Microfoundations of AI Empowerment Capability to Transform Organizations

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Abstract:

The advancement of artificial intelligence (AI) has sparked remarkable anxiety on how to empower AI capability to reap benefits and address the challenges. There is very limited knowledge on the operationalization of AI empowerment capabilities and their effects. Drawing on the microfoundations of dynamic capability (DC) theory, this study fulfils this research gap by presenting an AI empowerment capability model and its effects on organizational agility and firm performance. Using a systematic literature review, thematic analysis and in-depth interviews of 20 AI experts in Australia, the findings present theoretical insights, managerial guidelines and policy implications. The results show that technological sophistication, AI governance, AI literacy, training & development, and ethical orientation are the significant dimensions of AI empowerment capability.

Keywords:

AI empowerment capability, organizational agility, firm performance, responsible AI climate.

Introduction:

AI is already making impacts across a wide variety of industries. Pharmaceutical companies are using it to accelerate the pace and success rate of drug development. Retailers, such as Walmart, are deploying AI for predictive analytics so that they know when to restock inventory and how to optimize their end-to-end supply chains….However, despite the promise and hype around AI, many organizations are struggling to deliver working AI applications (Ryseff, Bruhl, Newberry 2024).

The global investments in AI, and related technologies are set to reach $232 billion by 2025 with significant growth in operational efficiencies (77%), employee productivity (74%) and customer satisfaction (72%) (Diasio, Gusher & Kappor 2024). However, despite the forecast investment boom, the success rate of AI projects is alarming (Ryseff et al., 2024; Mittal et al., 2024). The extant literature identifies empowerment issues regarding talent, technology or data governance issues at the heart of most AI success cases (Cooper, 2024; Diasio et al., 2024; Tse et al., 2020). To address AI success challenges, empowering employees with AI capabilities can help organizations achieve agility and enhance firm performance (Cook et al., 2024; McAfee et al., 2023) because "When employees are excluded from that process, they become averse to working with AI, never develop trust in its capabilities, and resist even the positive changes that come from using it" (De Cremer 2024).

According to Davenport & Mittal (2023, p.118), "the technological powerhouses of the world, such as Microsoft, Amazon, Meta (Facebook), Alphabet (Google), Alibaba and Tencent put AI at the heart of their businesses and to achieve success all "had to accomplish the same fundamental tasks: They put people in charge of creating the AI; they rounded up the required data, talent, and monetary investments; and they moved as aggressively as possible to build capabilities". Empowering talent can help firms catch up with the new age technologies, learn the governance of data, adapt with new knowledge and skills and predict the future with robust capabilities and a greater degree of certainty. To receive significant value from AI, each organization must rethink how to empower AI-human collaborations and interactions in work environments across key functions, operations, and processes to develop new offerings and solve business problems. Although AI is blessed with robust computational system and autonomous learning ability, it is beset with many demerits, such as lack of creativity, novelty, privacy and security concerns and, most importantly, contextual and cultural nuances (Akter et al., 2023; DeCremer 2024). Indeed, there is limited insight into how to empower AI capabilities in organizational settings for robust decision-making through dynamic human-AI collaboration to achieve organizational agility (Davenport and Harris, 2017). Also, the impact of such capabilities on firm performance is still unknown. Thus, our study puts forward the following research question: **What are the dimensions of AI empowerment capabilities and their overall effects on organizational agility and firm performance?**

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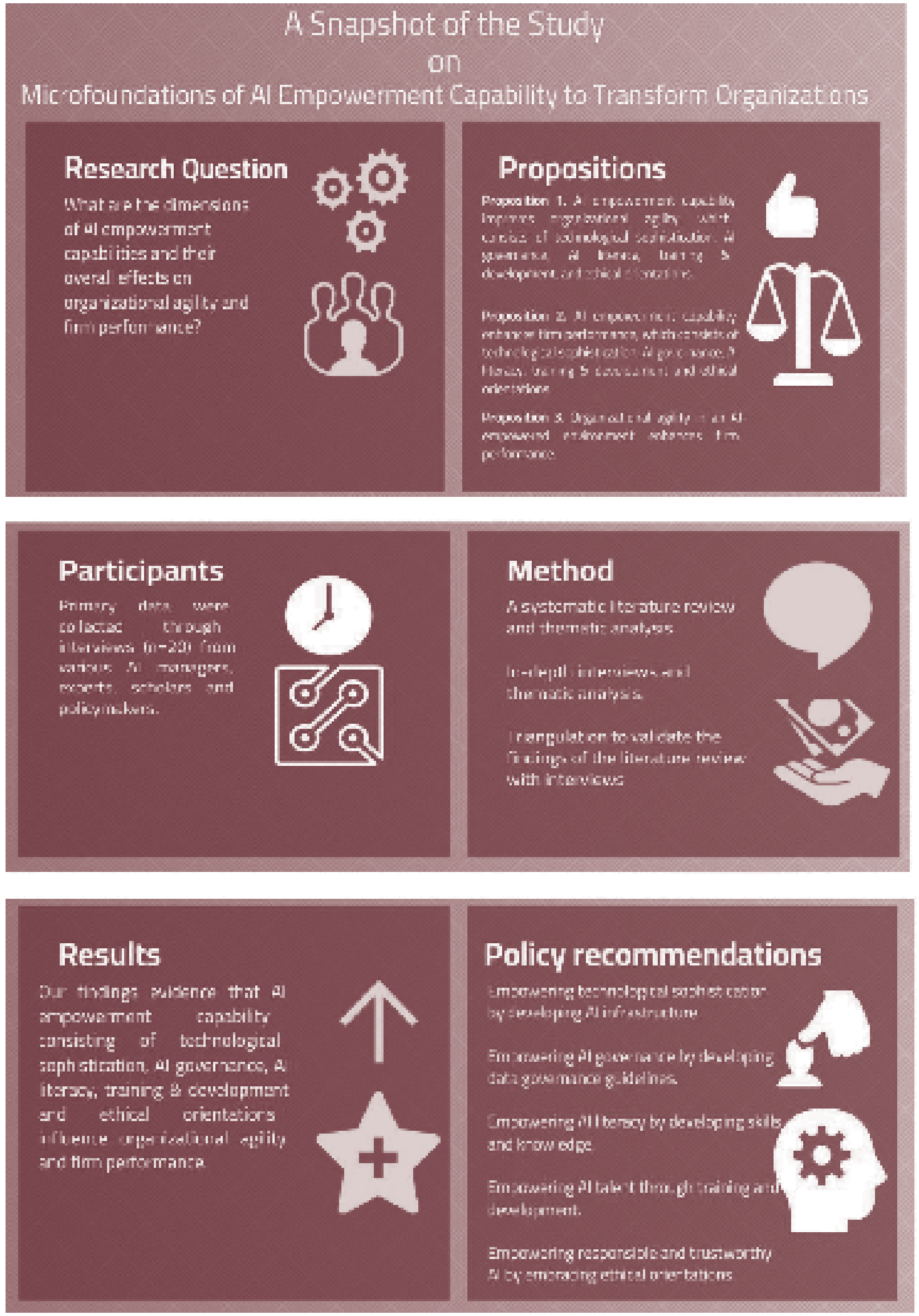

The study addresses this research question by drawing on the microfoundations of DC theory, which enables firms to contribute to agility and firm performance in a volatile, uncertain, complex and ambiguous environment. Theoretically, it explores the micro-foundations of AIEC and shows their impact on agility and firm performance. Practically, the research findings provide guidelines to policymakers on how to operationalize technological sophistication (a modular enterprise-wide IT application that integrates data, analytics and automation), data governance (managing data lifecycle to protect security and privacy), AI literacy (developing knowledge and skills to embed AI across the business process to achieve automation), training & development (upskilling and reskilling the relevant workforce in data science, data engineering, cloud analytics, AI initiatives) and ethical orientation (transparency, beneficence, justice, fairness, non-maleficence etc.). The study is structured to discuss the literature review next, followed by theoretical model and propositions, research methods, discussion and findings. The study concludes with a section on limitations and future research directions.

