From Tool to Capability

How Organizations Build Sustained Strategic Advantage with Artificial Intelligence

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Abstract:

This study tests whether dynamic capability processes mediate the relationship between AI-specific resources and AI capability maturity. A structural model is estimated using PLS-SEM with cross-sectional survey data from 46 senior professionals across industries. Of three resource categories, tangible resources show a significant positive path to dynamic capability processes; human and intangible resources are positive in the predicted direction but do not reach the conventional significance threshold. A mediation pattern is supported for tangible resources, with the evidence treated as exploratory. Discriminant validity limitations between the process and outcome constructs qualify the magnitude of the findings. The results provide preliminary evidence that AI capability development runs through organizational processes rather than through resource accumulation alone, with tangible resources operating as the most clearly supported precondition for those processes.

Keywords:
Artificial intelligence, dynamic capabilities, AI capability maturity, organizational resources, PLS-SEM, mediation

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Definitions

Artificial Intelligence (AI)	Computational systems that learn from data and can act, adapt, and produce outputs without continuous human direction.
Dynamic capabilities	A firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments.
Sensing	Identifying and evaluating opportunities and threats in the firm's environment.
Seizing	Mobilising resources to act on identified opportunities.
Transforming	Renewing the resource base by realigning structure, culture, and existing capabilities.
Digital transformation	An ongoing process of strategic renewal that uses digital technologies to refresh or replace an organisation's business model, collaborative approach, and culture.
AI capability	A firm's ability to select, orchestrate, and leverage its AI-specific resources.
AI capability maturity	The degree to which AI is embedded in core processes, deployed consistently across the organisation, and generates sustained value beyond pilot projects.
Tangible AI resources	Material inputs supporting AI work, including data infrastructure, computing capacity, and dedicated funding.
Human AI resources	Employee skills relevant to AI, including technical expertise, business judgment, and talent management.
Intangible AI resources	Organisational qualities supporting AI, including cross-departmental coordination, change capacity, risk tolerance, and strategic alignment.
AI readiness	The state in which an organisation has the data, skills, culture, and governance needed to support AI adoption.
AI governance	The structures, roles, and processes through which an organisation directs and controls AI use, including accountability and ethical guidelines.
Knowledge-intensive organisation	A firm where expert knowledge is the primary asset and authority is distributed among specialists rather than concentrated in formal hierarchy.

Statistical and methodological terms

PLS-SEM	Partial least squares structural equation modelling; a variance-based method for estimating relationships between multiple constructs, suited to mediation analysis and smaller samples.
Construct (latent variable)	An unobservable concept (e.g., AI capability) measured indirectly through multiple observable indicators.
Reflective measurement	A specification where the construct causes its indicators; the indicators are interchangeable reflections of the same underlying concept.
Formative measurement	A specification where the indicators jointly compose the construct; each indicator captures a distinct aspect.
Higher-order construct	A construct measured indirectly through lower-order dimensions rather than directly through items.
Path coefficient (β)	The estimated strength and direction of the relationship between two constructs in the structural model.
R^2	The proportion of variance in a dependent construct explained by its predictors.
f^2 (effect size)	The change in R^2 when a single predictor is removed from the model; benchmarks are 0.02 (small), 0.15 (medium), 0.35 (large).
Outer loading	The correlation between a reflective indicator and its construct; values ≥ 0.708 are preferred.
Cronbach 's alpha	A measure of internal consistency reliability across a construct's indicators; values ≥ 0.70 are acceptable.
Composite reliability	An alternative reliability measure that does not assume equal indicator loadings; values ≥ 0.70 are acceptable.
Average variance extracted (AVE)	The average proportion of indicator variance captured by a construct; AVE $\geq$ 0.50 indicates adequate convergent validity.
Heterotrait–monotrait ratio (HTMT)	A test of discriminant validity; values below 0.90 indicate that two constructs are sufficiently distinct.
Variance inflation factor (VIF)	A measure of collinearity between predictors; values below 5.0 indicate acceptable collinearity.
Bootstrapping	A resampling technique that draws repeated subsamples from the data to estimate the statistical significance of model parameters.

Mediation	A relationship in which one variable affects another through an intervening variable rather than directly.
Indirect effect	The portion of a relationship transmitted through one or more mediating variables; calculated as the product of the component path coefficients.
Common method bias	Variance attributable to the measurement method rather than the constructs being measured; a concern when all data come from a single respondent.
Cross-sectional design	A research design that collects data at a single point in time, limiting causal inference.

1. Introduction

1.1 Background: AI as an Organizational Challenge

Artificial intelligence appears to be reshaping how organizations create value, reach decisions, and position themselves competitively (Enholm et al., 2022). However, does the promise outrun the payoff? A systematic review of 43 studies finds that realizing AI capability requires employee skills, sound data governance, executive commitment, and cultural readiness rather than technology on its own (Enholm et al., 2022). Practitioner surveys tell us a similar story, that most large organisations have launched some sort of AI initiatives, but few seem to have transformed AI from a tool to a systematic capability (Fountaine et al., 2019).

Part of the challenge may lie in the distinct characteristics of AI, which differentiate its implementation from more conventional forms of technological adoption (Faraj et al., 2018; Stelmaszak et al., 2025). If access to AI technologies is becoming increasingly widespread, why do some organizations succeed in developing AI capability while others struggle to realize meaningful value?

