared Decision Making and Cognitive Load Balance

Currently the decision remains with the human. AI insights are provided for purchasing managers to help finetune the purchasing governance guideline for buyers. The AI application improves the buyers' **cognitive load balance** by taking over the complicated computation task. However, the project team is still discussing how to incorporate this predictive capability with human-machine decision making balance, which they recognize the **decision sharing** is a delicate balance.

Secure Interaction: Ethical, Reliable and Secure

From an **ethical** standpoint, the Senior Director of Supply Chain pointed out that it is important for employees to know that AI is not here to take their job but is an extension of their capabilities to free up time for more valuable activities. The Director of Manufacturing Systems concurred: "It's important not to use this application as the 'big brother' surveillance tool for buyers or something to take over buyers' job."

Reliability of the PoC is currently measured by training and testing dataset prediction accuracy and recallability. Data access **security** is a key teaming capability required to be implemented since the AI application will reside in the cloud.

Mutual Learning: Feedback Loop and Mutual Capability Growth

Currently the training/testing dataset is a small subset of the entire SKUs. The next step is to scale up the application to be able to analyze 10-20 times the data size of current pilot set. The **Feedback Loop** mechanism is not yet clear as to how the machine learning algorithm will continue to learn from real-time data. However, it is recognized by the project manager that this capability is important for next phase development.

The application is also intended to provide buyers with predictive analysis of what actions buyers should take with regard to ERP exception messages. This functionality should provide good education to the buyer on the consequence of the actions, which enables the buyers' **capability growth.**

<u>Additional Capability Considerations</u>

Besides the HMT capabilities, the data scientist of the project commented that an additional success factor for the project is "having the right team with right skills and chemistry." The project team consists of a cross-functional team including supply chain business subject matter expert, data scientist, ERP expert and machine learning specialist. However, the project owner discussed that the users (buyers) should have been brought in earlier (day one) in the project: "If they learn the machine learning methodology in a decision making environment, they can get a flavor on the architecture in terms of the complexity early on, then it will help them to appreciate the application and be more adoptable."

<u>Human Role</u>

Because the project is in the pilot stage, a human is currently playing a trainer role to provide feedback to the model and guidance to the follow-on development of AI capabilities and interaction processes. As the project moves into more mature phases, the rules will be more defined, and human involvement will be reduced only with periodic monitoring and updates when necessary.

5) Project Performance

The PoC has already demonstrated benefits in identifying unwanted behavior patterns that drove high Days-in-inventory (DII). Training and testing accuracy reached 96%. The PoC was also validated by buyers, who confirmed that the AI analysis was aligned with their intuitions.

6) Summary

MC's inventory optimization AI PoC is considered type 1 in the decision context group -- low decision risk and closed AI design. At its pilot stage, the project team focused on forming a foundation for **Interoperability** by focusing on **I2 indicators** (Ease of interoperability with other systems and staying connected), developing a strong **Explainability** capability especially on **E1 indicators** (User Interface simplicity and understandability of information presented) and establishing the trust of the human-machine relationship by emphasizing the human centric decision making role (activating HMT capabilities in **Ethical** and **Directability D1**). **Mutual Learning** is at low to medium level at this stage due to the project maturity.

4.2.3 TechnologyCo – Cognitive Supply Chain Advisor 360

1) Company Overview

TechnologyCo (TC) is among the world's largest IT companies, offering hardware, software, cloud solutions as well as consulting services. In 2019, it created sales of more than USD 70 billion in more than 150 countries with more than 350,000 employees. In the process, TC operates a complex supply chain of inhouse manufacturing operations, external (multi-tiered) suppliers as well as logistics operations including millions of daily deliveries.

In the preparation of this paper, interviews with five representatives of TC were conducted, including Senior Managers of Supply Chain Transformation, Supply Chain Managers, and users of the system. Additionally, supplemental documentation such as company presentations, have been obtained and analyzed for the purpose of this study.

2) AI Project Overview

TC set out to create a "cognitive" supply chain in which decisions of employees are enhanced through AI. The company stresses that it considers AI "augmented" intelligence to underscore the human-centricity of the effort, focusing on enhancement of supply chain professionals' ability to understand supply chain problems, estimating their impact and identifying correct countermeasures.

TC's supply chain organization utilizes a cognitive toolset as the project's technological backbone. The idea behind the creation of a distinct technological platform (deemed supply chain "Advisor") was to enable better resolution of business challenges covering different functions at faster speed (seconds vs. days or weeks). Currently, the company has included the functions of inventory, demand and supply planning, supply assurance, logistics, order management and manufacturing in the project. After its development, the platform was integrated into operations and continually enhanced through AI and advanced analytics.

The Advisor in its target stage utilizes live (un)structured transaction data from internal and external sources and derives predictive information and recommendations for TC's supply chain professionals. Currently, the focus is still predominantly on structured data sources. Supply chain subject matter experts with an understanding of field-specific terminology train the model and support its development by software. By including underlying data along with recommendations and by providing feedback functionality, the supply chain Advisor is continually learning through employee feedback. The solution includes chatbot functionality leveraging NLP, the ability to "drill-down" in the data as well as visualization features. In a mutually beneficial relationship subject matter experts continually train the Advisor, which in turn enhances their capabilities by providing recommendations and insights.

3) Strategic Project Goals

The Advisor is part of TC's data strategy which aims at including data across different business units and external data sources in a universally accessible central platform to enhance visibility for decision-makers. The Advisor aligns well with the three strategic supply chain goals of the organization, which are "flawless execution", enabling "digital transformation through AI, Blockchain, and Internet of Things", and "increasing expertise along the supply chain".

Moreover, the project allows for both the "upskilling" of the workforce (i.e. drive productivity) as well as the "rightsizing" of the workforce (i.e. drive efficiency). In a shrinking workforce, TC aims at democratizing supply chain knowhow, enabling employees to broaden skills, share best practices and show an end-to-end view of the supply chain.

Additionally, SC professionals should focus more on supply chain challenges rather than IT skills in retrieving and normalizing SC data.

4) Project Timeline

TC's journey to digitize and democratize supply chain knowledge stated in early 2017. The Advisor project was set out to include four stages, each including an increasing scope of "understanding", "reasoning", "learning", and "interacting" of increasing scope to be completed by 2019, which later was relaxed.

While first stage focuses on extraction of domain-specific knowledge using deductive rules, NLP and scripted conversations, the second stage delivers a proof of concept on unstructured data as well as descriptive insights with links to underlying evidence utilizing a free-form chatbot and ability to provide explicit feedback ("thumbs up and thumbs down").

In stage three, domain knowledge is expanded, predictive insights are included, and the Advisor's usage increases as AI and the employees are trained by applying it in daily operations. In the final stage (4), the Advisor's technical capabilities are further expanded by identification of hidden relationships across different domain as well as deductive, inductive and abductive reasoning (i.e. identification of gaps), unstructured learning and bi-directional dialogues between the human and the AI.

In the process of developing the Advisor, a team of developers and subject matter experts iteratively identified complex supply chain projects and (using agile methods) derived minimum viable products (MVPs) with valid resolutions frequently covering multiple data sources and both deep domain and cross functional challenges. When MVPs gained traction, they were quickly rolled out across the organization. TC also applied “new work” techniques such as design thinking, end to end scenarios, user personas, and scrum development with quick iterations.

5) Functionality

The Advisor’s functionality is twofold. The solution currently synthesizes different databases present within the company and brings it together in a central dashboard. Information can then be assessed proactively by asking questions (e.g. “What is the stock of item xy?”) to which the AI then delivers the correct answer as well as supporting evidence. The user can then provide feedback on the quality of the answer and data provided. Similarly, the AI also proactively gives recommendations (“Check in with supplier XY on item Z as the current inbound delivery is delayed”) based on AI calculations using an underlying business logic. Again, the employee can provide feedback on the suggestion. Currently, the firm does not yet track whether the recommended solution was implemented or not. However, it is intended to implement the option of providing richer contextual feedback in the future.

The Advisor uses NLP, which enables the asking and answering of questions in natural language in a conversation panel. TC built the solution to empower supply chain professionals with popular questions grouped by domain. At the current level this encompasses more 100,000 different questions. Answers can also be read out loud by the software. In the future, it is planned that the Advisor can also “hear” questions to obtain an even higher degree of interaction.

Users can ask questions directly into an interface or browse questions that the Advisor has been trained on along the different supply chain domains. In the following steps, users are presented with information using a chat format. The immediate answer is supplemented with underlying information and interactive charts.

The user interface is supplemented by reliable visuals and ‘drill downs’ functionalities to enrich the conversation by giving comprehensive background information on each scenario. By selecting elements of a chart, data in subsequent displays are modified. Supply chain professionals may have access to data and information from other domains. Currently, approximately 20% of requests are cross-domain, which eliminates the need to contact employees in other departments for information acquisition. Information access and data security is managed through an access approval process.

The Advisor's capabilities also encompass the resolution of potential disruptions in the supply chain before they materialize. For example, potential shortages can be addressed in advanced and scheduling is optimized by suggesting better ship dates. The advisor will quickly make recommendations to solve issues in anticipation of disruption in the supply chain. The advisor will make a recommendation and provide the user with evidence.

Within the field of big data and manufacturing intelligence systems, focus is put especially on cognitive tools and technologies, reporting technologies, predictive modelling, machine learning, optimization, cognitive visualization frameworks and data technologies. In the field of artificial intelligence, especially the cognitive technologies, such as natural language processing, translation of speech to text, and the processing of speech are important. The Advisor's predictive modelling technologies leverage SPSS and Python but also Watson Analytics and custom machine learning methods play a central role. As data structures are of fundamental importance for the success of the project, Technology uses robust, modern frameworks such as Hadoop, Spark, DashDB along with the company's ERP system. At the current stage, no IoT platforms, mobile platforms or advanced robotics have been integrated into the solution.

The usage of a high-quality technology stack is important in order to facilitate the incorporation of feedback, which to a significant degree should be further automatized. Hence, good interoperability and reliability of the different systems utilized is of high importance

6) Role of Human Team Members

Feedback is provided to the algorithm in a variety of ways and different players within the company take on different roles and provide feedback in separate ways. The most important source of feedback are the users, which after each interaction with the AI at the current stage have the option to show whether their experience was helpful and beneficial or not (as exemplified by a thumbs up and a thumbs down button). Users have told us that this is used most frequently in the weeks and months after a new feature is implemented. Later, when an equilibrium state is reached, less feedback is provided. A second channel of providing feedback is to channel it directly to the developers. Hence, if a user desires a new feature or observes a bug.