1. Literature Review:

1.1 The rise of AI

AI is defined as "making a machine behave in ways that would be termed intelligent if a human being behaved like this" in the Dartmouth Research Project in 1955 (Di Vaioa et al., 2020). Whereas traditional algorithms are rule-based and require extensive coding (Bishop 2006), AI is distinct from them in its unique capabilities to learn, adapt and predict. Focusing on business and organizations, Agrawal et al. (2018) identify it as a "prediction technology that reduces the cost of predictions." Prediction is at the core of all business decisions in volatile and uncertain situations, and AI makes predictions robust and precise. With its learning capability, AI can mimic human intelligence using various algorithms through machine learning (ML), deep learning (DL), natural language processing (NLP) and computer vision. Leveraging its varying degrees of learning capability, connectivity and adaptability, AI can analyze all types of numbers, voices, videos and images to provide automated services (Grewal et al., 2020). It is transforming modern-day organizations through its revolutionary ability to identify patterns, prescribe scenarios, and develop new products through recommendation engines, GenAI-based solutions and business model innovations (Akter et al., 2023). Scholars have defined AI

Relevant studies	Definitions of AI
McCarthy et al. (1955)	"Making a machine behave in ways that would be called intelligent if a human were so behaving".
Abail et al. (2023)	"Artificial Intelligence (AI) can be defined as the theory and application of machines—especially computer programs—to perform tasks that typically require human intelligence, such as image captioning and generation, speech recognition and synthesis, natural language understanding and, tool assembly and utilization, as well as various other perception-action based engagements".
OECD (2023)	"An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment."
Oxford Learner's Dictionaries (2024)	"The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages."
The Encyclopedia Britannica (2024)	"Artificial intelligence (AI), the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings."
Amazon (2024)	"Artificial intelligence (AI) is a technology with human-like problem-solving capabilities. AI in action appears to simulate human intelligence—it can recognize images, write poems, and make data-based predictions."
IBM (2024)	"Artificial intelligence (AI) is technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy".
ISO (2024)	"a technical and scientific field devoted to the engineered system that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives"
TechTarget (2024)	"Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems. Examples of AI applications include expert systems, natural language processing (NLP), speech recognition and machine vision".
McKinsey & Co. (2024)	"Artificial intelligence is a machine's ability to perform some cognitive functions we usually associate with human minds."
Accenture (2024)	"Artificial intelligence is a constellation of many different technologies working together to enable machines to sense, comprehend, act, and learn with human-like levels of intelligence".
Gartner (2024)	"Artificial intelligence (AI) applies advanced analysis and logic-based techniques to interpret events, and support and automate decisions and actions".
Current study	This study shows AI as a data-driven technological platform that simulates human intelligence through learning algorithms and produces automated content, predictions, decisions, and recommendations.

as "systems with the ability to act intelligently, correctly interpreting external data, and using these objectives to execute particular tasks by a flexible configuration, even to the extent of reproducing human behaviors with cognitive, social, and emotional intelligence" (Di Vaioa et al., 2020). It is distinctive from traditional IT systems or software due to its ability to adapt and self-learn and its inherent cognitive and intelligent skills to respond to a particular context (Brem et al., 2023). Table 1 presents seminal definitions of AI by scholars and corporations at the forefront of the AI revolution. Synthesizing all these definitions, we define AI as a data-driven technological platform that simulates human intelligence through learning algorithms and produces automated content, predictions, decisions and recommendations.

Table 1: Definitions of AI

2. Theoretical Foundations:

2.1 The Dynamic Capability View

Dynamic capabilities have garnered attention for over twenty years due to the increasingly global and organizationally dispersed nature of business operations and the growing need for companies to integrate various forms of invention, innovation, and manufacturing to provide value to consumers (Teece, 2007). From an evolutionary standpoint, DCs are regarded as the means via which organizational resource bases are developed and modified to achieve alignment with the external environment (Schilke, 2014). Hence, DCs are essential for firm's unique performance characterized as the firm's capacity to integrate, develop, and reorganize internal and external competencies to respond to fast-changing environments (Teece, Pisano and Schuen, 1997). However, it is becoming more difficult for firms to deal with unexpected shifts in their environments using their internal and external competencies. To address the challenges, companies are focusing on advanced technologies such as big data analytics, blockchain, the Internet of Things, artificial intelligence, and, more recently, the emergence of generative artificial intelligence (Dwivedi et al., 2019). In this context, the theory of DC is pertinent for comprehending how businesses cultivate, assimilate, and reorganize competences to enhance their performance (Baryannis et al., 2019). The dynamic capabilities strategy has recently been placed in the spotlight for its application to numerous challenges and circumstances. Therefore, the dynamic capabilities (DC) view has been utilized to examine firm performance (Lenka et al., 2018), with analytics recognized as a vital microfoundation of DCs (Mikalef et al., 2019). According to studies (Parker & Ameen 2018), DCs like resilience capabilities, are essential for effective empowerment capabilities during challenges or disruption. An organization must be extremely agile and adaptable, as pointed out by Bundy et al. (2017), to handle complexity and prevent uncertainty in a very unstable environment. As a result, recognizing the most important DCs are essential for organizations to respond and adapt quickly during unexpected situation. In order to place our inquiry in the proper framework, it is crucial to differentiate the AI empowerment capability (AIEC) as a higher-order DC.

2.2 AI empowerment capability – a dynamic capability

Empowerment has been shown to have a positive impact on individual employees' attitudes, performance, work behaviors, and wellbeing, as well as organizational agility and firm performance (Chebat & Kollias, 2000). The definition of empowerment has been defined in several different ways. For example, Conger and Kanungo (1988) define empowerment as a process that increases the perception of self-efficacy among the members of an organization. Some academics have also concentrated on the social-structural components of empowerment, whereas others have emphasized psychological empowerment (Motamarri et al., 2020). For instance, psychological empowerment is defined by Spreitzer (1995, p.1444) as a "motivational construct reflected in four perceptions: meaning, competence, self-determination, and impact". Again, Lin, Wu, & Ling (2017) state that psychological empowerment is concerned with employees' beliefs and experiences of empowerment, such as increased self-efficacy, while social-structural empowerment primarily centers on the transfer of power and responsibility from higher-level management to lower-level staff. Both dimensions of empowerment complement one another and have been identified as critical determinants of performance in organizations.

According to Wilder, Collier, and Barnes (2014) and Lin et al. (2017), employee empowerment is one approach to ensure service innovations and performance. Empowerment offers numerous benefits, including increased employee commitment and efficiency, higher quality products and services, improved responsiveness, enhanced management leverage, greater synergy, and increased competitiveness in the global marketplace (Lin 2002). Studies also indicate that enhancing job content, job redesign, and providing more information to employees are techniques that can be implemented to foster employee motivation stemming from psychological empowerment (De Treville & Antonakis, 2006). These methods enhance performance and service delivery by providing employees with greater empowerment (Spreitzer, 2008). It helps employees understand the overall context of their work, build confidence, inspire new ideas, improve problem identification, and accelerate decision-making (Bowen & Lawler, 1992). Several scholars have also noted that giving managers greater empowerment helps them deal with uncertainty. Therefore, possessing empowerment is paramount while dealing with organizational challenges (Lin, 2002).