1.2 Problem: The Resource-Capability Gap

For AI implementation to become a lasting organizational investment, it must be understood as an organizational challenge rather than merely a technical one. (Mikalef & Gupta, 2021). As pre-trained models become increasingly accessible on a quarterly basis, competitive differences among firms are progressively determined by their ability to adopt and customize AI tools in ways that develop coherent organizational capabilities (Mikalef & Gupta, 2021). Empirical studies reinforce this: for big data analytics, the link between technology-based resources and competitive performance appears to be fully mediated by dynamic organizational processes rather than operating directly (Mikalef, Krogstie, et al., 2020). AI readiness research paints a compatible picture, suggesting that readiness and adoption reinforce each other and that organizations build the readiness larger-scale deployment demands through incremental adoption (Jöhnk et al., 2021). Transforming AI tools to AI capability therefore appears to be a question of resource orchestration and dynamic processes, not of technology acquisition.

1.3 Contextual Conditions Around AI Capability Building

The way resources and processes work together isn't the same in every organization. For knowledge intensive firms the standards are different, they face unique conditions including dispersed authority, non-replicable domain knowledge, and innovation that requires conversion rather than top-down mandates (Anand et al., 2007; Sjödin et al., 2021). AI governance further raises questions about accountability and decision rights that standard implementation routines do not resolve (Mäntymäki et al., 2022; Papagiannidis et al., 2023). These conditions are entered in the study as context for implementation functioning as a mediation mechanism, not as tested moderators.

1.4 The Gap

Prior research has made great progress in identifying what matters for making AI a strategic capability: tangible, human, and intangible resources (Mikalef & Gupta, 2021), governance structures (Papagiannidis et al., 2023), organizational readiness (Jöhnk et al., 2021), and firm context (Anand et al., 2007). For big data analytics, the mediation finding is established: dynamic capabilities fully mediate the link from technology resources to competitive performance (Mikalef, Krogstie, et al., 2020). However, two problems persist;

First, this mediation has not been tested for AI capability specifically, despite the fact that AI's distinctive properties make the process dimension potentially more consequential than for earlier technologies.

Second, none of the examined studies have tested the full link from AI resources, through how organizations use them, to how strong their AI capability becomes, all in one model. If AI works differently, then AI investments are effectively based on what hasn't been properly tested.

1.5 Purpose and Research Question

The Dynamic capabilities theory developed by Teece, Pisano, and Shuen (1997) has been proven through literature to be a useful and effective tool for understanding how organizations turn resources (in general, not necessarily technical) to strategic capabilities. It separates what a company has (its resources) from how it uses them (its processes). Further, it states that long-term success is not only about having resources but rather how well a firm combines, develops, and changes them over time. In digital settings, these processes are usually described as noticing changes in the environment, taking action on opportunities by committing resources, and reshaping existing assets (Warner & Wäger, 2019).

Research on related technologies, particularly big data analytics, suggests that dynamic capability processes play a key role in translating organizational resources into stronger performance outcomes (Mikalef, Krogstie, et al., 2020). Whether the same logic applies to AI, however, remains unclear. Unlike earlier digital technologies, AI possesses distinct characteristics that may fundamentally reshape how organizations convert resources into actual capability.

Deriving from this gap, the purpose of this thesis is to build and test a model that explains how AI capability develops in organizations. The model looks at how AI resources (such as tools, people skills, and other assets) connect to key organizational processes (sensing changes, taking action, and making changes), and how these together lead to stronger AI capability. The study uses survey data from 46 senior professionals in different industries where AI tools are actively being transformed to strategic capabilities.

Against this background, and given the unresolved question of how AI-specific resources translate into capability, the thesis addresses the following research question:

To what extent do dynamic capability processes mediate the development of organizational AI capability from AI-specific resources?

2. Literature Review

2.1 AI and Digital Transformation

AI differentiates itself from earlier arising technologies mainly in four respects. Firstly, AI algorithms have a *learning capacity*. Meaning that they adapt through data in ways their designers never fully specified (Faraj et al., 2018; Stelmaszak et al., 2025). Secondly, their output is not always intuitive and often difficult to derive (*opacity*), even the developers of the AI often have a hard time explaining their output (Faraj et al., 2018). Thirdly, AI is *autonomous*, meaning that they can act without continuous human direction (Raisch & Krakowski, 2021). Lastly, AI can surface patterns that no one explicitly programmed (*generativity*) (Stelmaszak et al., 2025).

These properties place AI in the broader category of digital transformation. Warner and Wäger (2019, p. 326) defined digital transformation as *"an ongoing process of strategic renewal that uses advances in digital technologies to build capabilities that refresh or replace an organization's business model, collaborative approach, and culture."* AI is nonetheless distinct from earlier digitalization waves. It is crucial how an organisation deploys new technology not merely that they do it, the technologies themselves deliver little value (Vial, 2019).

These characteristics hold significant implications on the resource-capability relationship. When it comes to big data tools, they operate within certain paradigms once they are deployed, this is not the case with AI. AI systems operate often in uncertainty: the output shifts when the model retrains and makes new algorithms and systems, and are hard to explain (Faraj et al., 2018; Stelmaszak et al., 2025) The organizational processes required to manage AI may therefore differ qualitatively from those sufficient for earlier technologies, and whether the mediation pathway demonstrated for big data analytics (Mikalef, Krogstie, et al., 2020) holds for AI cannot be assumed.

2.2 AI Capability and Resource Architecture

2.2.1 What Constitutes AI Capability: Resource Taxonomies and Construct Definition

Mikalef and Gupta (2021) use Bharadwaj's (2000) way of grouping IT capabilities to explain AI capability. They say AI capability is made up of three main parts: physical resources (like tools and data), human resources (people and their skills), and intangible resources (things like knowledge and organizational culture). Taken together, these form *"the ability of a firm to select, orchestrate, and leverage its AI-specific resources"* (Mikalef & Gupta, 2021).