Developers are the closest to the development of the AI. Using agile methods they are deploying within short time frames new iterations of the Advisor based on the product roadmap, user feedback, and project team instructions. Business process owners and the project team are responsible for generating the general road map for the addition of functionality and improvement of existing tools.

Hence, one can summarize that business owners and the project team generally determine the general direction and scope of the AI while the developers decide how it is encoded and how feedback will be collected. The users then are the actual providers of feedback who train the AI during daily operations. The human team members therefore take on elements of both a coach and a decision maker. They train the AI by providing constant feedback on both an operational and a strategic level but also serve as the actual decision makers. If the Advisor were to increasingly take on decisions on its own, the human's role for sentinel or supervisor would arise.

7) Decision Context

Degree of Risk:

Decision-making in the supply chain function of a global technology firm such as TC inherently requires a high degree of accuracy as decisions on the sourcing, production, and delivery of goods and services worth USD billion are made. Hence, having a high degree of accuracy and reliability of the data is crucial and the context of the human-machine involves risk. However, this is also subject to the degree to which users are basing their decision on the advice and insight provided by the AI.

Similarly, the AI at the current level of implementation "only" provides recommendations and does not automatically implement them. The AI is also used on a case-by-case basis (e.g. a single product) and not on an aggregate level. Hence, if a mistake is made, it only affects this very decision and not every single item within the supply chain. On the other hand, errors (e.g. stockouts, excessive inventory, delays) will still lead to significant financial damage. Overall, however, the risk level can be assessed as moderate to low.

AI Design:

The AI at the current stage of implementation displays both elements of closed and open design. The AI has access to different databases which involve structured data for supervised learning. On the other hand, the Advisor solution also involves the field of natural language processing (NLP), which is widely considered unsupervised learning.

What should be noted is that the application is continually moving towards open AI design by including features such as unsupervised learning, the identification of hidden / implicit relationships, and extraction of information from incomplete data. In future stages, it is also intended to move from deductive and explicit rules towards abductive and inductive reasoning. Even at the current stage, the AI design can be deduced as rather open than closed due to the extensive usage of natural language processing.

8) HMT Framework Analysis

In the following sections, the authors evaluated the performance of TC's HMT capabilities (Transparency, Authority Balance, Secure Interaction and Mutual Learning) with the HMT assessment tool. The level of HMT capability presence is discussed and analyzed. An overall assessment of each HMT capability is provided at end of each sections.

Transparency

Observability & Predictability

A Senior Manager of Supply Chain Transformation at TC reported that users in early stages of the development were not satisfied with exclusively being provided with an answer. Rather, employees were skeptical whether the provided advice or information was correct. As a reaction, the developers adjusted the approach to also include underlying data and models to be displayed along with the answer. This includes information of which database the information is pulled from and provides for visibility on state parameters and capabilities of the system. Similarly, the AI’s purpose and intentions are transparent to the users. It is clear that the Advisor is intended to support the decision-making processes of supply chain employees.

While changes to the algorithm and upgrades to the system are communicated, there is no true “ability to anticipate mutual changes” between the human team member and the Advisor as there is currently a lack of technological capability to dynamically react to such changes. It has been reported, however, that employees have over time learnt to optimize their requests to the Advisor to enhance its output and get to the information more quickly. Consequently, with the exception of the concept of anticipation of mutual changes, the degree of observability and predictability can be considered as high.

Explainability

The Advisor’s interface is highly user-friendly and presents the information as well as the underlying data in a very comprehensive and easily usable manner. Especially the opportunity to drill down and visualizations enhance the understandability of the information presented.

According to a representative, users “want to see the evidence” and hence, the AI is providing underlying information. Hence, the Advisor application creates “one version of truth” within the organization, which also reduces the number of phone calls and meetings necessary within the organization. As can be seen, the ease of discerning how the AI system’s decisions are made is relatively high. At this point of sophistication, users are able to validate the results and recommendations by seeing the underlying data and having knowledge of the fundamental calculation basis. This clearly does not include the algorithms behind the NLP functionality of the chatbot, which already at the current level of implementations exceeds the comprehension of most supply chain managers.

Extensive training and coaching have been performed for employees using the Advisor. The employees therefore have a solid understanding of the underlying AI. The bigger problem according to company representatives currently is coping with the complexity of creating advanced models that unite structured and unstructured data analysis.

Whether this fairly high degree of ease of discerning how AI system's decisions are made and how the algorithms work can be maintained when more unsupervised learning methods are included is remains to be seen. According to a company representative, however, it is less important that the human employee understands the underlying calculations but rather that an understandable context of the recommendation (i.e. data and visualization) is given so that the human can verify for himself.

Common Ground

It is questionable to which degree a real common ground exists between the AI and human employees. While the employees certainly profit from the input of the AI, which in turn profits from the employees' training, deeming this "mutual awareness" would be a stretch. The AI receives feedback from the human employee but due to the relatively low basic nature of "thumbs up" and "thumbs down", this there is no true mutual consciousness or awareness of one another.

The AI is built around the idea of sharing a wide array of information with the supply chain professional. On the other hand, the degree to which the human team member share information with the AI is still limited at the current stage of implementation. Although, the AI facilitates the making of coherent connection for inputs from various sources, the presence of common ground should be considered relatively low.

Interoperability

Ensuring interoperability with other systems is one of the main strengths of the application. At the core of the supply chain Advisor is the ability to interact with different legacy databases, which provide the underlying information. In the future, the ability to include external data sources and more heterogeneous databases (as opposed to relatively homogeneous ERP-based data) potentially will require even further improvement of this capability.

Furthermore, making information easily accessible and understandable has been fundamental in the development of the system according to TC's management. Both the usage of natural language processing and the chatbot system as well as the dashboard style presentation ensure ease of use for the human team member. In future stages, this will be even further expanded as voice-to-text is integrated and the overall level of interoperability can be considered high for TC's Advisor solution.

Assessment

Utilizing the underlying indicators of Transparency, one can consider this capability as being developed well. While there is only limited “common ground” between the AI and the human team member, the ability to anticipate mutual changes could be expanded, and algorithms will likely be harder to understand as additional functionality is added. Most other concepts are very well developed. For example, the visibility of state parameters, user interface simplicity, ease of discerning the AI’s decisions, and interoperability are highly pronounced. Nonetheless, as the solution becomes more advanced and includes a higher degree of unstructured data and unsupervised learning, additional concepts might have to be included.

<u>Authority Balance</u>

Directability

Directability at the current stage of the implementation is established. The human is in full control of the actual decision being made and can therefore always override the AI’s suggestion. However, this approach is not adjusted based on the individual situations (e.g. automatically implementing the AI recommendation in low risk situations) and at the current point in time, all decisions are in the end taken by the human being.

A Senior Manager of Supply Chain transformation, however, indicated that even as the AI applications become more sophisticated and decisions become more “open”, it is likely that the human still has the final say. Hence, the Directability can be assessed as favoring the human but not sufficiently advanced to assess which decision maker (human or AI) is more apt in which situation.

Shared Decision Making

The AI strongly supports human decision making by providing the foundational data to take the decision in an easily interpretable manner and by showing specific suggestions to the human employee. At the current state, however, employees take all decisions and by automatically pulling data from the system, error rates are reduced and human slips can be prevented.

On the other hand, the AI’s ability to truly “understand” a problem and develop joint solutions with the human, leveraging each other’s knowledge and viewpoints is currently limited by the scope of the AI and its applications. While roles for each member of the human-machine team are clearly defined, it would be stretch to argue that both are “leveraging each other’s viewpoints”. At the current stage, according to TC representatives, the AI providing information and the human employee taking the decision using his / her contextual knowledge and intuition is the best option. In summary, the degree to which truly shared decision-making takes place is developed but could be further expanded.

Cognitive Load Balance

The AI greatly enhances the SCM employee's load balance. Human employees have to spend less time performing data acquisition tasks, modeling and monitoring for areas where action is required. Employees appreciate this feature which is confirmed by the fact that usage of the supply chain Advisor and net promoter scores are constantly increasing. Hence, the cognitive load balance for the human team member can be seen as very high.

Assessment

Authority balance is moderately developed. While the cognitive load balance makes the human team member's life significantly easier, there is no "shared" decision making in the narrow sense of the word as the human team member always takes every decision and this approach is not adjusted based on context. Rather, the AI is merely the provider of advice and information to the human employee. Nonetheless, the solution does significantly reduce the workload for TC's supply chain function.

<u>Secure Interaction</u>

Ethical

The Advisor does not raise major ethical questions. One could be whether it is the employee or the AI that should to be blamed if an error occurs. Similarly, one could debate at which point additional time for employees that has been freed up by the AI can still be used for value adding activities or when the headcount should be reduced. However, it is crucial for the buy-in of the employees that they do not feel like they are in danger of being replaced, according to representatives of TC. Discussions with employees show that this is the case and that the Advisor is considered an asset not a threat.

Reliable

TC reported a satisfactory and increasing reliability of the system. As the employees get better used to it, they ask fewer questions to the AI to arrive at the relevant information. Moreover, the AI can continually be extended and improved. The satisfaction with the reliability of the results is mainly measured through the thumbs up and thumbs down system. As the Advisor relies on previously existing rule-based recommendations and databases, reliability is no major issue and can be considered unproblematic.

Secure

The application is only available within the TC supply chain function and information is tailored according to individual job profiles and corresponding duties. All information is drawn from existing databases and systems that are exclusively accessible to TC's professionals. Select information can be assessed only with approval from the business owner. All other information is freely available to all supply chain professionals. There is also a robust process into verifying the credibility and reliability of the information that is integrated into the system. Over the past decade, TC has a very great record of accomplishment concerning both data security and privacy concerns of its employees. Hence, security of using the supply chain Advisor is assured.

Assessment

TC's supply chain Advisor provides highly secure interaction as the application poses no major ethical challenges, the information is reliable and the application is ethical.

Mutual Learning Effectiveness

Feedback Loop

TC's supply chain advisor provides a synchronized feedback loop. The human team member enters his or her requests, which are then addressed by the Advisor. Subsequently, the human team member can provide binary feedback on the usefulness and helpfulness of the information provided by giving a thumbs up or down. The feedback is then utilized by the AI as well as developers to make corresponding changes to its inner workings which iteratively improves the effectiveness of the application. There is, hence, a synchronous feedback loop which (as will be discussed later) could be extended with regard to its extent.