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Implementing AIEC is vital to organizational agility and firm performance. Its various components play a key role in ensuring effective response during challenging situations. Bowen and Lawler (1992) and Aguinis and Kraiger (2009) agree that technology and tools can be powerful agents of empowerment. For example, organizations can determine their future challenges and agility through predictive analytics tools. These tools enable accurate forecasting and predictions, providing insights into what will occur and why an event may transpire (Delen and Demirkan, 2013). The technological sophistication and data governance, encompassing the norms, beliefs, and behavioral patterns that systematically promote a data-driven culture within an organization, facilitates decision-making processes and procedures through data-driven insights (Mikalef et al., 2019). Wamba et al. (2020) advocate for the importance of robust technology in service adaptations.

Technological literacy in the form of knowledge and skills are critical components of empowerment, and this is no exception for AIEC (Spreitzer, 1995). A crucial component of empowerment is having access to knowledge, and today's advanced analytics and AI environments provide access to vast amounts of data (Bowen and Lawler, 1992). Access to information is thus acknowledged as an essential component of AIEC that aids organizations in better handling challenging circumstances. Advanced analytics and AI help employees become better data interpreters, process implementers, and outcome evaluators (Motamarri et al., 2020). An empowered manager makes optimal decisions through training and development (Voegtlin et al., 2015). In a similar vein, the extant literature stresses the importance of training and development components to ensure that decision-makers keep their skills up-to-date in challenging times. Due to the necessity of making real-time decisions in critical times, the empowerment capability is vital for organizational agility and performance (Motamarri et al., 2020).

3.3 The nature of microfoundations

Microfoundations research	Study type	Study	Major findings
Resilience of supply chain networks	Review	Golan, Jernegan, & Linkov (2020)	Considering the challenging circumstances, the authors demonstrated the vital need to include sophisticated analytics in supply chain processes to strengthen these networks' ability to cope with unpredictable and crisis-prone scenarios.
Organizational level DCs	Empirical	Mikalef et al. (2019)	An organization's DCs can benefit from big data analytic capability (BDAC) by gaining insights that can be used to develop both radical and incremental innovation capabilities.
Viability of supply chains during pandemics	Theoretical	Ivanov (2022)	Considering sustainability, agility, and resilience into account, the authors proposed a supply chain model for decision-makers that can handle both positive and negative changes.
Adaptation and performance during crises	Empirical	Jacob (2020)	DCs that have been able to maximize organizational performance by creating value for stakeholders have adaptable, inventive, and absorptive characteristics in effectively tackling the challenge.
Process-oriented DCs (PODC)	Empirical	Kumar, Vishwakarma, & Upadhyay (2020)	The study suggests that process oriented DCs (PODCs) play a significant mediating role in enhancing disaster risk reduction (DRR) through boosting digital humanitarian capability (DHC).
TMT leadership	Empirical	Friedman, Carmeli & Tishler (2016)	The research shows that organizations are adaptive when CEOs employ transformational leadership and promote microprocesses inside their top management teams when making strategic decisions.
Open service innovation	Empirical	Randhawa, Wilden & Gudergan (2018)	Identifying whether digital service platforms have higher-order DCs like marketing, empowerment, technology, and co-creation skills.
Rapid decision making	Empirical	Munnger, Hanmedi & Mahr (2019)	Quick decision-making and information flow across teams are facilitated by agile methods, which include top-management support, iterative testing and learning cycles, and team empowerment.
Organizational adaptive behaviour	Empirical	Makkonen et al. (2014)	By combining the existing literature on the DC view, organizational transformation, and innovation, this study triangulates the empirical results on organizational adaptive behaviors used during crisis situations.
Sustainable enterprise performance	Theoretical	Teece (2007)	Organizational sensing, seizing, and reconfiguring capacities are conceptualized as having unique microfoundations that include underlying processes, procedures, skills, disciplines, organizational structures, and decision-making norms.
Routines and capabilities	Theoretical	Felin et al. (2012)	Organizational routines and skills are supported by micro-level components, which can be categorized as social processes, individuals, or structures.
Sustainable enterprise performance	Theoretical	Eisenhardt & Martin (2000)	The critical microfoundations of DCs include knowledge and technology transfer, cross-functional research and development teams, new product development capacities, certain performance measurement systems, and quality control procedures.
AI Empowerment capability	Theoretical	Present study	The study identifies the microfoundations of AI empowerment capability using microfoundations of DC as the theoretical framework. The study fills the research gap in the evolving field of AI in management research.

Scholars have taken an interest in the microfoundational perspective of routines and skills in an effort to construct a better explanation for the diversity in organizational performance (Barney & Felin, 2013). The seminal studies in this line, such as Teece (2007), Felin and Powell (2016) clarify that the microfoundations of DCs consist of small-scale components that support routines and capabilities. These components include procedures, unique skills, decision-making rules, organizational disciplines and structures, the design of decision-making activities, information processing, knowledge development and sharing, as well as integration and coordination. The microfoundations are crucial for effective decision-making and more accurate forecasting during challenges (Teece 2007). Advanced analytics and AI are essential in complex situations, enabling improved forecasting and more effective decision-making. Table 2 shows seminal studies on the micro-foundations of DCs, identifying their applications in various contexts.

Table 2: Microfoundations of dynamic capabilities

4. Methods:

4.1 A systematic Review and Thematic Analysis

Drawing on the seminal studies on systematic literature reviews (Durach, Kembro, & Wieland, 2017; Tranfield, Denyer, & Smart, 2003), the study adopted a three-stage process to discover, screen and synthesize the findings of the review process. At the first stage, to answer the RQ: "What are the dimensions of AI empowerment capabilities and their overall effects on organizational agility and firm performance?", we explored EBSCOhost Business Source Complete, Emerald insight, ScienceDirect and other important peer-reviewed journals across the disciplines as AI has become a predominant topic of research enquiry. Using the keywords mentioned in Table 3, the study initially found 2560 relevant papers in the period of 2014-2024 (November). At the second stage, the study then screened out 2450 papers following the guidelines of Sheng et al. (2020) and Dada (2018) by assessing duplication criteria, quality of the peer review process and relevance. Another 65 papers were excluded due to their non-relevance to the research topic after a thorough analysis. Thus, we selected 45 papers, and a cross-citation analysis yielded another 5 papers. We obtained 50 papers to synthesize our findings and address the RQ of algorithmic empowerment capabilities. At the final stage, following Braun and Clarke (2006), we applied a thematic analysis of the 50 papers and found five themes of AI empowerment capabilities: technological sophistication, data governance, AI literacy, training & development and ethical orientations. We identify these themes as the five microfoundations of AI empowerment capabilities.