Tangible resources, including data, computing infrastructure, and technical platforms, are the material preconditions for any AI initiative. Enholm et al. (2022) found that the quality of data is the key enabler in the effective implementation of AI capability. Tangible resources are, however, comparatively easy to acquire, which limits their potential as a source of differentiation (Mikalef & Gupta, 2021).

Human resources connect what technology can do with what the organization actually needs. This includes both technical skills and understanding of the business. Sjödin et al. (2021) found that knowledge about a specific industry is hard to copy, and that outsourcing things like algorithm development without this understanding often doesn't work well.

Intangible resources are generally more abstract, such as cross-departmental coordination and willingness and capacity for change in an organisation. These at the same time are the hardest to replicate and therefore become particularly important (Mikalef & Gupta, 2021). They make the alignment, learning, and reconfiguration processes possible through which AI becomes embedded in organizational routines.

Each type of resource is important, but none of them is enough on its own. Mikalef et al. (2020) showed that in big data analytics, resources only improve performance through how organizations use them (their processes), not directly. But we still don't know if all these resource types matter in the same way for AI, since AI may require different things when it comes to data, human judgment, and coordination within the organization.

2.2.2 AI Readiness and Organizational Preconditions

Readiness and adoption develop together, not step by step. Jöhnk et al. (2021) show that organizations need to start using AI little by little to build the readiness needed for bigger use later. Holmström (2022) found that the technology is often ready before the organization is. This means the main limitation is the organization, not the technology. If that is the case, then how the organization uses and manages its resources becomes the most important factor for building AI capability.

2.2.3 From Tool to Capability: The Entity-Capability Distinction

There is a debate in AI research. Should AI be seen as just a tool, or as something that grows into a broader capability in an organization? The first view sees AI as something you can measure, built from different types of resources.(Mikalef & Gupta, 2021). Stelmaszak et al. (2025) challenged this framing, defining AI as *"a connective, codependent, and emergent capability of a system of relations, among human and algorithmic actors"* that *"cannot merely be imported, automated, or 'plugged in' via algorithms, it must be continually produced."* Hillebrand et al. (2025) support this idea and show that AI becomes part of how an organization works through a process called institutionalization, meaning it gets built into everyday activities and routines.

None of the views seem to disqualify the other, rather both views have merit. The first view helps us measure AI, while the second helps us understand how it develops over time. Raisch and Krakowski (2021) found that success in the long-term comes from how people and AI work well together, in a cooperative way, not from just using AI alone. Lebovitz et al. (2022) showed that people get better results when they question and check AI outputs instead of just trusting them. These findings suggest that AI capability is something that is constantly being developed through how an organization works, not something fixed. If that is the case, then the processes that connect resources to capability are the most important thing to study.

2.3 AI Governance as Organizational Complement

Now, AI is going beyond pilot programmes and organisations are rushing to be at the forefront of the new technology development. This comes with the need of rules and structures (governance) that help them use AI while also controlling risks (Mäntymäki et al., 2022). Birkstedt et al. (2023) dug into 68 studies and through this process found that only three had real data, which suggests that most research on this topic is still theoretical. Papagiannidis et al. (2023) showed that governance needs to keep changing over time, and Mikalef et al. (2020) found that good data governance helps link big data capabilities to innovation. In this study, governance maturity is only used to help understand the results, not to test its direct effect. It is still unclear how governance affects the link between resources and AI capability, and this should be studied in future research with larger samples.

2.4 Knowledge-Intensive Organizations

Knowledge-intensive organizations are companies where expert knowledge is the most important asset, and decision-making is shared among specialists instead of being controlled only by managers (Anand et al., 2007). Industry specific knowledge is important for building AI capability in the particular domain and at the same time it is hard for other organisations to copy because of the lack of the specialized knowledge (Sjödin et al., 2021). This means that how resources turn into results may work differently in these types of organizations compared to companies where knowledge is more standardized. In this study, the direct effect of knowledge intensity will not be tested, it will only be used to describe the context.

2.5 Summary and Research Gap

Studies closest to the present research

Three studies are the closest to this topic. Mikalef et al. (2020) found that for big data analytics, dynamic capabilities fully explain how resources lead to performance, using survey data and PLS-SEM (N = 202), but their study was not about AI rather it was about big data as mentioned. Warner and Wäger (2019) described how organizations sense, seize, and transform during digital change, but they did not test these relationships with data. Tavoletti et al. (2022) looked at knowledge-intensive companies going through technology change, but they did not use a dynamic capabilities framework.

The research gap

These studies leave a gap along three lines. *Theoretically*, the mediating role of dynamic capabilities has been demonstrated for big data analytics (Mikalef, Krogstie, et al., 2020) and conceptualized for digital transformation (Warner & Wäger, 2019), but not tested for AI capability specifically, despite AI's distinctive properties as priorly discussed. *Empirically,* no quantitative study has tested the full link from AI resources, through organizational processes, to AI capability. This is surprising because we already have strong academic interest in big data research, and companies are investing heavily in AI. *Contextually*, factors like governance and how knowledge-based a company is seem important in theory, but they have not yet, to the authors knowledge, been included as background context in a full statistical test of how AI capability develops.

Purpose of the present study

This thesis builds and tests a model that explains how AI capability develops. The model focuses on whether dynamic capability processes act as the link between AI resources and AI capability maturity (mediator). Dynamic capabilities theory is suitable for this because it separates what an organization has (resources) from how it uses them (processes) (Teece et al., 1997). This fits with earlier findings in big data research, where similar processes explained how resources lead to results (Mikalef, Krogstie, et al., 2020). The next chapter turns this idea into a clear model and develops the hypotheses that will be tested.