Mutual Capability Growth

As previously laid out, the supply chain Advisor solution is considered a major success within TC since it enables employees to broaden their view of a situation and revise solutions. As many employees now access information outside of their immediate environment, which previously only was accessible by contacting other departments or learning about other databases, better decisions are made. Usage of the tool is consistently growing and feedback, according to TC, has been very positive. This can only be expected to further increased as more functionality and more information sources are added to the tool and options to interact (i.e. voice commands) are expanded. In fact, a representative quoted the Natural Language Interface as the most important capability of the entire platform, which stresses the high degree of importance that ease of use plays in the project.

Technology Co's supply chain Advisor currently is being trained by the human team member but this is still limited as user explanations (the complexity and breadth of human feedback) are not developed to their full extent. This is predominantly due to the fact that the feedback options provided to the employee are currently binary as employees can give thumbs up and thumbs down to assess whether they are satisfied with a particular solution. Currently, the information whether the AI's recommendations implemented or not is being translated back into the algorithm. In the future, this functionality is planned, however. Additionally, the AI is currently restricted to supervised, rules-based learning. Hence, the solution is not yet leveraging all options for the AI's capability growth at the moment but will likely do so in the future.

"Learning" in the classical sense is limited for the human being. The AI does not teach the human fundamental skills in doing its job more effectively. However, the human's capabilities are significantly enhanced. As a Senior Manager of Supply Chain Transformation reports, employees are now leveraging more sources of data than previously and are consequently making better decisions. Hence, they certainly consider their professional performance enhanced. Additionally, the project management team could verify that users are increasingly getting more efficient in their usage of the AI, getting to the core information with fewer and fewer questions. In monthly meetings, the AI solution is adjusted. Hence, one can summarize that mutual capability growth between the AI and the human team member is present but despite significant upside potential remains.

Assessment

At its current stage, the mutual learning effectiveness can be assessed as only moderate to high. While the solution is useful for employees, the mutual capability growth may still be expanded. This is mainly due to the fact that the feedback and interaction between human and the machine is limited as it mostly relies on binary feedback. In future stages there is certainly a chance to grow Mutual Learning Effectiveness, for example, by using information whether a recommendation was implemented or by also utilizing more qualitative written feedback using natural language processing.

<u>Additional Capability Considerations</u>

A Senior Manager of Supply Chain Transformation also stressed the importance of considering the AI-employee teaming effort as a journey and not as a quick win. Rather, she argued, it is important that employees understand that success takes time and that errors at early stages will occur. In this way, it is possible to set realistic expectations early and to prepare for eventual setbacks. Using this long-term perspective on AI projects also allows for implementing features iteratively which in turn increases acceptance of the new process among employees as they may learn the new approach step by step.

Similarly, TC also highlights the role of a cross-functional perspective to profit from AI. Whereas previously, analyses involving input from different departments would have required significant investment in manpower and analytical capabilities, they may now be automatized and made easily accessible to supply chain professionals to better solve problems. However, employees must be open to also include information they previously did not consider and refrain from a "that's how we have always been doing it" mentality. In a related notion, it was frequently mentioned that strong relationships between the users and the technical developers are important to make the plethora of data and information actually useful in a decision-making context. It is required to involve both technical and domain expertise to strike the right balance between technological feasibility, deep supply chain knowledge, and pragmatism to enhance the quality of the AI solution. The roles of corporate culture, inclusion of employees in development of the solution, and usage of agile methods also played a crucial role for the success of the project as will be discussed in more detail in the next section.

9) Project Performance

TC reports widespread benefits of the implemented supply chain Advisor. The company measures internal approval of the tool by using daily usage and using net promoter scores (twice a year). TC has won a several awards for the supply chain Advisor.

According to TC, the supply chain Advisor's success has been strongly supported by the transparency and the corresponding changes to corporate culture. Due to the automatized processing of data across different fields, information in different departments becomes easily available. Due to the ease of the intuitive interfaces, supply chain professionals report that they are now able to take better decisions even with limited technological knowhow. Data is now available without being reviewed and processed iteratively before being presented to company leadership, which greatly accelerates processes. In turn, this also required leadership to adjust its approach to information and data it is receiving. Now, there are meetings are less focused on the presentation of data but more on the derivation of measures.

Similarly, employees have appreciated that they were heavily involved in the development of the tool, which also has contributed to the project's success. In the process, Agile teams and user centric design techniques have been utilized to accelerate the process and to always maintain a customer perspective. For example, the development team has used ideation workshops, usability games, and design thinking workshops to collect user input and make the Advisor solution available faster, more stable, and easier to work with. Hence, employees are highly content with the supply chain Advisor has they have a significant stake in its development and face an easier day-to-day work environment thanks to the tool.

But also on the business side, TC has profited significantly. For example, the consequences of inventory decisions are more understandable due to a higher degree of transparency. Inventory in general is now allocated more optimally at individual sites and total inventory could be reduced. Similarly, logistics cost was lowered as now less expedite freight costs with regard to suboptimal inventory structure due to higher supply chain visibility are incurred.

TC has also been utilizing the Advisor project for marketing and new project acquisition. In the process, the sales organization partnered with the Advisor project team to showcase the internal project to potential clients. The project is very well received and TC's supply chain professionals act as credible ambassador for the application of the company's AI capabilities across different functions and sectors.

In terms of tangible benefits, TC reports the following advantages of the solution:

Financially:

- Increase in revenue
- Reduction in inventory carrying costs
- Reduction in supplier expense
- Reduction in scrap reserves

Headcount:

- Reduction in labor cost

Additionally, a shift in headcount towards more value-added activities and a faster learning curve when transitioning between roles was observed.

The overall return on the investment of USD 5 million can therefore be calculated as follows: Cost reduction of USD 15 million plus revenue increase of USD 6 million amount to an ROI over 400%.

Additionally, TC reports intangible benefits such as quicker problem solving, more accurate decisions, introduction of "one version of truth", insights into previous problem resolutions, upskilling of supply chain personnel (facilitating data retrieval and normalization), capturing of tribal knowledge, improvement of morale / ownership / client centricity, quicker onboarding of employees, and keeping experts in the driver seat while making them feel more competent.

According to TC, the most relevant business process improvement opportunities lie in the reduction of data retrieval and analysis, the usage of insights previously not captured by humans, the digitization of problem resolution for future usage, the identification and resolution of supply chain imbalances, improved demand planning, lower inventory investment, and higher performance transparency.

Assessment

TC's Supply Chain Advisor 360 can be considered highly successful. This concerns both the financial return to TC and the satisfaction of the team, which are both high. However, there is still significant room for improvement once more unsupervised learning and additional functionality is brought in.

10) Summary and Discussion

The case of TC's introduction of the supply chain Advisor predominantly confirms the findings of the previously discussed case studies. Again, the importance of certain concepts of Transparency, such as the visibility of state parameters, interface simplicity, the ease of discerning how the AI is making decisions, and interoperability a highlighted whereas other concepts appear to be less important. Similarly, the ability to have a final say in the decision that is taken and the reduction in the employee's workload is of high importance for the Authority Balance. Security, Ethics, and Reliability play a central role for the acceptance of the solution and contribute to the capability of Secure Interaction. At the current stage of implementation, it should also be highlighted that the solution works well even if the degree of human feedback is currently binary. However, a central learning here is from the interviews is that significant upside potential exists when richer feedback and more unsupervised learning is introduced into the solution.

Despite being a frontrunner, TC's case also highlights that there remains work to be done and that there is still untapped upside potential. For example, decisions could be distributed between the human and the AI depending on decision context. Moreover, the case highlights potential additional capabilities, such as the integration of employees in the development process and the usage of iterative development in cross-functional agile teams.

4.2.4 MC&TC Assessment Rating

The authors conducted assessments for MC and TC's AI project leveraging the HMT capability assessment tool used in section 4.2. A comparison of the ratings with the previously assessed 20 cases is illustrated in Figure 18 below. In summary, TC's HMT capability indicator ratings are mostly aligned with the 20 cases and in some cases, TC's rating is superior, which can be explained by its maturity and team experience. It performs especially well within the Observability, Interoperability, and Secure Interaction capabilities. MC's AI project is at pilot stage, therefore most of HMT capabilities are still in development which is reflecting in low ratings. It particularly lags in the dimensions of Secure Interaction and Mutual Learning.

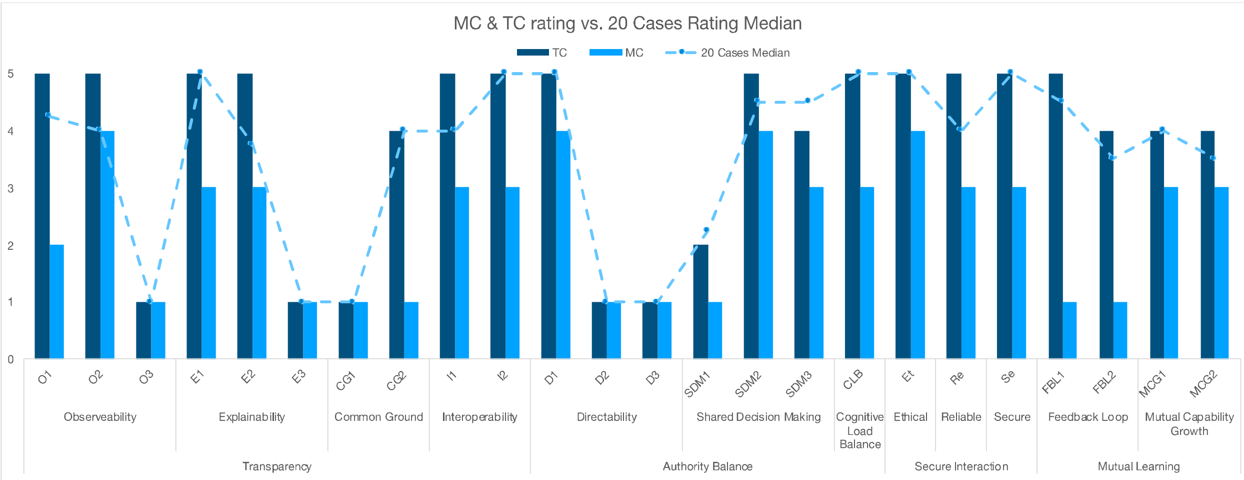


Figure 18: MC & TC Rating vs. 20 Cases Rating Median

4.3 Stage Three: Company in-depth Webinars Results

The authors conducted two webinars with TC and one webinar with MC to review the research findings and AI project assessment results of their respective AI projects. Both TC and MC confirmed that the HMT capabilities, framework and assessments concluded by the authors aligned with the internal evolution and efforts along their AI implementations.