4.2 Interviews and Thematic Analysis

The study conducted 20 in-depth interviews with AI practitioners and experts in Australia across diverse industries. The respondents have at least two years' experience working with AI in various capacities, from data science to data managers, data cloud architects to cyber-security experts and marketing managers to fintech enthusiasts. The

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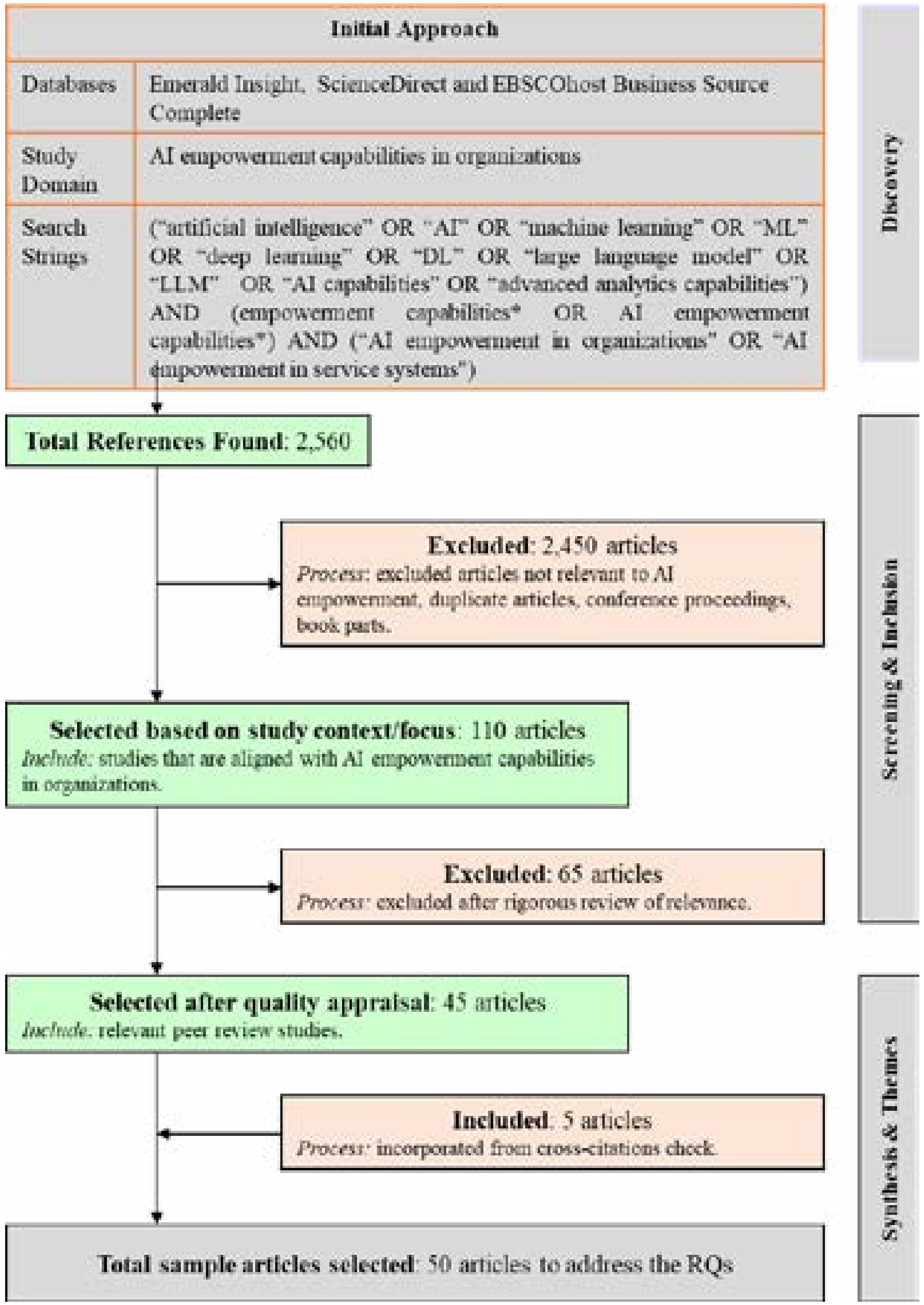
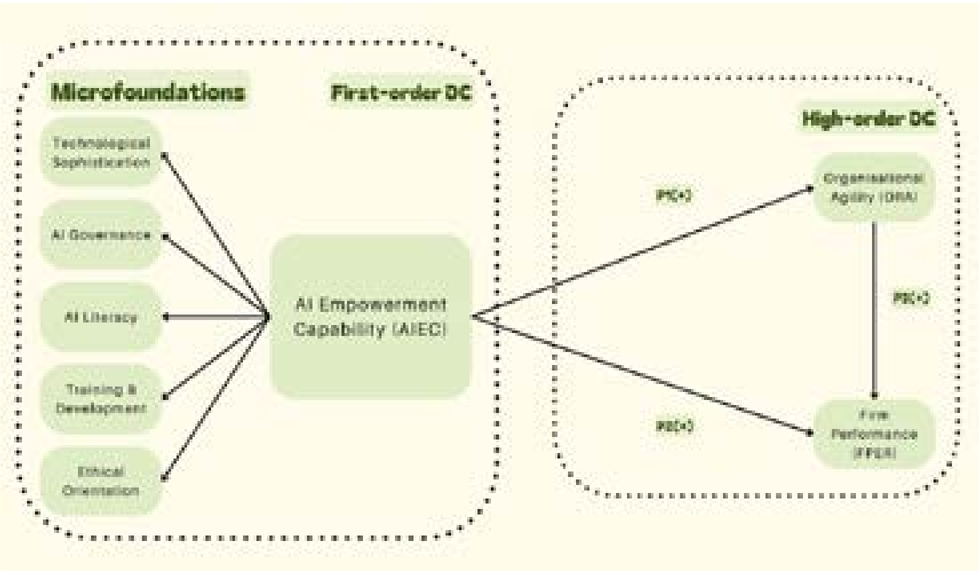
diversity in sample size helped us to reach thematic saturation (Guest et al., 2006).



4.3 Triangulation

In the absence of reliability and validity, like quantitative research methods, the study adopted triangulation to validate the findings of the literature review with interviews (Carter et al., 2014). This is a well-established practice in qualitative research, which establishes findings by triangulating two separate sources of data. In our case, the primary data collected through interviews (n=20) from various AI managers, experts, scholars and policymakers have been aligned with the secondary data from peer-reviewed journals, newspapers, industry magazines collected through the reviews.

We applied a six-step protocol in applying thematic analysis (Braun and Clarke's 2006). In step one, we read the 50 selected papers repeatedly to identify the dimensions of AIEC. In step two, we placed each of the articles in each of the five categories: technological sophistication, data governance, AI literacy, training & development and ethical orientations. In step three, we have coded key terms from the articles that are relevant to our research objective on AIEC. Coding is critical at this stage to derive meaningful insights from the articles to address the research question (Miles et al., 1994; Tuckett, 2005). In step four, five industry experts assess the coded terms of fifty articles with five themes identified in the previous section. In step five, using Krippendorff's Alpha,



the authors found that key coded terms are strongly aligned with five key themes, a robust process of measuring the reliability of themes (Krippendorff, 2007). The findings identify that inter-rater reliability scores of all five themes exceed the threshold value of 0.80 using IBM SPSS 28. Hence, in step six, we confirmed five themes of AI empowerment capability, and the findings provided us additional insights into the connections between AI empowerment capabilities and their effects on organizational agility and firm performance.

The overall findings confirmed the following themes as the dimensions of AI empowerment capabilities: technological sophistication, data governance, AI literacy, training & development and ethical orientations. The next section will discuss each dimension under a conceptual framework and their overall effects on organizational agility and firm performance.

Table 3: Protocols for Systematic Literature Review

5. Conceptual Model and Propositions:

A capability refers to actions and interactions of employees within an organization, a high-level routine or collection of routines that enable the capacity to perform activities in a patterned or practiced manner (Barney & Felin, 2013; Schilke, Hu and Helfat, 2018; Winter 2003, p.991). In the context of the current volatile, uncertain, complex and ambiguous external environment due to the rapid proliferation of advanced AI technologies, we propose AI empowerment as a distinctive, first-order capability rooted in various microfoundations. Drawing on Schilke (2014), we argue that microfoundations are routines that help in building AI empowerment capability. In Figure 1, we propose AI empowerment capability as the first-order dynamic capability that influences higher-order dynamic capabilities, such as organizational agility, to influence firm performance. Our proposition intertwines microfoundations to develop AI empowerment capability to achieve agility and productivity. Thus, we answer our research questions by conceptualizing technological sophistication, data governance, AI literacy, training & development and ethical orientations as the microfoundations of AI empowerment capability to achieve organizational outcomes.