3. Theoretical Framework

3.1 The Dynamic Capabilities Framework

3.1.1 Origins and definition

The resource-based view is a key idea in strategy that explains why some combinations of resources can give a company an advantage. However, it does not clearly explain how companies should change or adjust those resources when conditions change. To address this, Teece, Pisano, and Shuen (1997) introduced the idea of dynamic capabilities. They define this as *"the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments"*. Their main idea is that long-term success does not come from resources alone, but from how organizations manage and use them. They also argue that capabilities *"typically must be built because they cannot be bought"*. If that logic extends to AI, then AI-specific resources should produce AI capability maturity only through organizational processes.

3.1.2 The sensing-seizing-transforming framework

Teece (2018) refined the framework into three capability clusters. *Sensing* refers to identifying and evaluating opportunities and threats through scanning, learning, and interpretation. *Seizing* involves mobilizing resources toward those identified opportunities. *Transforming* concerns the ongoing renewal of the resource base by realigning structure, culture, and existing capabilities (Teece et al., 1997; Teece, 2018).

These three parts are different, but they are closely connected. If an organization only senses opportunities but does not invest resources, the knowledge is wasted. If it seizes opportunities but does not change how the organization works, the benefits do not last long. For AI, this connection is even more important. Because AI is uncertain and keeps changing, organizations need to constantly go through all three steps together (Raisch & Krakowski, 2021; Stelmaszak et al., 2025).

3.1.3 Microfoundations for digital contexts

Warner and Wäger (2019) operationalized the framework for digital transformation, identifying nine microfoundations (three per criteria) through a qualitative study of seven industrial firms.

Under *sensing*, these include digital scouting and scenario planning; under *seizing*, strategic agility and rapid prototyping; and under *transforming*, structural redesign and maturity improvement. This framework still acts as the mostly in depth analysis of the dynamic capabilities framework into plausible activities for technology-driven transformation, and the present study adopts it as the primary reference for operationalizing the three process clusters.

3.2 Hypothesis Development

The hypotheses below are based on the framework in Section 3.1 and the research reviewed in Chapter 2. Three hypotheses (H1a, H1b, H1c) examine the resource-to-process paths for tangible, human, and intangible resources respectively. These direct relationships are needed to test the main idea about mediation, which is presented in H2.

3.2.1 Tangible AI resources and dynamic capability processes

Dynamic capabilities theory says that resources only lead to strong results when organizations actively use and manage them through processes like integrating, building, and reconfiguring them (Teece et al., 1997). For tangible resources, Mikalef and Gupta (2021) explain that things like data systems, computing power, and funding are the basic foundation for AI capability. Without these, the more advanced parts of AI cannot work properly. Enholm et al. (2022) found that good-quality data is especially important for AI success. Jöhnk et al. (2021) also show that having mature and well-prepared data systems is part of being ready to use AI in an organization.

There is another way to understand this literature. Mikalef and Gupta (2021) argue that tangible resources are relatively easy for firms to obtain, which means they are unlikely to create lasting competitive advantage on their own, suggesting their effect on outcomes may depend on how they are used in organizational processes rather than having a direct impact. This is supported by big data research, where Mikalef et al. (2020) found that the link between technology resources and competitive performance was fully mediated by dynamic capability processes, with no significant direct path. However, it is still unclear whether this same pattern applies to AI, even though AI systems are more complex than earlier analytics tools due to their learning ability, lack of transparency, and capacity to generate new outputs (Faraj et al., 2018; Stelmaszak et al., 2025), which likely place even greater demands on data and infrastructure.

In the AI context, tangible resources seem to be the basic foundation that sensing, seizing, and transforming processes rely on. Sensing needs data and computing power to detect opportunities in the AI environment. Seizing needs infrastructure and funding to run small tests and scale useful solutions. Transforming needs data and computing resources to keep updating systems as AI models are retrained. Based on this, we establish the following hypothesis:

H1a: *Tangible AI resources are positively associated with dynamic capability processes.*

3.2.2 Human AI resources and dynamic capability processes

Human resources for AI include technical skills, business understanding, and domain knowledge (Mikalef & Gupta, 2021). Theory suggests that people contribute to results mainly through the actions they make possible (Teece et al., 1997). Skilled employees help spot opportunities, put resources into action, and change how work is done in ways that resources on their own cannot.

Prior research highlights how important human resources are as a link between technology and results. Sjödin et al. (2021) found that when AI development is outsourced to providers without industry knowledge, it often does not lead to useful business results. Mikalef and Gupta (2021) also emphasize the fact that human resources are needed to turn basic technical inputs into real, useful applications within organizations. AI is especially challenging because it is often hard to understand how it produces its outputs (Faraj et al., 2018), so people must interpret results they cannot fully explain. Lebovitz et al. (2022) show that how people interact with AI matters a lot, since professionals who question and critically evaluate AI outputs get better results than those who simply accept them. This makes it difficult to argue that human resources alone lead directly to capability without being used through organizational processes.