4.4 Summary

In this chapter, the authors tested the HMT Capability conceptual framework via multiple case study research methodology by assessing 22 case studies and the in-depth semi-structured interviews conducted with two companies. The result confirms the presence of the HMT capabilities and provides insights into the similarities and differences of the HMT capability configurations among different decision context and application groups. In the next chapter, the authors will further discuss the capability framework, observations, propositions and managerial recommendations derived from the results.

CHAPTER 5: DISCUSSION

Chapter 4 presented a detailed assessment of the case studies and interviews conducted in this study. The validation of the HMT conceptual framework is established through the evaluation of the HMT capability indicator rating and spread analysis. This chapter examines the interpretation of the data analysis, derive propositions and make related managerial recommendations.

5.1 Case Study Research Observations

Observation 1: Predictive Maintenance and Quality Assurance tasks are the most prevalent AI applications in a supply chain context.

Although a broad variety of different types of applications (such as Job Scheduling, Safety and Security improvement, Production Efficiency, etc.) were uncovered during the research, it became evident that Predictive Maintenance and Quality Assurance applications are clearly the most prevalent. While the number of cases studied is small, the research on scientific databases as well as on the internet clearly indicate that dispersion of these two types of AI applications is well advanced.

Especially with regard to Predictive Maintenance, one could observe that across industries that revolve around the manufacturing or operation of physical goods, one could see that a significant number of examples exist, especially within the industrial goods and automotive industries. The dispersion has in part been supported by the emergence of software providers, such as Senseye, which offer off-the-shelf solutions that can be adjusted to individual organizations' settings and machinery set up at a reduced cost. It could also be observed that throughout many projects, firms leveraged existing AI toolboxes and modules from large technology firms. Providers of enterprise software and infrastructure have integrated AI applications into their cloud offerings and provide clients with a standardized toolset that can be tailored to their individual needs. Integrating such modular components into one's individual AI project solution has the significant advantages of providing cost savings and enabling faster implementation of the project.

Similarly, Quality Assurance solutions leverage advances in related areas, such as image recognition and leverages them in a supply chain context. What also contributes to the popularity of these two particular types of applications is that they have the potential to lead to significant savings for the corporations (as they prevent system downtime and product recalls, respectively) without being viewed as a threat to employees' jobs.

While the number of case studies in the present research is too small to be statistically significant, there is a clear indication that Predictive Maintenance and product-related Quality Assurance applications are currently the most prevalent ones, potentially also driven by the availability of off-the-shelf-solutions.

Observation 2: Companies leverage AI applications in a supply chain context to both increase quality of operations and to reduce cost

In public debate, fear of job loss due to tasks being performed by artificial intelligence is frequently highlighted. Our research certainly confirms that firms are also using AI to decrease cost within this goal, reduction within the number of jobs is not very pronounced. Rather, by teaming with the employee, AI applications allow for improving processes which simultaneously reduce cost while also increasing quality. For example, in predictive maintenance, the AI enables the human to perform his / her task more effectively which creates millions in savings due to reduced downtime without endangering even a single job. Similarly, by identifying microcracks in metal-sheets the AI helps the human service engineer to perform his job better and to prevent potential financial damages due to product recalls.

In fact, out of the 22 projects researched, none had a primary focus of cost reductions through headcount reductions. In each case study, the overall process quality was enhanced, which in many cases also led to cost savings but without leading to a decrease in the number of jobs. Rather, the human employee is an integral member of the team and necessary to effectively put the AI's power to action. As the value-creating levers of the AI are so significant because they can be applied at scale and at minimal variable cost, there is no need to additionally remove human labor which is facilitating the human-machine teaming process. However, companies monitor the number of labor hours that is saved by the AI application and keep track of the corresponding financial value. In many cases, increasing the latter value is one of the targets of the AI project. Yet, at the current stage, time saved for employees is being put to use at more value-adding tasks rather than eliminating jobs altogether.

At the same time the quality of operations and final products is enhanced by the human-machine teaming in ways that the human employee alone would be unable to do. Through the combination of computing power and ever-improving algorithms with human intuition, experience and ability to “sanity-check”, operations can be significantly improved. For example, in predictive maintenance applications the AI supports the human service engineer in performing millions of calculations to identify potential future breakdowns, which would be impossible for either party to successfully perform alone. Similarly, in demand planning, algorithms can calculate millions of scenarios and present recommendations to humans in a rapid manner.

Future research could first validate observation 2 and further focus on how and why human-machine teaming efforts in AI-driven supply chains successfully manage to increase both process quality and reduce cost. Specifically, it could be worthwhile to investigate which role the application at scale, the AI's minimal variable cost as well as the human team member's indispensability play.

5.2 HMT Capability Framework Propositions

Based on the results of the quantitative assessment of the HMT framework and the in-depth interview a number of propositions can be made, which later on are complemented by different Managerial Implications that can be deducted from them. While these propositions could be further extended, the authors have decided to limit themselves on the most important ones.

Even though the number of observations in the sample limits the degree to which the aggregate scores of different case studies are representative, the scoring as described in the previous section enables for prioritization of the different HMT capabilities. Seven indicator concepts ranging from the three capabilities were especially pronounced across the different studies. These capability indicator concepts have a strong prevalence among all the successful case studies researched and appear therefore to be fundamental to AI-driven supply chain applications. The authors therefore propose:

> Proposition 1a: Concerning Transparency, the fundamental HMT concepts for AI-driven supply chain applications are User Interface Simplicity and Understandability of Information presented (E1) as well as the Ability of Making Coherent Connections for Inputs from various Sources (I2).

> Proposition 1b: Concerning Authority Balance, the fundamental HMT concepts for AI-driven supply chain applications are Ability to Control and Override Decisions (D1), Ability to assist Human to eliminate Oversight Slips and Errors (SDM2) as well as Ability to assure a Manageable Human Workload by balancing Workload Distribution between Human and Machine (CLB).

> Proposition 1c: Concerning Secure Interaction, the fundamental HMT concepts for AI-driven supply chain applications are Accordance to Acceptable Social Conduct Principles (Et) and Validated Method to protect Interaction Processes and prevent Unintended Access (Se).

Among the different concepts that HMT capabilities are based on, some are more pronounced than others in successful AI project implementations. Within the capability of

Transparency, User Interface Simplicity and Understandability of Information presented (E1) and the Ability of Making Coherent Connections for Inputs from various Sources (I2) were the most strongly developed concepts.

It should be noted, however, that also User's Visibility of AI System's Intentions (O2), Ease of Discerning how AI System's Decisions are made (E2), and Ability of making coherent Connections for Inputs from various Sources (I1) were quite strongly developed and may also have a positive influence, while Ability to anticipate of Mutual Changes (O3) and Ease of Understanding of Algorithms (E3) played a smaller role.

Concerning Authority Balance, Ability to assist Human to eliminate Oversight Slips and Errors (SDM2), which is part of the Shared Decision Making Indicator, showed the highest importance along with Ability to Control and Override Decisions (D1), which is part of the Directability concept and the Ability to assure a manageable Human Workload by balancing Workload distribution between Human and Machine (CLB). This combination of factors highlights the power of leaving final decisions with the human being while still bringing in the AI's viewpoint and ability to correct human errors to lower the human employee's workload.

Concerning Secure Interaction all three concepts proved to be very developed with Accordance to Acceptable Social Conduct Principles (Et) and Validated Method to protect Interaction Processes and prevent Unintended Access (Se) being especially developed. It is likely that these concepts are considered prerequisites in AI teaming efforts as will be elaborated upon later.

It is surprising that among the concepts of Mutual Learning Effectiveness each concept missed the highly developed ranking despite the presumed importance of this indicator. Only Ease of Incorporating User Explanations into Learning Algorithms (MCG2) reached a high rating. One could in this case hypothesize that in many of the applications at the current state, the degree to which feedback is provided to the AI is still underdeveloped and hence even in comparably successful projects, Mutual Learning is still not being realized to its full potential.

Another interesting aspect is that several of four of the seven strongly developed concept fell within the realms of Authority Balance and two within the field of Secure Interaction. However, these findings should be further explored using a larger sample size in future research efforts.

From the overall assessment, no evidence for the need for human and machine team members to anticipate mutual changes, and for the AI to be capable to redirect and re-allocate tasks can be derived. The authors therefore propose:

Proposition 2: Ability to anticipate mutual Changes (O3) and the Ability to dynamically redirect and reallocate Tasks between the Human Team Member and the AI (D3) are features that are not critical for AI project success.

Quantitative analysis of the different case studies showed that the Ability to anticipate mutual Changes (O3) and the Ability to dynamically redirect and reallocate Tasks between the Human Team member and the AI (D3) did not significantly impact the successful outcome of the case studies. However, the authors still maintain that these concepts are relevant to further advance the success of human-machine teaming projects in AI driven supply chains. Yet O3 and D3 likely only become truly relevant in projects that are already very mature and have a high level of sophistication.

While the quantitative analysis presented has a number of observations that is too low to be statistically significant, there is indication that projects may be successful even without these two concepts present. Intuitively, these conclusions make sense as for example in static environments it is not necessary to dynamically change the way in which tasks are being redirected and reallocated between the human and the AI. Rather, it may in many cases be more efficient to determine a specific distribution of tasks between both team members and then optimize performance. This is especially true in a rigid context, when it is relatively clear which tasks the AI's computing power and which tasks the human's intuition is more apt at performing.

In more advanced applications in highly dynamic settings (heterogeneous tasks are performed in short periods of time) this may no longer hold true. In this case it may be required to be able to dynamically reallocate tasks and to be able for both team members to anticipate mutual changes. These capabilities ensure that depending on the nature of the task the right team member addresses it and that reactions of individual team members are taken into account quickly by the other team member. However, this proposition needs to be further addressed and quantified by researchers before being deemed correct.

According to the decision context group analysis, the higher risks and more open decision context, the higher observability in system state and intentions, mutual awareness and information sharing, teaming level in joint solution development, and level of synchronized feedback loop are required. Another observation is that higher risk decision context groups, such as group 2 and 4, require higher presence of teaming capabilities across the thematic range, compared to group 1 and 3. Based on the foregoing, the authors propose:

Proposition 3: As AI projects evolve from low-risk, closed design to high-risk, open design context, a higher level of Observability, Common Ground, Shared Decision Making and a synchronized Feedback Loop are required.

Depending on the individual decision context, different capability configurations are required for successful human-machine teaming. The most polarizing combination of decision contexts is between low-risk, closed design and high-risk, open design context. Hence, it is quite intuitive that also the capability configurations between the scenarios are required to change accordingly. While overall successful configurations were relatively rigid, one could observe differences in importance regarding individual capabilities and indicators.