Figure 1: Research Model

5.1 Technological sophistication

In an AI environment, managers need to be equipped with robust tools and technologies to make decisions in real time. For example, cloud technologies have enabled organizations to store and retrieve data efficiently. According to Davenport and Mittal (2023, p.122), "Shifting to the cloud made strategic sense partly because it would drive down the costs of data storage. In 1960, storing one gigabyte cost $2 million, according to data from USC's Marshall School of Business. That cost dropped to $200,000 in the 1980s, $7.70 by the early 2000s, and—thanks to cloud storage—as low as 2 cents by 2017". Many of our respondents have supported the viewpoint of investing in technologies, such as dashboards, to provide critical insights and remove the need to switch between tools. For example, respondent 3 (an AI manager in a bank) stated "…my organization has partnered with a leading AI startup in Silicon Valley, which offers cloud-based analytics tools to assess and predict customer needs and offer services accordingly. We use high-performance hardware from NVIDIA, cloud applications from AWS and machine learning support from XGBoost libraries. We also use privacy-preserving technologies, dynamic user interfaces and integration technologies for AI empowerment in banking". Technological sophistication paves the way for AI empowerment capability through handling massive data volumes, tackling complexity in model building, scaling, and deployment (e.g., ML or DL-based models using transformer-based technologies) and optimizing resource use. Since explainability and transparency have become critical components of AI models, technological sophistication helps identify potential biases and establish trust among users. In this regard, respondent 1 states (a data miner in an insurance company), "…digital firms heavily rely on technologies such as SQL databases, NoSQL options like MongoDB and Cassandra, and data lakes like Amazon S3 and Hadoop HDFS, which are crucial for storing large volumes of both structured and unstructured data".

5.2 AI governance

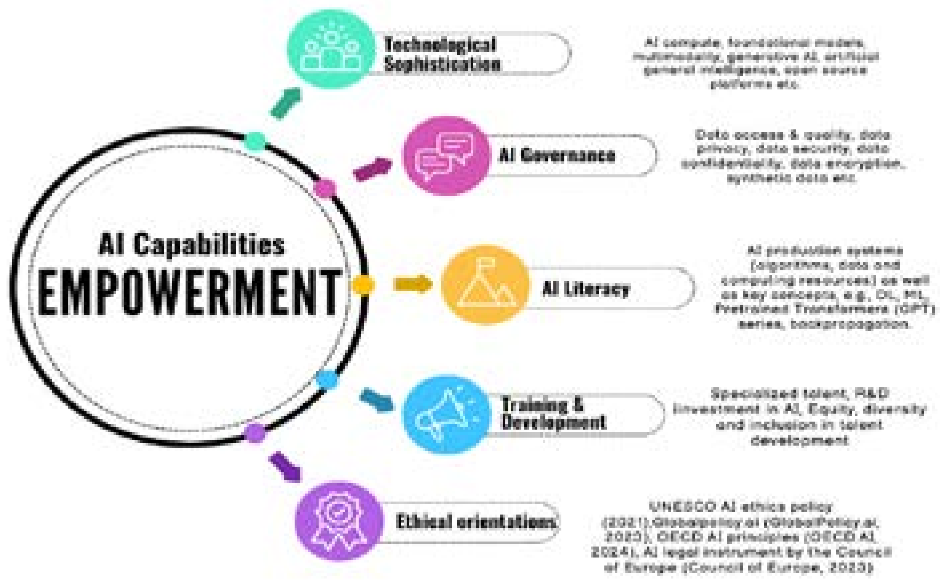
AI governance refers to the policies, processes, organizational structure, regulations, responsibilities, regulations, roles and risk management frameworks that advocate AI's responsible and safe use to safeguard people and ensure equality (P& M, 2023). The challenges of AI can be tackled by combining technical, financial, social and legal capabilities to address privacy, security, ethics, diversity and inclusion, human rights, intellectual property and risks. The adaptability of AI governance is critically important in protecting public interests, maintaining ethical standards, and promoting innovation. The AI governance includes data governance, risk management, standards and procurement. According to UNESCO AI ethics policy (2021, p.20) "data governance strategies that ensure the continual evaluation of the quality of training data for AI systems including the adequacy of the data collection and selection processes, proper data security and protection measures, as well as feedback mechanisms to learn from mistakes and share best practices among all AI actors". Data is at the core of the quality of an AI model's output. Hence, a robust data management practice should ensure that data are representative, authenticated, accurate, reliable and aligned with country-specific legislations and administrative obligations (e.g., GDPR in Europe). AI governance also includes managing risks across the AI lifecycle, such as phase 1 (design, data and models), phase 2 (verification and validation), phase 3 (deployment) and phase 4 (operation and monitoring) (OECD, 2024). It is also critical to embrace relevant standards, such as guidelines, procedures, and specifications to ensure effective, safe, consistent and responsible use of AI across various situations, such as AS ISO/IEC 23894:2023 Information technology - Artificial intelligence – Guidance on risk management is followed in Australia (P&M 2023). Aligned with this argument, the MIT policy brief stresses, "The development, sale, and use of AI systems should, whenever possible, be governed by the same standards and procedures as humans" (Huttenlocher et al., 2023). Finally, AI governance also suggests exercising due consideration in procuring AI equipment to manage risks around the "black box" and ensure transparency and accountability. For example, respondent 13 (an IT expert in an investment bank) states, "AI can heighten existing risks, like those related to privacy and security. Governments need to assess whether current standard contractual clauses sufficiently address these emerging and intensified risks."

5.3 AI Literacy

AI literacy refers to the skills and knowledge that generally covers a variety of computational algorithms designed to process tasks typically associated with human intelligence, such as identifying patterns, making choices, interpreting natural language, and learning through experience (Castelvecchi, 2016; Winston, 1993, cf., Banh & Strobel 2023). Managers in modern-day organizations must have substantial knowledge of AI, and its application in various aspects of their business, organizational routines and cutting-edge skills to serve customers. AI literacy refers to understanding data, models and deployment issues related to the AI lifecycle (Bowen & Lawler 1996; Spreitzer 1996). It also refers to the ability to engage with, understand, and thoughtfully assess AI systems in core AI concepts like machine learning (ML), deep learning (DL), and algorithms, along with merits, limitations, and ethical concerns. In this context, respondent 7 (an AI expert in a consultancy firm) comments, "From programming skills to data analytics, domain knowledge, critical thinking, model development, and monitoring are critical knowledge for developing AI literacy". For example, managers need to understand AI-driven insights and conclusions (Spector, 2024). The insight can come in the form of a plausible relationship between variables of interest, whereas the conclusion can come in the form of predicting a consequence, recommending an action, clustering a group of customers based on variables, classification of customers, transformation and optimization. AI literacy includes ML and DL knowledge, which might come in the form of "symbolic logic, knowledge representation and reasoning, theorem proving, specific natural language processing techniques, alignment, robotic sensing, manipulation, and related algorithms" (Spector, 2024, p.9). The recent development of generative AI (GAI) using transformers-based neural network architecture has transformed this emerging field. GAI has allowed us to create a "generalist" AI system that can produce a variety of outputs using biometrics, natural language, simulated environments, robotics and computer vision (Vaswani et al., 2023). Thus, it is critical for managers to acquire AI literacy in the realm of GAI's foundational models that have been used in OpenAI's Generative Pretrained Transformers (GPT) series, Copilot, Github, Midjourney, Codex, Dall-E2, Amazon Q, Bard, Alpha code etc. With regard to GAI, respondent 11 (a GenAI expert in a digital startup) expresses, " …Foundation models provide a way to speed up and expand the use of generative AI, as they are theoretically adaptable to numerous fields. They can be tailored for tasks like classification, summarization, semantic search, translation and prediction".