This suggests that human resources work through organizational processes rather than having a direct effect. Domain experts with both business and technical knowledge help shape seizing decisions, meaning identifying which opportunities are realistic and deciding which AI projects should be scaled up, and adjust work routines once AI is in use. Without these processes being activated, skills and knowledge tend to remain unused. Based on this reasoning we establish the next hypothesis:

H1b: *Human AI resources are positively associated with dynamic capability processes.*

3.2.3 Intangible AI resources and dynamic capability processes

Intangible resources for AI include how well different departments work together, how capable the organization is at handling change, how willing it is to take risks, and how well its strategy is aligned (Mikalef & Gupta, 2021). Theory says these are the most important type of resources because they determine how well a company combines and changes its other resources (Mikalef & Gupta, 2021; Teece et al., 1997). At the same time, they are also the hardest to get from outside the organization.

Prior research shows that AI work usually involves many parts of the organization. Enholm et al. (2022) explain that AI projects often go across departments, meaning they need coordination between data teams, IT, business units, and risk management. Holmström (2022) and Jöhnk et al. (2021) found that organizations are often not ready internally even when the technology is ready, and that the main limits come from coordination, culture, and the ability to handle change rather than from the technology itself. AI's autonomy and generative ability (Raisch & Krakowski, 2021; Stelmaszak et al., 2025) make this challenge even stronger because AI can produce results that no one directly programmed. This means organizations need to be willing to experiment, adjust their approach, and share decision-making even when things are uncertain.

In the AI context, intangible resources seem to operate discretely through the organizational processes. Here, they notice functions that no single department would notice independently. This makes decisions where different departments share responsibility for risk, and change roles and structures when AI is introduced. Without these kinds of intangible foundations, the same technical resources often only lead to small experiments that do not develop into fully working systems. On the back of the aforementioned, the following hypothesis is established:

H1c: *Intangible AI resources are positively associated with dynamic capability processes.*

3.2.4 Mediation by dynamic capability processes

The three direct relationships discussed above lead to the main question of this study: whether the link between resources and AI capability works through organizational processes rather than directly. Dynamic capabilities theory says that resources on their own do not lead to strong results; they need to be actively used and managed through processes that build, combine, and change them (Teece et al., 1997). The strongest similar evidence comes from big data research, where Mikalef et al. (2020) showed that resources only improved performance through these processes, and not directly, in a study with 202 observations.

Several features of AI make it even more likely that this process-based explanation applies here, perhaps even more accurately. First, AI capability is not something a company simply gets once and has; it is something that is continuously developed through how people and algorithms work together (Faraj et al., 2018; Stelmaszak et al., 2025). This means that the processes used to build the capability are part of the capability itself, and resources cannot turn into real capability without these processes. Second, AI readiness and adoption develop together over time, not step by step (Jöhnk et al., 2021). Organizations build the readiness they need by starting small and gradually expanding, which makes how they manage this process very important. Third, research shows that organizations are often less prepared than the technology itself (Holmström, 2022), suggesting that the main gap between having resources and achieving capability lies in how the organization works, not in the technology.

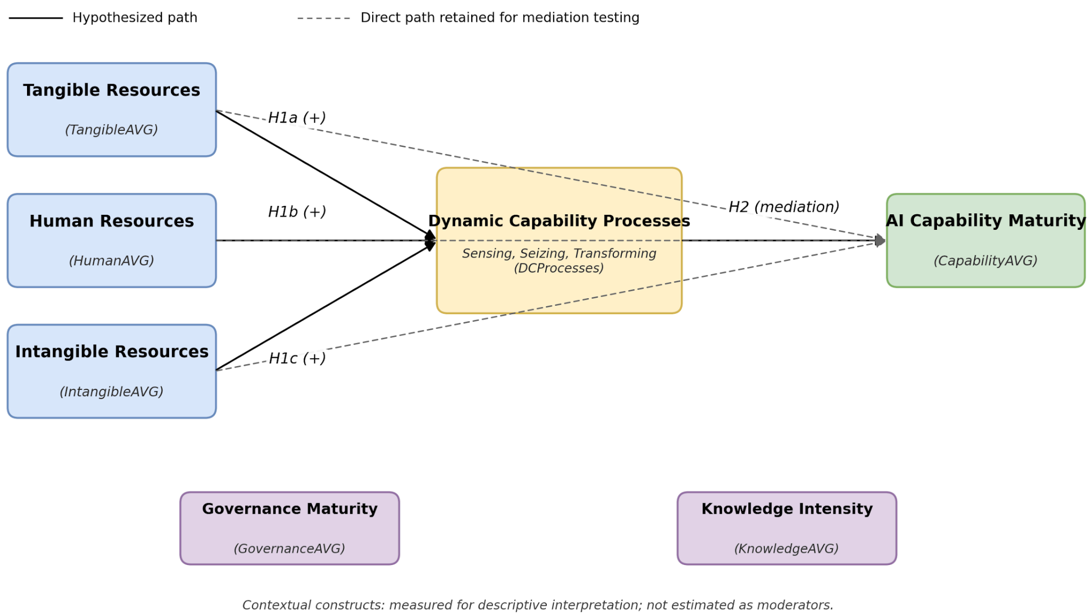
There is another way of observing this, if tangible resources are enough on their own, then they might translate into capability through routine deployment without requiring sustained sensing, seizing, or transforming activity. However, research on big data analytics does not support this idea (Mikalef, Krogstie, et al., 2020), and the specific features of AI suggest that the need for these processes is at least as strong, and possibly even stronger. Based on this reasoning:

H2: *Dynamic capability processes (sensing, seizing, and transforming) mediate the relationship between AI-specific resources and AI capability maturity.*

3.3 Conceptual Model

Figure 3.1 shows the model used in this study, based on the four hypotheses. AI resources are the starting point, dynamic capability processes, which include sensing, seizing, and transforming, act as the link in between, and AI capability maturity is the final outcome. Helfat and Peteraf (2003) explain that operational capabilities are the routines that produce results, while dynamic capabilities are the processes that build and change those routines. In this model, AI capability maturity is the outcome at the operational level, while sensing, seizing, and transforming are the processes that create it. Direct links from resources to capability are also included so mediation can be tested. Governance maturity and knowledge intensity are only used to help understand the results, not to test their direct effects.