The necessity of differing configurations depending on decision contexts pertains not just to different projects. Rather, it also implies that companies must reconsider their capability configurations as projects mature and move for example, from Group 1 to Group 4 as time progresses. Hence, firms should carefully monitor their human-machine teaming projects and regularly assess whether the decision context and AI design still fit the capability configuration.

Specifically, the authors found indications that higher levels of risk and a more open AI design require higher levels of Observability, Common Ground, Shared Decision Making and a synchronized Feedback Loop, which is intuitive. As the degree of risk rises and AI design becomes more open, it is important to have additional insight into Observability concepts, such as state parameters, in order to be able to monitor potential risks and erratic behavior. Similarly, with higher risk and open design arises additional need for Common Ground between the human and the machine, such as signaled by mutual information sharing. Again, this is reasonable as higher risk requires that both members of the team exchange information in order to hedge against such risks. In this context, successful project performance also necessitates that decision-making is shared to a higher degree for example by leveraging the human and the AI's unique capabilities more extensively towards a shared solution.

Finally, synchronized feedback loops are needed more in decision contexts marked by risk and open AI design. The underlying reason for this is potentially that as unsupervised learning is included and risk-levels rise, it is crucial to have more frequent iterations in which both parties give feedback to one another to more quickly arrive at the correct solution. Yet, to substantiate this proposition it is necessary to validate it with a higher number of firms and projects researched. In summary, proposition 1 to 4 can be summarized in Figure 19.

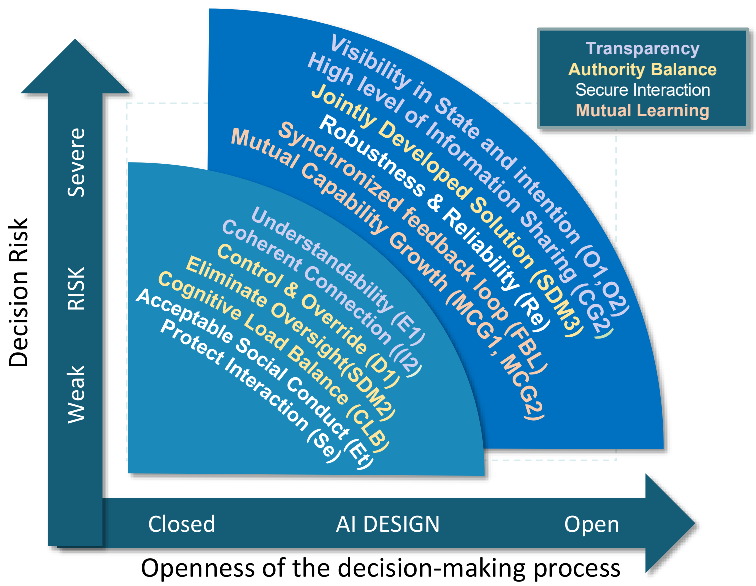


Figure 19: HMT Capability Framework Key Findings

As part of the case study analyses as well as particularly the interviews conducted, the authors observed that human-machine teaming efforts in AI-driven supply chains over the course of their lifetime change their position within the decision-context matrix. Consequently, different capabilities are required to be successful within each quadrant, which leads to the following proposition:

> Proposition 4: As AI projects evolve, they change their position within the decision-context framework and as a result, require different capabilities as learning takes place.

Within the different projects researched, the authors could observe that the position of human-machine teaming efforts in the decision context matrix are not static but rather move as over time and as learning takes place. This can occur both passively but also proactively through management decisions. As a consequence, different capabilities are required to navigate these changes successfully. For example, as risk and open design of AI increases, the required degree of observability rises as well. Hence, the company has to react accordingly to strengthen this capability.

Companies taking part in in-depth interviews reported that their AI projects were not built to instantly achieve a dedicated target state. Rather, they considered AI projects as a journey or a constantly moving entity, which continually added functionality or better adapted to its environment. Along with the addition of new functions, firms indicated that the organizational capabilities required in the project changed accordingly. This was particularly true for the change from supervised towards more unsupervised learning methods (hence moving from closed to more open AI design) and use-cases in higher risk situations. Companies also reported that they were aware that these shifts in decision context also required the potential development of new capabilities.

On a related notion, one could also hypothesize that firms also have the option to voluntarily change their position within the framework matrix. For example, when a firm tried out a new feature it was temporarily moving into a higher risk quadrant of the decision context framework and accordingly had to increase the Observability of the AI to better assess the consequences while the AI was able to learn. As the learning had enabled the AI to become more reliable and stable at the specific task, the risk level decreased, and a lower degree of monitoring and Observability capability was required. However, for the above proposition to be broadly accepted, it is necessary to further explore it using a higher number of observations.

Besides these clear capability-based propositions, the authors also observed the important role that select managerial best practices from the fields of project management and finance played. The authors therefore propose:

> Proposition 5: Presenting a business case, executive sponsorship and agile project management are precondition to successful AI project design and implementation

In close connection to the capabilities outlined the authors also observed during focus interviews that successful human-machine teaming applications in AI-driven supply chains also shared that they early on outlined a business case, obtained executive sponsorship and used agile project management techniques. In this context, it is important to mention that there is heterogeneity into the definition of a business case. While in some companies, a specific ROI is expected, others target broader KPIs or even learning related benefits. Still, company leadership usually expects to achieve economic benefits from the initiative. Potentially, there may be interactions between these preconditions and individual capabilities. For example, a business case and executive sponsorship might facilitate high scores in Transparency, for example through development of better “User Interface Simplicity and Understandability of Information Presented” or the “Ability to Making Coherent Connections for Inputs from Various Sources” due to more funds being available. Similarly, agile project management approaches may facilitate Mutual Learning, for example by enabling better synchronized feedback loops and higher “ease of “Incorporating User Explanations into Algorithms”. However, more research is required to better investigate the relationships

Based on the analysis of application groups, the HMT capability configurations are more similar than different across three types of AI supply chain applications (demand planning, predictive maintenance, and quality assurance). It is common that a high level of Explainability, Interoperability, Shared Decision Making are present. However, it shows that Quality Assurance application requires a higher level of shared decision making and mutual learning interactions, which are correlated to the characteristics of the decision context group these applications fall in. More homogeneity can be observed with regard to the application type. Therefore, the authors propose:

> Proposition 6: Human-machine teaming capability configurations are more strongly driven by the difference in decision context rather by difference in application type.

In addition to testing how different capability configurations and their success are driven by individual different decision context, the authors also investigated how capability configurations are influenced by AI application type. The results show that application type influenced the capability configurations and the success of human-machine teaming efforts less than the decision context. This result generally underscores the validity of the framework as it shows that capability configurations and their success correlate with the level of risk and design of the artificial intelligence solution.

One potential explanation why decision context is a better indicator for capability configuration than AI application type is that different AI applications may be utilized in differing situations and for different business problems which represent different decision context. For example, a predictive maintenance application could be applied to a high risk or a low risk decision context depending on the impact and scale of the underlying business context. However, in each case a different capability configuration would need to be applied to have success. This is only captured by the present framework. To validate this finding through a higher number of observations could be the subject of future research initiatives.

5.3 Managerial Recommendations

On the basis of the propositions laid out in the previous section, several managerial recommendations can be deducted. While they are by no means exhaustive and can be a worthwhile exercise for managers to consider what the propositions mean in the context of their organizations, the managerial implications outlined below may still provide helpful guidelines. A summary of the 8 managerial recommendations is illustrated in Figure 20.

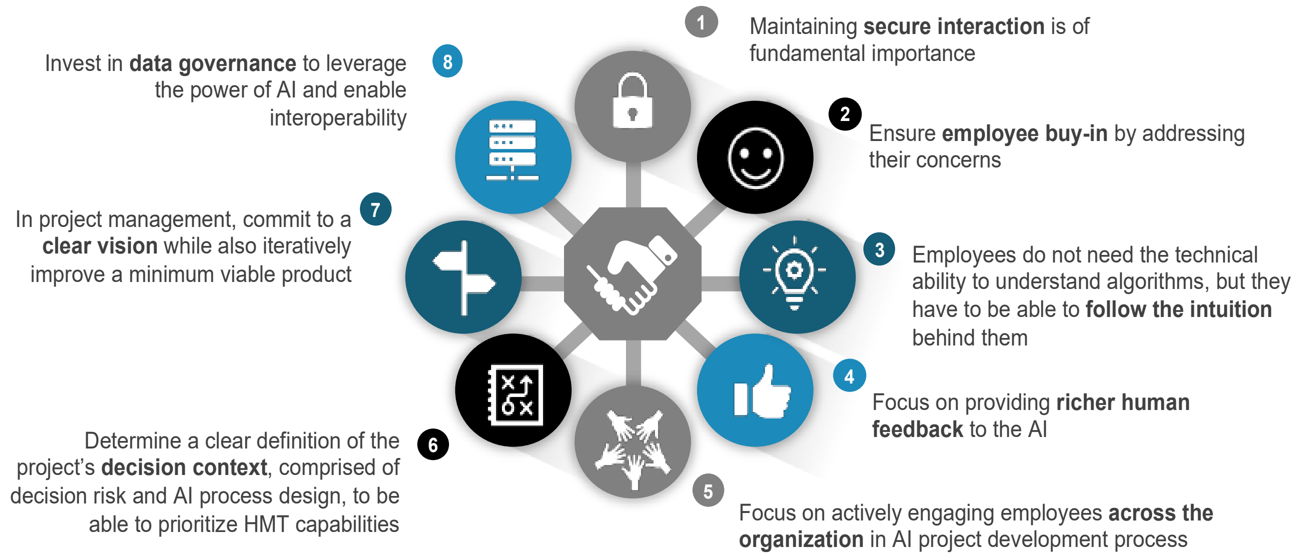


Figure 20: Managerial Recommendation Summary

Managerial Recommendation 1: Maintaining secure interaction is of fundamental importance

As discussed, several concepts and indicators are important to ensure project success. The degree to which they function, however, is differentiated. The capability of Secure Interaction follows a different set of rules. Both from the case studies and the in-depth analysis of TC and MC, the authors could see that considerations concerning Ethics, Security, and Reliability showed limited variability and were consistently highly developed. Therefore, the authors hypothesize that Secure Interaction as well as its sub-concepts of Ethics, Security, and Reliability can be considered as preconditions for AI project success. While these concepts do not marginally increase the success of the initiative, their absence fundamentally endangers it.