5.4 Training and development

Organizations must offer sufficient training on tools, enhance managers' abilities to effectively utilize information, establish routines, interpret results, and make well-informed decisions (Teece 2007). For example, large language models (LLMs) consist of extensive neural networks with a vast array of connections, yet they are still minuscule compared to the human brain. "Our brains have 100 trillion connections," says Hinton (Cf., Heaven, 2023). "Large language models have up to half a trillion, a trillion at most. Yet GPT-4 knows hundreds of times more than any one person does. So maybe it's actually got a much better learning algorithm than us." (Heaven, 2023). Thus, it is critical to train managers in LLMs or GAI, specifically Generative adversarial networks (GANs), Variational autoencoders (VAE), Transformer models and Latent diffusion models with respect to bias, transparency, hallucinantions, misuse and societal impact (Banh & Strobel 2023). In our context, respondent 17 (an expert in cloud analytics) reflects, "…In the age of AI, organizations should provide practical sessions centered on widely used AI tools and frameworks such as Python, scikit-learn and TensorFlow. These sessions can include step-by-step exercises on handling datasets, setting up and executing models, and applying algorithms". In addition, mentorship and collaboration with data science teams, case studies and project-based learning, foundational workshops on data and model building and hands-on training with emerging AI tools and frameworks can help



establish competitive advantages in a volatile time (Teece 2007).

5.5 Ethical orientation

AI influences virtually every aspect of our lives, requiring many organizations to adopt and implement initiatives to establish a responsible and trustworthy AI environment. In this regard, Floridi and Cowls (2019) propose a unified framework of ethical AI containing five principles: beneficence, non-maleficence, autonomy, justice and explicability. In this framework, beneficence refers to promoting well-Being, presperving dignity, and sustaining the planet; non-maleficence refers to privacy, security and 'capability caution' of not doing any harm; autonomy indicates the power to decide or the human autonomy to decide not relying on technological artefacts; justice refers to the ability to ensure fairness, preserve solidarity promote prosperity; and finally, explicability means embracing intelligibility and accountability. For example, highlighting non-maleficence, our respondent 20 (an IT solution architect) states, " …AI should take on their responsibility by addressing the risks that come from their technological advancements." In a similar spirit, respondent 18 (an AI model developer in a retail firm) reflects on autonomy, "The concern is that the rise of artificial autonomy could threaten the development of human autonomy. Consequently, the principle of autonomy should be clearly established, indicating the necessity to strike a balance between human and machine decision-making". In a similar spirit, UNESCO (2021) proposes proportionality and do no harm, safety and security, fairness and non-discrimination, sustainability, right to privacy, and data protection, human oversight and determination, transparency and explainability, responsibility and accountability, awareness and literacy, multistakeholder and adaptive governance and collaboration in AI adoption and implementation. Drawing on Floridi and Cowls (2019), Hermann (2021) identifies the microfoudnations of AI ethical foundations and identifies explicability as the antecedent of beneficence, non-maleficence, autonomy and justice. This finding is aligned with our in-depth interview findings, in which respondent 14 (an AI expert in healthcare) states that explicability can be considered the building block for beneficence, justice, and all other principles. For example, turning AI from a black box into a glassbox, the need for intelligibility, accountability and disclousure". Consistent with other ethical frameworks, CSIRO (2019) has introduced an ethical framework of AI for Australia outlining eight core principles as follows: generates net-benefits, do not harm, regulatory and legal compliance, privacy protection, fairness, transparency and explainability, contestability and accountability. Figure 2 synthesizes the microfoundations of AI empowerment capabilities with examples.

Figure 2: AI empowerment capabilities

6. Research Propositions:

6.1 AI Empowerment capability and organizational agility

A firm's agility refers to its ability to identify uncertainties and respond to opportunities in a timely manner by addressing volatility, uncertainty, complexity and ambiguity (VUCA). Teece, Peteraf and Leih (2016, p.17) refer to agility as " the capacity of an organization to efficiently and effectively redeploy/ redirect its resources to value-creating and value protecting (and capturing) higher-yield activities as internal and external circumstances warrant." Agility varies with context, and it is a valuable organizational capacity in a changing environment. The extent of agility is dependent on a firm's DCs, which sense, seize and reconfigure internal and external competencies to tackle the VUCA environment (Teece 2007). Specifically, the microfoundations of DCs determine a firm's capacity to innovate and adapt, create value for customers and make it difficult for competitors to copy. For example, technological sophistication has empowered companies to quickly adapt to the AI environment, such as Microsoft Copilot, Salesforce's Einstein, Oracle's Crosswise and IBM's Interact (Akter et al., 2023). AI empowerment capability is an integrated dynamic capability, which includes technological sophistication, AI governance, AI literacy, training & development and ethical orientations. This viewpoint is supported by recent AI research, which has emphasized technology, data and human capabilities to develop AI capabilities (Mikalef and Gupta, 2021). According to Fountaine et al. (2019, p.64), "one of the biggest mistakes leaders make is to view AI as a plug-and-play technology with immediate returns. Deciding to get a few projects up and running, they begin investing millions in data infrastructure, AI software tools, data expertise, and model development". In order to develop a full-fledged capability for AI empowerment, organizations need to go beyond technology and embrace governance, literacy, ethics, and robust training to create an AI environment that empowers its capabilities. According to Davenport & Mittal (2023, p.118), "Because this technology is relatively new, however, no company was powered by AI a decade ago, so all those that have been successful had to accomplish the same fundamental tasks: They put people in charge of creating the AI; they rounded up the required data, talent, and monetary investments; and they moved as aggressively as possible to build capabilities". Thus, the study puts forward the proposition:

Proposition 1. AI empowerment capability improves organizational agility, which consists of technological sophistication, AI governance, AI literacy, training & development, and ethical orientations.

6.2 AI empowerment capability and firm performance

Greater uncertainty in an organizational environment demands greater organizational agility, which is supported by the microfoundations of DCs for profitability, growth, and firm performance (Teece et al., 2016). As a higher-order dynamic capability, AI empowerment capability can influence innovation, new product development, market performance and financial growth (Germann, Lilien, & Rangaswamy, 2013). Thus, we argue that a firm's AI empowerment capability will influence its profitability by achieving a return on sales, unit performance, financial sustainability and competitive advantages (Vorhies & Morgan, 2005). For example, Salesforce Einsten helps companies achieve higher returns by designing multi-channel selling processes, predicting trends, facilitating cross-selling and recommending product customizations (Akter et al., 2023). The study of firm performance using AI capability has gained traction in recent years due to the recent evidence of AI failures in many industries. In the dynamic technological environment, firm performance has become a top priority for managers as a critical metric to track financial sustainability (Fay, Feng, & Patel, 2022). Thus, we put forward the proposition:

Proposition 2. AI empowerment capability enhances firm performance, which consists of technological sophistication, AI governance, AI literacy, training & development and ethical orientations.