Figure 3.1 shows the model of how AI capability develops. AI-specific resources (tangible, human, intangible) feed into dynamic capability processes (sensing, seizing, transforming), which translate into AI capability maturity. Direct links from resources to capability are also included to test whether this relationship is mediated. Governance maturity and knowledge intensity are only used to describe the context and are not tested as moderators.



The next chapter describes how these hypotheses are operationalized and tested.

4. Method

4.1 Research Philosophy

This study uses a positivist approach which means that it focuses on items that can be observed and measured (Saunders et al., 2023) and it uses hypothesis testing to build the knowledge. The research question looks at how strong and important the relationships are between different concepts in the model, which makes this approach a good fit (Saunders et al., 2023).

4.2 Research Approach

Furthermore, this study also uses a deductive approach (Saunders et al., 2023). This means that it starts with existing theories and research, and then tests them with data. The model and hypotheses in Chapter 3 are based on dynamic capabilities theory (Teece et al., 1997) and earlier studies on AI capability (Mikalef, Krogstie, et al., 2020; Mikalef & Gupta, 2021). A deductive approach is suitable because there is already strong theory and previous research to build on, and the goal is to test clear relationships (Saunders et al., 2023).

4.3 Research Design

This study uses a cross-sectional survey design to collect data (Saunders et al., 2023). A similar approach was used by Mikalef et al. (2020) to test a mediation model using cross-sectional data. One important limitation is that this type of design cannot prove cause and effect. The arrows in the model show expected relationships based on theory, not proven causal links.

4.4 Population and Sampling

4.4.1 Target population and sampling frame

The study focuses on professionals that have direct involvement in AI projects in their organisations. This includes roles like project leaders, data science managers, digital transformation leaders, consultants, and senior managers responsible for AI. The sample includes people from different industries, since knowledge intensity is only used to describe the context, not to decide who is included.

4.4.2 Sampling technique and sample size

Sampling uses a mix of convenience and purposive methods, meaning participants are selected in a non-random way (Saunders et al., 2023). The survey was distributed through the following channels: Email, sms, LinkedIn, and industry networks. Profiles with high likelihood of being involved in AI initiatives in their organisations were targeted. This approach introduces a self selection bias and limits statistical generalizability but the approach fits the specialized knowledge required

The final sample included 46 respondents from senior professional roles with direct experience in organizational AI initiatives, such as project leads, data science managers, digital transformation leaders, consultants, and senior managers responsible for AI. The PLS-SEM "ten-times rule" states that the minimum sample size should be at least ten times the largest number of structural paths pointing to any one construct (Hair et al., 2022). This model has 4 paths, which sets the minimum sample size at 40. The sample of 46 meets this requirement.

The structural model includes three types of resources, dynamic capability processes as a higher-level mediator, and AI capability maturity as the dependent variable. Governance maturity, knowledge intensity, firm size, industry, and AI experience duration are included only as background information to describe the sample, not as variables that are tested as moderators or controls.

4.5 Measurement Instruments

The structural model includes seven multi-item reflective constructs and two contextual constructs that are only used for description. All measures were adapted from established and validated scales and used a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The full survey items are listed in Appendix B, and an overview of the constructs, sources, and dimensions is provided in Appendix D.

Independent variables. The three AI-specific resource categories are based on Mikalef and Gupta's (2021) classification. *TangibleAVG* measures the average requirement for successful AI implementation through three items covering data infrastructure, computing power, and dedicated funding. *HumanAVG* measures the average requirement for the knowledge and capability of employees, which covers technical AI skills, business understanding for AI use, and management of AI talent through three items adapted from Mikalef and Gupta and Sjödin et al. (2021). *IntangibleAVG* measures the average requirement in intangible capabilities of the organization covering coordination across departments, ability to handle change, risk tolerance, and strategic alignment through four items adapted from Mikalef and Gupta and Jöhnk et al. (2021).

Mediator. *DCProcesses* is measured as a higher-order construct made up of three first-order reflective dimensions (Hair et al., 2022). The three first-order dimensions are the following: *SensingAVG,* which measures activities like scanning the environment, monitoring the AI field, and comparing competitors using three items in the survey based on Warner and Wäger's (2019) framework and Teece's (2018) categories. *SeizingAVG* measures actions such as running pilot projects, committing resources and quickly reallocating them, also measured through three iteams in the survey. *TransformingAVG* measures changes like restructuring the organization, working with partners, and training employees, again using three items. Since there is no established survey for sensing, seizing, and transforming in AI settings, the items were created based on Warner and Wäger's qualitative framework.

Dependent variable. *CapabilityAVG* reflects how deeply AI is integrated into organizational work beyond small pilot projects. It is measured using three items that focus on institutionalization, regular use across the organization, and ongoing value creation (Hillebrand et al., 2025; Mikalef & Gupta, 2021).

Contextual constructs. *GovernanceAVG* is based on governance dimensions from Papagiannidis et al. (2023) and Mäntymäki et al. (2022). It covers role clarity, formal evaluation processes, accountability, risk management, and ethical guidelines using five items. *KnowledgeAVG* is based on the characteristics of knowledge-intensive firms described by Anand et al. (2007). It includes expertise as the main asset, authority based on expertise, project-based work, and professional independence, measured with four items. Both constructs are only used to describe the context and are not included in the main model.