Employees are not engaging increasingly successfully as the degree of Secure Interaction rises but rather, they require this as a prerequisite in order to confidently engage in the human machine-teaming effort. This intuition is supported both by our quantitative analysis of the case studies, but it also was a recurring theme in the interviews conducted for this research. Firms should therefore ensure that the elements of Secure Interaction (Ethics, Security, Reliability) are present in order to fully profit from the human-machine teaming effort. In interviews and case studies, companies researched reported that fulfilling these requirements, especially with regard to security and reliability, were not problematic. The ethically most challenging aspects that have been observed repeatedly are whether the AI is on track to replace human team members, questions of accountability, and potential surveillance of the employee's actions. Yet, companies researched managed to keep these concerns in check. Interview partners confirmed that secure interaction is of high importance and doubts in it will cause employee support quickly, which is why firms should invest proactively into preventing such concerns.

Managerial Recommendation 2: Ensure employee buy-in by addressing their concerns

In order to secure buy-in from employees, it is crucial that they do not perceive the human-machine teaming effort as a threat. Rather, employees should see the support of artificial intelligence as a tool that empowers them in performing their work and in progressing in their career. However, similar to the general sentiment across the population also employees that work together with an AI are not free from concerns about potential negative consequences that working with AI may have on their career as has been confirmed in interviews. Particularly, this concerns the fear among employees that the AI will take their job or that they will be blamed for mistakes that the AI makes.

Our research confirms that successful firms proactively address this fear both through considerate design choices and communications strategy. A manager at a large technology company told us that it is crucial that employees do not see the AI as a threat. This sentiment is also shared by the company's CEO who set out for AI to represent “augmented intelligence”, so that the AI should complement and enhance but not replace the human team member’s intelligence. This is further reinforced by human team members remaining in control for the final decision. While the authors agree that it may make sense to later on delegate additional decision making power to the AI, it is likely the better choice to first give employees the opportunity to get accustomed to working alongside an AI and to trust it before later delegating decision making power to it. In this way, the authors have learned, the risk of employees refusing to take part in or even sabotaging the AI implementation effort is significantly produced. For example, the authors were able to observe that decisively building the AI tool around the needs of the human team member successfully builds confidence in the AI facilitating and empowering the employees. As a result, one can observe a rise in the employees’ confidence and openness towards delegating more tasks and decision-making power to the AI. Users, for example, told us that they were not concerned about the AI taking over individual tasks as long as the human team member’s individual skills could not be reciprocated by the AI. Moreover, the case studies even suggest that users have started proactively working on their skillset and maintaining their edge over the machines.

Another way in which the employee buy-in may be ensured by management is to focus the human-machine teaming effort not just on cost savings but also quality improvements. As has been discussed, firms who successfully implemented AI projects predominantly did not set them up simply as means to cut cost but rather to also reach other objectives, such as the improvement of product quality, process quality, process stability, or growth.

These goals of the initiatives are also highlighted proactively among successful firms. Finally, firms are communicating that tasks being conducted by the AI free up time for employees to take on more meaningful value-adding work. In fact, in the cases researched, the authors did not find evidence of layoffs due to AI projects and as the sophistication of AI projects is still in its early stages, the danger of substantial job losses in the mid-term seems limited. Hence, by implementing building AI solutions around the enhancement of human capabilities and by actively communicating this in the organization, companies can enhance employee buy-in.

Managerial Recommendation 3: Employees do not need the technical ability to understand algorithms but they have to be able to follow the intuition behind them

In general, it was found that human-machine teaming efforts frequently do not perform well with regard to the ease of understanding algorithms. This is especially the case as applications become more advanced and unsupervised learning algorithms are utilized. However, the research suggests that this capability does not necessarily have to be present but that it is of higher importance that employees are able to discern the AI's suggestions and decisions. While some interviewees mentioned that they sometimes tried to validate the AI's calculations manually in the early stages of the project introduction, they reported also that this was done mainly to provide feedback to engineers.

Successful human-machine teaming, however, manages to ensure that users still make sense of the AI's output, i.e. they can still provide an explanation of why the AI responds the way it does. This is achieved by creating a user-friendly interface, frequently involving visualizations, insight into state parameters, and explanations of the underlying functioning of algorithms. Especially as employees need to base their judgement on AI and are dependent on its reliability, is crucial for them to understand the intuition that the machine applies in order to gain trust.

Managers have expressed concern about AI becoming a black box and this is in part shared by employees. Currently, this is still manageable as supervised learning approaches and heterogeneity of data sources is still processable for many employees. However, as AI applications work increasingly independently, draw conclusions from unlabeled data, and connect a plethora of different data sources, this becomes more challenging and companies will have to look for new ways to help employees cross this chasm of comprehension. At the current stage, companies should strongly consider investing proactively into enabling employees to discern the algorithms decisions as our research shows that this is an important element to increase acceptance of AI initiatives and enhance employees' interpretation of results.

Managerial Recommendation 4: Focus on providing richer human feedback to the AI.

As has been discussed, mutual learning effectiveness is a major driver of human-machine teaming success. Only by the provision of rich, reciprocal feedback in frequently repeated feedback cycles can the AI solution continually improve and reach its intended effectiveness. However, the case studies researched have shown that the breadth and depth of human feedback is still very limited and that enriching the feedback could potentially accelerate the evolution of the human-machine effort.

The lack of rich feedback varies between different case studies. In some cases, only a “thumbs up” or “thumbs down” answer is used to assess the AI’s answers effectiveness while in others, the decision whether the AI’s suggestion is implemented is fed back to the system. Among the cases researched the most advanced examples included a questionnaire to be filled out by the human team member. While all of these approaches certainly improve the algorithm over time, especially “binary” feedback is not sufficient to quickly enhance artificial intelligence. The underlying reason is that binary feedback does not capture proper explanations why the AI’s suggestion or action was not helpful or effective. To incorporate such information into the feedback, firms have to think how to first capture it and then encode it in a way to make it processable for algorithms.

While the incorporation of human feedback is certainly challenging, recent advancements in related fields provide for the opportunity to perform it more successfully. Firms should, for example, consider using natural language processing technology to analyze written explanations and assessments of the artificial intelligence’s decision. Following this approach, the human’s observations and intuition can be translated into machine-processable feedback without significant effort required from the employee. Due to increasing popularity and sophistication of speech-to-text, this could even be soon extended to employees giving feedback verbally. But even if NLP and speech-to-text features are not available yet at companies, they should still consider incorporating more extensive feedback mechanisms to tie human knowhow back into the learning process. Not only will this help the AI improve, it may also make employees and their evaluations feel more appreciated. Similarly, it is crucial for better learning by the AI that it receives information on whether the employee actually implemented the AI’s recommendation or not. In this way, the AI can better assess the effectiveness of its own solutions and adjust accordingly in the future.

On the other hand, the authors observed that feedback from the AI towards the employees is important but was less of a pain point. Almost all of the AI projects researched conveyed the information and feedback provided by the AI in an easily processable manner and with sufficient depth. While in some cases the provision of feedback from the AI could still be expanded, it appears to be better developed than the provision of feedback from the human to the machine. Hence, managers should increasingly focus on the latter to enhance the effectiveness of the AI project.

Managerial Recommendation 5: Focus on actively engaging employees across the organization in AI project development process (e.g. using cross-functional teams, user-centric design, and agile methods)

As has been discussed, achieving the buy-in from employees across the organization is vital for the successful introduction of AI projects. One major driver of this beyond the lack of fear of losing one's job, is that employees feel in control and also responsible for the human machine teaming effort. In order to achieve this, successful firms show a number of communalities in their approach of engaging employees, such as the usage of cross-functional teams, applying user-centric design as well as agile methods.

Cross-functional teams are well established to ensure that different departments in the organization are engaged in the project development project to facilitate a holistic approach to the AI solution. For example, teams have reported bringing together data science teams, IT departments but also subject matter experts from the field of supply chain management. Similarly, it has also proven to be successful to have a small core project team with volunteers from different departments who bring in different perspectives and champion the effort in their business units.

Another communality appears to be the application of customer-centric design methodologies in the creation of the AI solution. It can be observed that in the development process, successful firms use customer journeys and design thinking methods, which again enhances the user experience and subsequently the acceptance of the human machine teaming effort.

Agile project approaches, such as scrum, enable organizations to dispatch new iterations of product in small batches and to collect feedback on them, which in turn is then applied to the next iteration. As agile approaches are built upon the provision of feedback by employees, they are another way in which the implementing company can actively engage employees across the organization in the AI project and enhance employee acceptance.

Managerial Recommendation 6: Determine a clear definition of the project's decision context, comprised of decision risk and AI process design, to be able to prioritize HMT capabilities.

Managers of AI projects should proactively use the proposed framework in order to consider which capabilities need to be present or developed to enable human-machine teaming project success. As resources are frequently limited, not all desired capabilities can be built but using the framework, it is possible to identify which competencies should be prioritized.

As a first step, managers can determine the risk level of the decision context in which the human-machine teaming effort is set in. To test this, one can refer specifically to the indicators that determine a higher or lower risk level. Similarly, the level to which the AI's design is open or closed can be estimated using different concepts, such as the presence of unsupervised learning. Having then identified one's position within the framework's matrix, managers can determine which capabilities are required.

A subsequent gap analysis can be utilized to establish which capabilities are already present in the organization and which ones still need to be built in order to successfully implement the AI solution. Again, as the framework allows for drilling down from capabilities to individual indicators and concepts, it provides practical advice for managers to know which levers to focus on. As the present analysis provides details an indication of which capabilities are more important than others, it also allows for easy prioritization. To facilitate this, managers can also use the framework for justification of their investment decisions in project meanings to support the credibility of their suggestions.

Managerial Recommendation 7: In project management, commit to a clear vision while also iteratively improve a minimum viable product.

Successful companies portray ambidexterity in their project management of human-machine teaming in AI-driven supply chains by simultaneously committing to a clear vision for the project and by using iterative approaches in the development of minimum viable projects (MVP).

Using this combination of top down and iterative bottom up approaches enables the project team to be committed to the long-term vision of the AI solution while allowing for incrementally improving and tailoring product while utilizing employee feedback. A product roadmap can facilitate that functionality is being added over time without exhausting the development team's capacity and users' ability to learn. As has been discussed previously, it is of utmost importance to have a dedicated core project team of members who serve as champions for the project and extend around different departments. Similarly, successful projects also utilize AI modules provided by large technology firms, enabling both for cost savings as well as flexibility in tailoring a custom-solution.

In the early stages it is crucial to gain buy-in from executive leadership who sponsor the project and also defend it during times when progress is slower than expected. To achieve executive sponsorship, it is important to show proof early on with a pilot or minimum viable product that the project has a positive return on investment and that it fits the strategic agenda of the corporation. Subsequently, promoting the benefits of the MVP to other departments facilitates adoption across the organization.

Managerial Recommendation 8: Invest in data governance to leverage the power of AI and enable interoperability.