6.3 Organizational agility and firm performance in an AI environment

Organizational agility is identified as an immutable quality that requires firms to transform in a constant manner (Teece et al., 2016). In the age of AI, strong empowerment capabilities are required to facilitate agility, address uncertainty and enhance firm performance. Organizational agility largely depends on the microfoundations of DCs, which are flexible, adaptive and dynamic. Firms with stronger microfoundations of DCs tend to be more agile and achieve growth and competitive advantages. Microfoundations are lower-level constituent factors that explain higher-level dynamic capabilities to enhance firm performance (Eisenhardt et al., 2010). We argue that agility has a direct impact on financial performance (Zhou et al., 2019), innovation capability (Hern, 2014) and stock market performance (Schultz, 2018). Thus, we present the proposition:

P3: Organizational agility in an AI-empowered environment enhances firm performance.

7. Discussion and Implications:

7.1 Theoretical Contributions

Due to the dramatic rise of AI, AI empowerment capability has emerged as a transformative force in organizations to sense, seize and reconfigure opportunities. Our research findings answer the key research question of identifying the core dimensions of AI empowerment capabilities and framing their effects on organizational agility and firm performance. We advance the theoretical findings in several ways.

First, our findings evidence that AI empowerment capability consisting of technological sophistication, AI governance, AI literacy, training & development and ethical orientations are consistent with the extant research on AI and capabilities (e.g., Akter et al., 2023; Davenport & Mittal 2023; Mikalef & Gupta 2021). However, our findings advance this line of research, forming the five microfoundations of AI empowerment capability to influence organizational agility and firm performance.

Second, the findings also identify organizational agility as a higher-order dynamic capability, which can be achieved by AI empowerment capability. Our findings clarify the process or routines by illuminating organizational agility that addresses technological turbulence, market turbulence and customer turbulence. This is one of the few studies that uncovered AI empowerment capability and its microfoundaitons to influence organizational agility in tackling business failure or core rigidity or a firm's inability to refine and upgrade in an uncertain environment.

Finally, the AI capability theory needs to be improved to address technological failures across organizations. Recent studies on AI show a gloomy picture, as 87% of AI projects never end up in implementation (Dilmegani, 2024) and a staggering failure rate of 80% (Cooper, 2024). In addition, a significant number of AI pilot projects face insurmountable obstacles to scale up; the failure rate of AI projects is more than that of IT projects a decade ago and higher than the failure rate for new product development (Cooper et al., 2024; Knudson et al., 2023). Our findings show how to address AI failure by empowering AI capabilities using technological sophistication, AI governance, AI literacy, training & development and ethical orientations and connecting them with organizational agility and firm performance.

7.2 Managerial and Policy Implications

In order to enhance AI empowerment capability, managers should engage with various stakeholders, including scholars, industry partners, policymakers, civil society groups and global think tanks (e.g., OECD). We propose the following implications for managers and policymakers based on our research findings.

Empowering technological sophistication by developing AI infrastructure

AI infrastructure largely depends on AI computing, which is built on specialized hardware and software, as well as physical infrastructure. For example, in the 1960s, each chip used to contain around 50,000 transistors, whereas now each chip contains more than 50 billion transistors, which indicates the transition in AI infrastructure for applying new age algorithms like backpropagation or artificial neural net architecture like transformers (Davenport & Mittal 2023). In addition, specialized hardware like Tensor Processing Units, Graphics Processing Units (GPUs), and Neural Processing Units indicate the necessity of advanced AI infrastructure (OECD 2023). Furthermore, integrated circuits or computer chips are referred to as the brains of advanced AI infrastructure for data storage and logic operations, which indicates managers need to establish a sustainable supply chain for this infrastructure to address any volatility (OECD 2019). Overall, managers and policymakers need to focus on a robust cloud infrastructure for data storage, sophisticated processors for data transmission, optical computing and robotics, quantum and distributed computing capabilities and next-generation cellular networks (Wu et al., 2023).

Empowering AI governance by developing data governance guidelines

Data is the fuel for AI empowerment capability. Access to quality training data, data refinement, integration and validation is crucial for various types of AI models, including large language models. AI models rely on various sources of data, such as transaction data, clickstream data, voice data, video data, curated data and scrapped data from publicly available sources. Data governance is crucial, first, to address various data biases that might stem from inadequate data, non-representative samples or deep-rooted social biases embedded in the training dataset (Akter et al., 2023). Second, from a data privacy perspective, data governance can help protect personally identifiable information or copyright materials. Third, by embracing corporate digital responsibility (Lobschat et al., 2021; Wirtz et al., 2023), managers can reduce the risk of malleable AI systems, which can be at risk of exploitation for unintended purposes. Our findings suggest using privacy-enhancing technologies (e.g., security safeguards, data use limitation or data minimization) or confidential computing methods in hosting or accessing data using

various encryption techniques (O'Brien 2020). Third, cybercriminals launch complex attacks daily, and the arrival of generative AI significantly amplifies their capabilities. With generative AI, criminals can impersonate individuals via email and phone calls, making it easier to access sensitive information (Okta, 2024). Fourth, data governance can also help protect an organization from misinformation or disinformation, which has risen in recent years due to the proliferation of AI bots. Finally, the vast amount of data used in building modern AI models depends largely on the English language, which is more than 50% of all other languages. This could limit the benefits for various linguistic groups or minority languages, which could potentially create a diversity and inclusion gap (OECD 2024). Therefore, our research findings propose to address the abovementioned data governance issues and policies in developing AI governance policies by organizations and countries.

Empowering AI literacy by developing skills and knowledge

Since Alan Turing's first question, "can machine think" in 1950, AI has gone through various rounds of evolution, including symbolic AI in 1956, AI winter in the 1970s, the Hopfield network and Boltzmann machine in the 1980s, chess-playing computer deep blue in 1990s, machine learning based predictions in early 2000 and multi-layer neural nets in the last decade. We have very recently witnessed the emergence of generative AI in late 2022, which has completely transformed our notion of AI by creating novel content in the form of text, images, code and video in response to prompts (Davenport & Mittal, 2023). In order to empower AI literacy, managers and policymakers need to understand basic AI production systems (algorithms, data and computing resources), terminologies (OECD 2023) and corporate digital responsibility (Lobschat et al., 2021; Wirtz et al., 2023). Whereas the production system focuses on linking data, algorithms and computing power, the terminologies refer to various types of machine learning and deep learning models. For example, a foundational model used in developing modern-day generative AI (e.g., OpenAI's Generative Pretrained Transformers (GPT) series) that is trained on large amounts of data using self-supervision at scale to produce various customized outputs, such as text or image (Bommasani et al., 2021). This development also requires managers and policymakers to know various language models, which may not be generative in nature but are used in virtual assistants, machine translation, and chatbots (OECD 2023). Furthermore, neural networks and deep learning have evolved as fundamental branches of machine learning that are able to learn and adapt without explicit instructions through pattern recognition using algorithms and statistical models (Akter et al., 2022).

Empowering AI talent through training and development

The findings of our research show that AI models vary in size, context and application. More or less, most AI models are trained on billions of data points that can be adapted to various types of tasks. It has become apparent that AI models have shifted from task-specific models to more general foundational models. However, training these models requires specialized AI talent. With the help of the right talent, foundational models can be adapted, fine-tuned and deployed to various contexts with limited resources (Dunlop, Moës and Küspert, 2023). Since foundational models do not require large datasets or computing power, AI developers can use them to enhance their AI empowerment capabilities. However, due to the black box nature of these models and the control of these models by large corporations, it is often hard to fathom the quality of data or modelling techniques, which might result in biases and exploitation. It has also become a challenge for policymakers and managers to address these challenges to create a level playing field for both startups and tech giants in AI implementation. As part of training and development, recent reports show that the European Union has invested EUR 1 billion per year in AI, including R&D, within the broader EUR 100 billion budget for the Horizon Europe and Digital Europe programmes (European Commission, 2023). Similarly, USD 1.7-5.7 billion was invested by China in 2018, USD 2 billion was invested by USA in 2023, Turkey invested

USD 50 million in academic research and USD 150 million in industrial research in 2023 and Australia invested USD 124 million in 2021 (OECD 2024). Thus, training and development are going to be key empowerment capabilities in the landscape of AI adoption and use.