Some items are only collected to describe the sample, these are: firm size, industry, and AI experience duration. The dynamic capabilities process items were newly developed, so clarity and how well they fit the concept were important.

4.6 Data Collection Procedure

For the study, the online platform Qualtrics was used to gather the information. Following GDPR guidelines of consent. The survey is initiated by asking the respondents if they are or were professionally involved in AI initiatives and whether their organization had at least one active AI program. During data cleaning these were not used to exclude participants since the response patterns suggested uneven interpretation by respondents. Eligibility was based on the goal of reaching the right participants, and not using formal screening questions was considered a limitation. The survey was shared through email, LinkedIn, and professional industry networks.

The final dataset that was used for the PLS-SEM analysis was filtered by removing preview responses, incomplete submissions, blank attention-check responses, answers that failed the attention-check criteria, and records with missing data on key variables. Figure 4.1 below shows the filtering process of the responses, from the initial raw data export to the final cleaned sample used for analysis

4.7 Data Analysis

4.7.1 Analytical method

Partial least squares structural equation modeling (PLS-SEM) is used as the primary analytical method (Hair et al., 2022). It is chosen over other suitable models for three main reasons; it suits models extending established theory into new empirical territory, it handles mediating relationships effectively, and Mikalef et al. (2020) and Mikalef and Pateli (2017) used PLS-SEM in directly comparable settings. R and the seminr package are used for the analysis.

4.7.2 Analysis procedure

The analytical model follows a three step procedure. **Step 1** evaluates the measurement model by checking internal consistency (Cronbach's alpha ≥ 0.70, composite reliability ≥ 0.70), convergent validity (AVE ≥ 0.50, outer loadings ≥ 0.708), and discriminant validity (HTMT < 0.90) (Hair et al., 2022). **Step 2** checks the collinearity in the structural model (VIF < 5.0), this by using bootstrapping with 5,000 samples to test coefficients of the different paths, further it assesses the R^2 and f^2 using standard benchmarks (0.02, 0.15, 0.35) (Hair et al., 2022). **Step 3** tests mediation using bootstrapped paths and calculated indirect effects. The mediation results are exploratory because separate confidence intervals for indirect effects are not calculated.

4.7.3 Dynamic Capabilities Model specification

DCProcesses is not measured directly as a first order construct, rather it is treated as a second order construct, meaning that it is not measured directly with single items (Hair et al., 2022). As mentioned before it is made up of *SensingAVG, SeizingAVG, and TransformingAVG.* These three together form one overall concept.

The analysis is done in two steps. In the first step, each of these three parts is measured and scores are created for them. In the second step, these scores are combined to form the higher-level DCProcesses variable, which represents the overall idea of dynamic capability processes.

In the model, TangibleAVG, HumanAVG, and IntangibleAVG are linked to DCProcesses, and both the resources and DCProcesses are linked to CapabilityAVG. Direct links from resources to capability are also included to test whether DCProcesses explains the relationship between them (mediation). For clarification, the mathematical formulas are shown in Appendix A

4.8 Quality Criteria

All data come from single respondents, which can create a risk of common method bias (Podsakoff et al., 2003). To reduce this risk, several steps were taken: responses were kept confidential, the order of questions was randomized, and the predictor and outcome variables were separated in the survey. A Harman's single-factor test was also used after data collection to check for bias, although this test has known limitations (Podsakoff et al., 2003). To check for non-response bias, early and late respondents are compared on key variables (Armstrong & Overton, 1977).

4.9 Ethical Considerations

Before conducting the study an informed consent statement detailing the handling of information, purpose of the study, the right of withdrawal and the voluntary participation was all laid out in accordance with the Stockholm School of Economics research ethics guidelines. Only the participants who gave explicit consent proceeded to take part in answering the survey. No identifiable keys were collected in the survey including individuals name and organisational names; all answers are given in aggregate. The handling of data complies with GDPR, including a privacy notice on legal basis, retention period, and respondent rights.

4.10 Use of AI

The study has been partially aided by AI tools, particularly Claude.ai (Anthropic, 2026).

Scope of assistance. AI was mainly used for partial writing assistance and limited support in analysis; mainly paraphrasing text for clarity, drafting structure and brainstorming analysis ideas. Images have partly been made through Claude. Claude was also used for revision of the PLS-SEM R code and for generating the research definitions list.

Exclusion. The AI was not used for making any source selections, decisions relating to methods of analysis, or drafting of any material in the paper. All the theoretical approaches, source selections, methodology choices, and conclusions drawn have been made by the authors independently.

Review by the authors. All text created with AI was checked, edited, and approved by the authors before being included. The AI-generated text was only used as support and not as finished text.

5. Results

5.1 Data Screening and Final Sample

Upon exclusion of preview responses, incomplete responses and failed attention checks, the final sample consisted of 46 respondents. The sample is mainly concentrated in consulting and professional services (43.5%) and healthcare and life sciences (21.7%), with the rest being distributed across financial services, technology, retail, manufacturing, energy, telecommunications, and the public sector. The company sizes span from fewer than 250 employees (37%) to 10,000 or more employees (6.5%), with AI experience mainly focused in the 1-2 year range (52.2%), whereas smaller groups reporting less than one year (15.2%), 3-5 years (21.7%), and more than five years (10.9%). The full breakdown appears in Appendix C.

5.2 Descriptive Statistics

Table 5.1 reports construct-level descriptive statistics. *GovernanceAVG* and *KnowledgeAVG* are reported as contextual constructs and are not predictors in the structural model.