The importance of data governance has been highlighted throughout most of the interviews conducted for this research paper. In fact, "getting the data right" is considered a prerequisite to successfully implementing the human-machine teaming effort as data that is not clean and structured in a coherent manner will lead to bugs and errors during the analysis phase.

The need for good data governance becomes even more pronounced as the number of different database and systems utilized increases. Managers should dedicate sufficient resources on the establishment of clear data standards and governance guidelines as this will significantly reduce the amount of time and investment required at later stages of the human-machine teaming project, such as data analysis. Potential goals of data governance could include accuracy, accessibility, completeness, consistency, and timeliness of the data managed.

As a result, interoperability between different data sources utilized should be ensured. Only if a clear matching mechanism between databases, unique nomenclature, and coherent reading and writing rights must be ensured to prevent analytical errors and to maintain smooth interaction. While ensuring interoperability is less appealing work, it is crucial for AI project success. Managers should therefore be careful to not focus resources exclusively on the development of algorithms but also to ensure that these efforts are built upon stable data governance and interoperability between different databases.

5.4 Summary

In this chapter, the authors provided in-depth interpretations of the analysis results and offered managerial recommendations, which company leadership and supply chain professionals can leverage for designing and implementation of AI projects. In the next chapter, the authors will propose an assessment instrument which can be used for future research purposes.

CHAPTER 6: Instrument Development

6.1 Objective

In the previous chapters, the authors assessed the HMT capability indicators through multiple case studies and semi-structured interviews. The result of the assessment provided basis for development of an assessment tool for further validation of the antecedent and postcedent relationships of the HMT capabilities. The instrument assesses the decision context, HMT capabilities and project performance. Using this instrument, one can develop a benchmark baseline for AI projects from different decision context groups. The benchmark scores can then be used for companies to compare their HMT capability effectiveness against the benchmark.

6.2 Questionnaire Structure

6.2.1 Target Population

The target profiles of the population for taking this survey are AI project process owner, project manager, system architect and users. For example, for a demand planning AI project, the ideal respondents for the survey would be the planning director, project manager, data scientist, material planners and buyers.

6.2.2 Structure and Questions

The authors developed a set of questions around the HMT capability indicators using the concepts developed and validated in the previous chapters. The full questionnaire is included in Appendix A. The following is a brief summary of the different sections of the questionnaire, weightage and result calculation.

Section 1 – Introduction

This section provides explanation of the objective of the instrument and how to use it.

Section 2 – General information

This section collects general demographic data such as respondent's name, company name, role in the project, AI project under assessment and implementation phase, etc.

Section 3 – Decision Context Assessment

This section assesses the decision context of the AI project based on “AI design openness” and “Decision Riskiness.” Definitions and instructions on how to assess are included.

Section 4 – HMT Capability Assessment

This section is the self-reporting section where respondent rates the AI project under assessment. It begins with explanations on each of the HMT capabilities, and then asks respondent to rate the level of presence of each of the indicators on a scale of 1 to 5, where 1 means “weak” and 5 means “strong.”

Section 5 – Performance

This section collects quantitative data on AI project performance. It requires respondents to provide inputs on the metric(s) he/she uses for AI performance measurement and then rates the performance based on the level of improvement.

6.2.3 Weightage

Based on analysis explained in chapter 4, each of the indicators will be assigned the weightage as in Table 13:

Table 13: Assessment Instrument Indicator Weighting

HMT Capability	Transparency										Authority Balance							Secure Interaction			Mutual Learning			
Indicator	Observability			Explainability			Common Ground		Interoperability		Directability			Shared Decision Making				Ethical	Reliable	Secure	Feedback loop		Mutual Capability Growth	
Indicator Code	O1	O2	O3	E1	E2	E3	CG1	CG2	I1	I2	D1	D2	D3	SDM1	SDM2	SDM3	CLB	Et	Re	Se	FBL1	FBL2	MCG1	MCG2
Weighting	45%	50%	5%	60%	30%	10%	10%	90%	40%	60%	85%	10%	5%	10%	35%	20%	35%	100%	100%	100%	50%	50%	50%	50%

6.2.4 Survey Result

After receiving the responses from companies, the instrument will calculate the overall score by multiplying each indicator’s weight and self-reported rating. The scores then can be consolidated at the indicator and HMT capability level for further statistical analysis.

6.3 Limitations of the instrument

Limitations exist for this proposed instrument. The first limitation is subjectivity in the assessment of the HMT capabilities due to the nature of self-reporting survey. However, this limitation could be overcome by incorporating statistical analysis to test reliability and validity of the responses. The second limitation is the comprehensiveness of the questions as they are developed based on literature review. It would be advisable to further test the understandability of the questions by conducting pilot surveys with a small group of companies.

CHAPTER 7: CONCLUSION

This Capstone project contributes to addressing the academic research gaps in human-machine teaming capabilities in AI driven supply chain by expanding the HMT conceptual framework and validating it with empirical AI projects. This chapter concludes the overall findings, reviews the research questions addressed and discusses the limitations of the research and the potential future work.

7.1 Research Questions Addressed & Summary of Findings

This capstone project successfully addressed the research questions set forth in Chapter 1. It discussed the first research question by expanding HMT Capabilities dimensions. They now can be used to better guide business professionals in the successful implementation of AI projects. The conceptual HMT framework for the capstone was developed based on the framework proposed by Saenz et al. (2020) and expanded by the authors through an extensive literature review. The HMT framework hypothesizes that the HMT capabilities, namely Transparency, Authority Balance and Secure Interaction, facilitate the mutual learning capability between human and machine and therefore positively influenced the team relationship and consequently the positive outcome of the project performance. It is now more easily possible to identify the underlying concepts and to pursue a more detailed academic discussion of the relevance of different capabilities and related concepts. Moreover, a fundamental effort to empirically test the conceptual HMT capability framework has been successfully undertaken.

Through the literature review, the authors identified the measurable indicators which can be used to evaluate the level of presence of the HMT capabilities. Leveraging a multiple case study methodology, the authors assessed 22 case studies and conducted in-depth interviews with two companies. The presence of the HMT capabilities was validated, and the underlying indicators' concepts were fine-tuned. While the number of observations was relatively small, the qualitative research approach enabled the authors to identify patterns in real-world applications that will be highly useful for further quantitative analysis in future research efforts.

Additionally, insights from the results were derived for organizations and supply chain leaders to better handle AI implementation. The authors identified the foundational HMT capability indicator concepts that contribute to AI project success and the different HMT capability configurations for AI projects in different decision context groups based on the decision risks and AI designs. The findings also informed managerial recommendations, which companies' leaderships and supply chain professionals can use to develop AI project design and implementation plans. This accomplishment is especially relevant at a close relationship between the academic soundness of the research and its applicability to real world business problems.

Finally, the authors were able to develop the first HMT capability assessment tool to further validate the conceptual framework. An assessment instrument was developed based on the results of the multiple case studies. This assessment instrument can be applied for further research and validation of the structural relationship of the HMT capability framework and development of benchmark baseline. While future research efforts and business managers may refine it and tailor it to their needs, its sound academic foundation and easy applicability ensure that it is a viable tool.

7.2 Research Contributions

The present research makes both academic and practical contributions to the literature. It presents an in-depth literature review covering the field of artificial intelligence, highlighting not only AI definitions and origins but also the most prevalent applications and challenges. Similarly, the literature on human-machine teaming capabilities has been reviewed and investigated, tracing down underlying indicators and concepts. Additionally, the present paper performed an in-depth review of the HMT framework, adjusted it where appropriate and added additional level of detail.

Additionally, an analysis of more than twenty real-world examples of human-machine teaming projects in AI-driven supply chains complemented with in-depth interviews and review of internal data provided the opportunity to validate the HMT framework empirically. Furthermore, the paper illustrates which capabilities are required to succeed in different decision contexts and different dynamics between quadrants of the framework could be revealed. In particular, the influence of riskiness and artificial intelligence design on the effectiveness of different HMT capabilities was analyzed and corresponding propositions were put forward.

Based on these academic insights, eight insightful managerial implications were presented and discussed, providing insight into how to assess and build the right capability configurations, how to monitor them over time, as well as how to successfully manage HMT projects. Finally, the authors have provided a research instrument to further validate the research findings using a larger number of observations. Finally, this paper also provides an overview of potential limitations of the research effort and points at adjacent areas future research could focus on. Hence, the present paper utilized sound academic practice to advance the field of human machine teaming, while at the same time making these insights available to practitioners in the field.

7.3 Limitations

The present paper was created diligently over the course of several months and iteratively improved through critiqued by fellow academics. Nonetheless, the study has limitations.

This paper’s focus is qualitative discussion of human-machine teaming capabilities. While the authors have tried to identify a representative cross-section of artificial intelligence projects, the number of projects analyzed does not qualify for statistical relevance but this was also not the main priority. In the process, several different keywords revolving around artificial intelligence, supply chain management, operations, as well as well as different subdomains and specific AI applications and techniques were utilized both on academic databases and web search engines. To include a higher number of case studies was restricted both by time constraint as well as by the richness of available information. In this context, it should also be made transparent that analysis of the information presented was conducted predominantly on the basis of secondary sources of information.

In order to also account for the variety of different AI applications, the authors set a limit on the number of predictive maintenance projects chosen. While predictive maintenance is likely the most common artificial intelligence application in the business world, the authors decided to ensure that the entire breadth of AI applications was represented in the study. Yet, it would have been possible to include additional predictive maintenance examples in the study, as these initiatives are well represented, especially in the automotive, industrial goods, and process industries. In many cases, companies take advantage of off-the-shelf solutions such as Senseye, which is part of this study. Yet, the authors are confident that striking a balance between showing the variety of AI solutions and highlighting the prevalence of predictive maintenance solutions is the best way to illustrate the current AI implementation landscape and to draw general conclusions from it. Still, it is recommendable for future researchers to further validate the finding that predictive maintenance is the most prevalent application as well as that the tentative general distribution as indicated in the study is confirmed.

Additionally, there may be some degree of self-selection bias as companies predominantly share information on projects which are considered successful. This behavior involves both internal press releases as well as access to project information to third parties such as journalists or academic researchers. While the authors tried to safeguard against this, the risk of overrepresenting positive examples in the sample should be mentioned. In fact, it should be of interest to future research initiatives in this field to also analyze projects that clearly failed and identify which human-machine teaming capabilities were present and which ones were lacking. For example, this could be conducted by approaching companies and asking them to share both their best- and worst-case examples in the introduction of artificial intelligence projects, which would potentially allow for a more representative sample.