Table 3: A synthesis of research findings and implications

Research Question	Research Findings	Practical and Policy Implications
What are the dimensions of AI empowerment capabilities and their overall effects on organizational agility and firm performance?	**Technological sophistication:** Handling massive data volumes, tackling complexity in model building, scaling, and deployment (e.g., ML or DL-based models using transformer-based technologies) and optimizing resource use.	Organizations should focus on installing specialized hardware such as integrated circuits or computer chips, e Tensor Processing Units, Graphics Processing Units (GPUs), and Neural Processing Units indicate the necessity of advanced AI infrastructure.
	AI governance: Managing risks across the AI lifecycle, such as phase 1 (design, data, and models), phase 2 (verification and validation), phase 3 (deployment) and phase 4 (operation and monitoring).	Managers should develop AI governance framework to protect data privacy, data security, data bias, model bias and deployment bias, misinformation, or disinformation.
	AI Literacy: the ability to engage with, understand, and thoughtfully assess AI systems in core AI concepts like machine learning (ML), deep learning (DL), and algorithms, along with merits, limitations, and ethical concerns.	Managers and policymakers need to understand basic AI production systems (algorithms, data and computing resources) as well as terminologies. For example, linking data, algorithms, and computing power as well as terminologies like machine learning, large language models, deep learning, transformers etc.
	Training and development: Training managers in LLMs or GAI, specifically Generative adversarial networks (GANs), Variational autoencoders (VAE), Transformer models and Latent diffusion models with respect to bias, transparency, hallucinations, misuse, and societal impact.	Managers should focus on developing specialised talent embracing equity, diversity and inclusion, R&D investment. With the help of the right talent, AI models can be adapted, fine-tuned, and deployed to various contexts with limited resources.
	Ethical orientation: Embracing five principles of an ethical AI framework: beneficence, non-maleficence, autonomy, justice, and explicability.	Managers and policymakers should consult with UNESCO's 2021 recommendation on the ethics of AI, Global Partnership on AI (GPAI), Globalpolicy.ai, OECD AI principles and AI legal instrument by the Council of Europe (Council of Europe, 2023).

Empowering responsible and trustworthy AI by embracing ethical orientations

The findings of our research recommend developing and deploying an AI model that embraces beneficence, non-maleficence, autonomy, justice and explicability. A responsible and trustworthy AI is a force for good, which can be achieved through continuous dialogue and collaboration between academia, industry, policymakers and community. Using interdisciplinary theories, a socio-technical perspective is critical to developing a human-centric, responsible, and inclusive AI to address the needs of our community. By embracing corporate digital responsibility (Lobschat et al., 2021; Wirtz et al., 2023), policymakers can engage in broader consultations to protect fundamental human rights and prevent high-risk use of AI (e.g., deepfakes). Due to the nature of AI business models, developers often restrict information disclosure, which results in complex processes and outcomes. Thus, policies at both national and international levels are critical to transforming the black-box nature of AI into a glass box that will be transparent, explainable and beneficial to users. In this regard, managers and policymakers can consult with UNESCO's 2021 Recommendation on the Ethics of AI (UNESCO, 2022), a multistakeholder initiative called The Global Partnership on AI (GPAI) (GPAI, 2023), a coalition of various government organizations known as Globalpolicy.ai (GlobalPolicy.ai, 2023), OECD AI principles (OECD.AI, 2024) and AI legal instrument by the Council of Europe to protect human rights (Council of Europe, 2023).

8. Limitations and future research directions:

Due to the cross-sectional nature of the study, the study has some inherent limitations with regard to the findings on context and generalizability. Future research can collect data in a longitudinal manner to provide more in-depth findings in the research context. Although the current study provides a solid conceptual framework for AI empowerment capability, future research can validate the conceptual model using both qualitative and quantitative data. Future studies can also increase the sample size and collect data from multiple countries, including developed and developing ones, for robust generalization of the research findings. Future studies can also use experimental design to test the effects of AIEC in small, medium and large firm contexts. Future studies can also focus on a particular type of AI (e.g., ML, DL, LLM) and measure its effects on various individual (e.g., customer satisfaction, engagement, customer lifetime value), organizational (e.g., agility, firm performance, return on investment etc.) and social (e.g., quality of life) outcomes. Future studies can also investigate the possibility of formative vs reflective conceptual modeling for empirical studies using the lens of dimensions vs antecedents.

9. Conclusions:

AI has evolved significantly since the 1950s, and its dramatic rise in recent years has started transforming various nations and economies. We are at the crossroads of the fourth industrial revolution, which is ushered by new age technologies such as, AI, Blockchain, cloud, Internet of Things, robotics and data analytics (Akter et al., 2022). It is predicted that the fourth industrial revolution will have the shortest adoption cycle compared with the first industrial revolution of the steam engine, the second revolution of electricity and the third revolution of information (Cooper, 2024). Although AI promises to enhance productivity and wellbeing by addressing the world's grand challenges (e.g., poverty, healthcare, gender equity, innovation, climate actions, etc.), the microfoundations of its empowerment capabilities did not receive enough attention. Hence, this study answers the critical research question of how AI will herald the fourth industrial revolution through its dynamic capabilities by sensing, seizing and reconfiguring organizations. To answer this question, the findings of the study present technological sophistication, AI governance, AI literacy, training & development and ethical orientations as critical microfoundations of AI empowerment capabilities and build their overall connection with organizational agility and firm performance.

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الأسس الدقيقة للقدرة على تمكين الذكاء الاصطناعي لتحويل المؤسسات

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المستخلص:

لقد أثار التقدم في مجال الذكاء الاصطناعي قلقًا ملحوظًا في كيفية تمكين قدراتِه لتحقيق الفوائد المرجوة ومعالجة التحديات المُصاحِبة له. لا تزال المعرفة محدودة بشأن كيفية تشغيل قدرات تمكين الذكاء الاصطناعي وتأثيراتها في المؤسسات. ومن خلال الاستناد إلى الأسس الجزئية لنظرية القدرة الديناميكية؛ تسعى هذه الدراسة إلى سَدِّ هذه الفجوة البحثية من خلال تقديم نموذج لقدرة تمكين الذكاء الاصطناعي وتأثيراته في المرونة التنظيمية والأداء المؤسسي. ومن خلال مراجعة منهجية للأدبيات، والتحليل الموضوعي، وإجراء مقابلات مُعمَّقة مع 20 خبيرًا في الذكاء الاصطناعي في أستراليا؛ تُقدِّم هذه الدراسة رُؤًى نظرية وتوجيهات إدارية وتوصيات لوضع السياسات. وتكشف النتائج أنَّ التطور التكنولوجي وحوكمة الذكاء الاصطناعي والوعي بالذكاء الاصطناعي والتدريب والتطوير والتوجه الأخلاقي؛ تُعَدُّ من الأبعاد الأساسية لقدرة تمكين الذكاء الاصطناعي.

الكلمات المفتاحية:

قدرة تمكين الذكاء الاصطناعي، المرونة التنظيمية، الأداء المؤسسي، مناخ الذكاء الاصطناعي المسؤول.

الأسس الدقيقة
لقدرة تمكين
الذكاء الاصطناعي
لتحويل المؤسسات