However, the effort to proactively request negative case studies from companies could still prove difficult as the acquisition of companies for in-depth analysis was very difficult. Despite contacting more than forty companies, only two agreed to open for in-depth analysis. The most predominant reason for not agreeing to a research partnership was that potential projects were not yet mature enough to be researched. In particular, companies had not yet implemented an AI project at all or were running only a pilot, which did not satisfy the requirements concerning the evaluation of the project's outcome. Similarly, even among projects that had come from a pilot to a large-scale implementation many companies indicated that it was too early to give feedback on key learnings on the project. While also other issues were quoted such as time constraints and internal restructuring, it was surprising given the sometimes-aggressive PR efforts by firms as well as the widespread press coverage on AI that the actual level of implementation in firms is still lagging.

As has been touched upon previously, another aspect that made the acquisition of projects more difficult was that companies at times labelled mere machine learning projects without mutual learning feedback loops as artificial intelligence. However, in the present project the authors argue that only when there is a dynamic process of mutual feedback-giving and learning present can it be considered artificial intelligence and therefore be included in the research. This notion also hints at a more general problem. Despite a general consensus on what constitutes artificial intelligence and what it entails (cp. Chapter 1) in the academic world, there still is significant variation in terms of definitions of AI and its key concepts in the business world. While the authors have been careful to translate interview and research input into the standard terminology as defined in this paper, it is still likely that some inaccuracies may have occurred due to different interpretations of concepts such as "artificial intelligence", "reinforcement learning", "(un)supervised learning", and "(un)labelled data" among people interviewed.

Finally, it must also be acknowledged that the present research and its results are dependent on its temporal context. As has been noted, many AI implementations in the supply chain context are still at early stages in their development. The field of artificial intelligence is highly dynamic and so is its application in the business world. Therefore, academic research on the topic also needs to adjust frequently and be adjusted iteratively as the field matures. In our specific case, it would be worthwhile to investigate whether over time the effectiveness of different capabilities and concepts changes.

7.4 Future research

The limitations outlined in the previous section raise opportunities for future research that require additional analysis by researchers. In this context it should also be mentioned that collaboration of academics from different fields should be beneficial. For example, research efforts in the field of human-machine teaming should strive to bring together experts from organizational theory, computer science, (supply chain) management but also sociology and anthropology to obtain a holistic view on the questions at hand. The authors therefore encourage researchers to reach out to colleagues in different departments to collaborate on further exploring this dynamic field.

First, this research is intended to develop a conceptual framework and validate it empirically. The rich content nature of the multiple case study methodology utilized, and the limited academic term limit the numbers of samples, which could be and can be obtained and analyzed. Future research could expand the sample size by combining broader survey and company interviews methodologies. The collected data leveraging the proposed assessment instrument can be used for further validation of the structural relationships of the HMT capabilities, which would improve the practical utility of the framework.

Second, future research should also explore potential differences with regard to different sectors, application types, or maturity levels of human-machine teaming projects in a supply chain context. While the present research provides some initial propositions in this regard, it may be worthwhile to think about how the peculiarities of different industries or even functional areas within the supply chain context influence how different capabilities work and interact. Similarly, as the field of artificial intelligence is ever expanding it would be an interesting aspect to further research whether individual AI applications require specific capability configurations potentially not captured by the framework.

Third, the interviewed company also illustrated the importance of the foundations in organization culture and agile project management mindset. Future research can contribute to better understanding how corporate and organizational culture interacts with the successful establishment of different capability configurations. In this context, it may also be interesting how the framework can better take into account new ways of work, such as agile methods, and how this potentially influences successful AI project design planning and implementation.

Fourth, researchers should focus on putting additional emphasis on the dynamics by which human-machine teaming projects’ decision contexts change over time. This is especially interesting as it involves both internal and external factors, such as the risk level but also the AI design. As a result, different capabilities are required for companies and decision makers to obtain a better perspective on how to build the fitting capabilities to succeed under such changing environments scenarios. Similarly, it could be worth investigating if different capabilities are required as AI projects mature, for example, as the risk level decreases due to the company gathering more experience.

Fifth, the authors have observed that not only the field of Artificial Intelligence but also the external environment companies operate in is highly dynamic. Therefore, the opportunities and the constraints that human-machine teaming are subject to often change quickly and strongly. It could therefore be a potential future research area to investigate how changes in external environment and technological capabilities may influence the efficiency of different HMT capability configurations.

Closing Remarks

In summary, this paper advances research in the field of human-machine teaming in AI-driven supply chains by providing both academic and practical insights. The detailed literature review and expansion of the HMT framework developed by Saenz, Revilla, and Simon (2020) enables a better understanding how different capabilities are defined and how they can be measured. Applications of these concepts to more than 20 case studies further advanced the understanding of how these capabilities function under changing circumstances and how practitioners can leverage these insights. Even when taking into account the limitations of this research, predominantly driven by the low number of observations, the authors believe that the present research advances the field and provided a basis for further investigation.

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APPENDIX A: HMT ASSESSMENT INSTRUMENT

Section 1: Introduction

Objective: The purpose of this questionnaire is to gain greater understanding and knowledge about which human-machine teaming (HMT) capabilities can help maximize the value of AI systems and enable mutual learning opportunity.

About the survey: Participation in the survey is voluntary. No names or personal information will be registered. There are no "correct" or "wrong" answers to the questions in this questionnaire and it is your own opinions that we are interested in. Please kindly answer **ALL** questions. Your response to each question will only be analyzed in aggregate forms. The survey may take approximately 15-20 minutes.

The questionnaire is divided into 7 sections.

Section 1: General Questions

Section 2: General AI Design

Section 3: Transparency

Section 4: Authority Balance

Section 5: Security

Section 6: Mutual Learning

Section 7: AI project performance

Section 2: General Questions

Please tell us something about you and the company you work in:

A. Please describe your role and responsibility in the company: [Text input]

B. Your age:
   a. 20-35
   b. 36-45
   c. Over 46
   d. Prefer not to disclose

C. Your gender:
   a. Male
   b. Female
   c. Prefer not to disclose

D. Industry sectors:
   a. Financial Services
   b. Human Resources
   c. Transportation & Logistics
   d. Manufacturing
   e. Retail
   f. Other [Text input]

E. Company annual revenue:
   a. over $500M
   b. $250M - $500M
   c. $100M - $250M
   d. $50M - $100M
   e. $25M - $50M
   f. $10M - $25M
   g. $ 1M - $10M

F. Please describe your computer programing knowledge level:
   a. Very knowledge
   b. Only high level
   c. No knowledge at all

G. For the AI application you are currently interacting with, please describe the specific process it is used in:
   a. Demand planning
   b. Logistics
   c. Manufacturing
   d. Product development
   e. Other [Text input]

H. Please describe how often you interact with the AI applications/systems on a daily basis?
   a. No interaction at all
   b. Only interact a little
   c. Interreact at all times

Section 3: Decision Context Assessment

The questions below apply to the specific AI application that you described in Section 1.

AI Design	Whether the AI system is designed as "closed" or "open" by defining the boundaries and sources of variability. “Closed system” means a well-established decision parameter structure is already defined within the AI algorithm. “Open system” refers to an AI algorithm that is capable to discover the underlying structure of the contextual information without reference to known or labeled parameters.				
Rating	1 - Closed	2 – Rather closed	3 - Rather open	4 - Open	
Risk Level	The level of risk (“weak” to “severe”) of the decision making in which the AI system is involved.				
Rating	1 - Low	2 - Rather low	3 - Rather high	4 - High	

Section 4: HMT Capabilities Assessment

HMT Capability	Code	Survey Questions (Please read the statement below and provide rating based on your perception of the level of presence of the capability in question)	Level of Agreement 1- Strongly Disagree 5 - Strongly Disagree				
			1	2	3	4	5
Transparency							
Observability	O1	The AI system provides visibility on state parameters, capabilities of the system					
	O2	The AI system provides users visibility of AI system’s intentions					
	O3	The AI system is able to anticipate users’ situational changes					
Explainability	E1	The user Interface is simple, and information presented is understandable					
	E2	It’s easy to discern how AI system’s decisions are made					
	E3	It’s easy to understand algorithms behind the AI decisions					
Common Ground	CG1	There is a high level of human-machine mutual understanding each other’s situations					
	CG2	There is a high level of information sharing between humans and machines					

HMT Capability	Code	Survey Questions (Please read the statement below and provide rating based on your perception of the level of presence of the capability in question)	Level of Agreement 1- Strongly Disagree 5 - Strongly Disagree				
			1	2	3	4	5
Interoperability	I1	AI is able to make coherent connections for inputs from various sources					
	I2	There is great interoperability with other systems					
Authority Balance							
Directability	D1	AI is able to control and override					
	D2	AI is able to allocate decision authority based on situation					
	D3	AI is able to redirect, re-allocate tasks					
Shared Decision Making	SDM1	AI presents simultaneous or sequential decision making					
	SDM2	AI is able to assist human to eliminate oversight slips and errors					
	SDM3	AI is able to understand the problem and develop solutions jointly with human leveraging each other's knowledge and viewpoints					
Cognitive Load Balance	CLB	AI is able to assure a manageable human workload by balancing workload distribution between human and machine					
Secure Interaction							
Ethical	Et	The AI is designed accordance to acceptable social conduct principals					
Reliable	Re	There is a high level of system robustness and reliability					
Secure	Se	There are validated methods to protect interaction processes and prevent unintended access					
Mutual Learning							
Feedback Loop	FBL1	Human-machine is able to provide synchronized feedback loop					
	FBL2	It's easy to incorporate user explanations into learning algorithms [judge the complexity& breath of feedback					

HMT Capability	Code	Survey Questions (Please read the statement below and provide rating based on your perception of the level of presence of the capability in question)	Level of Agreement 1- Strongly Disagree 5 - Strongly Disagree				
			1	2	3	4	5
Mutual Capability Growth	MCG1	AI helps users broaden their view of the situation and help users revise solutions					
	MCG2	The AI solution enables human team member to work more effectively and shorten learning curve for their work					

Section 5: Project Performance

1- Please describe the metrics you are using to measure the success of the AI systems [Text input]

2- Please describe the metrics you are using to measure the human-machine teaming satisfaction [Text input]

HMT Capability	Code	Survey Questions (Please read the statement below and provide rating based on your perception of the level of improvements the AI project achieved)	Level of Improvement 1. I have not measured the improvement rates 2. No improvement 3. 10~30% improvement 4. 30~50% improvement 5. Over 50% improvement				
			1	2	3	4	5
Teaming Performance	TP1	Level of AI project improvements in target performance metrics					
	TP2	High level of human satisfaction working with AI					