Table 5.1. Construct-level means and standard deviations (N = 46, 7-point scale).

Construct	Mean	SD
TangibleAVG	4.522	0.851
HumanAVG	4.022	1.145
IntangibleAVG	4.147	0.873
SensingAVG	3.928	1.126
SeizingAVG	3.826	1.058
TransformingAVG	3.797	1.132
CapabilityAVG	3.601	1.143
GovernanceAVG	3.700	1.091
KnowledgeAVG	4.717	0.616

Construct means cluster around the scale midpoint. The highest scores are for *KnowledgeAVG* (4.717, the lowest variance at SD = 0.616, reflecting the consulting and healthcare concentration in the sample) and *TangibleAVG* (4.522). The lowest score is for *CapabilityAVG* (3.601), which is consistent with the early-adoption profile of the sample.

5.3 Measurement Model

The first-stage measurement model estimated the first-order constructs. Table 5.2 reports internal consistency and convergent validity statistics.

Table 5.2. Internal consistency and convergent validity.

Construct	Cronbach's alpha	rhoA	Composite reliability	AVE
TangibleAVG	0.695	0.728	0.833	0.629
HumanAVG	0.880	0.882	0.926	0.806
IntangibleAVG	0.734	0.744	0.836	0.564
SensingAVG	0.875	0.878	0.923	0.801
SeizingAVG	0.801	0.834	0.884	0.720
TransformingAVG	0.729	0.737	0.848	0.651
CapabilityAVG	0.756	0.765	0.860	0.673

All constructs cleared the composite reliability and AVE thresholds. *TangibleAVG*'s Cronbach's alpha (0.695) sits marginally below 0.70 but was retained given adequate composite reliability (0.833) and AVE (0.629).

Two indicators had outer loadings below the 0.708 guideline. *Tangible_1* loaded at 0.641 on *TangibleAVG*, and *Intangible_3* loaded at 0.595 on *IntangibleAVG*. Both were retained because AVE values remained above 0.50 and removal would have narrowed construct coverage.

Discriminant validity was not fully supported. In the first-stage model, the HTMT value for *CapabilityAVG-TransformingAVG* was 1.145 and for *CapabilityAVG-SensingAVG* was 0.918, both above the 0.90 threshold. In the second-stage model, *DCProcesses-CapabilityAVG* was 1.094 and *TangibleAVG-DCProcesses* was 0.910. The empirical separation between some dynamic capability and AI capability maturity measures is limited. The structural results should be read with this caveat in mind.

5.4 Higher-Order Dynamic Capability Construct

The second-stage model used stage-one scores as formative indicators of the higher-order *DCProcesses* construct. Table 5.3 reports formative weights.

Table 5.3. Formative weights for the higher-order DCProcesses construct.

Indicator	Weight	t	p	95% CI
SensingAVG -> DCProcesses	0.379	4.043	< .001	[0.193, 0.571]
SeizingAVG -> DCProcesses	0.255	2.524	.021	[0.054, 0.457]
TransformingAVG -> DCProcesses	0.518	5.019	< .001	[0.304, 0.707]

All three weights are significant. *TransformingAVG* carries the largest weight (0.518), followed by *SensingAVG* (0.379) and *SeizingAVG* (0.255). Collinearity is below threshold: VIF values were 2.139 (*SensingAVG*), 1.788 (*SeizingAVG*), and 1.818 (*TransformingAVG*).

5.5 Structural Model

Structural VIF values were below 5.0 for all predictor sets. For *DCProcesses*, VIF values were 1.936 (*TangibleAVG*), 1.996 (*HumanAVG*), and 2.111 (*IntangibleAVG*). For *CapabilityAVG*, VIF values were 2.243 (*TangibleAVG*), 2.195 (*HumanAVG*), 2.257 (*IntangibleAVG*), and 2.455 (*DCProcesses*).

The model explained 59.3% of the variance in *DCProcesses* ($R^2 = 0.593$, adjusted $R^2 = 0.564$) and 83.3% of the variance in *CapabilityAVG* ($R^2 = 0.833$, adjusted $R^2 = 0.817$). The structural model figure with path coefficients is presented in Section 6.5 alongside the synthesis discussion.

Table 5.4. Bootstrapped structural path coefficients (5,000 subsamples).

Test	Path	beta	t	p	Decision
H1a	TangibleAVG -> DCProcesses	0.353	2.311	.008	Supported
H1b	HumanAVG -> DCProcesses	0.285	1.946	.101	Not supported
H1c	IntangibleAVG -> DCProcesses	0.244	1.665	.088	Not supported
H2 path	DCProcesses -> CapabilityAVG	1.027	11.122	< .001	Significant
Direct	TangibleAVG -> CapabilityAVG	-0.063	-0.680	.442	Not significant

Test	Path	beta	t	p	Decision
Direct	HumanAVG -> CapabilityAVG	0.121	1.094	.341	Not significant
Direct	IntangibleAVG -> CapabilityAVG	-0.262	-2.391	.025	Significant

Among the H1 paths, only *TangibleAVG → DCProcesses* reached significance at the 5% level. *HumanAVG* and *IntangibleAVG* showed positive effects in the expected direction but did not cross the threshold. The mediator-to-outcome path *DCProcesses → CapabilityAVG* is large and highly significant. Of the three direct resource-to-capability paths, only *IntangibleAVG → CapabilityAVG* is significant, with a negative sign that is interpreted in Section 6.4.

Figure 5.1. Bootstrapped structural path coefficients with 95% confidence intervals.

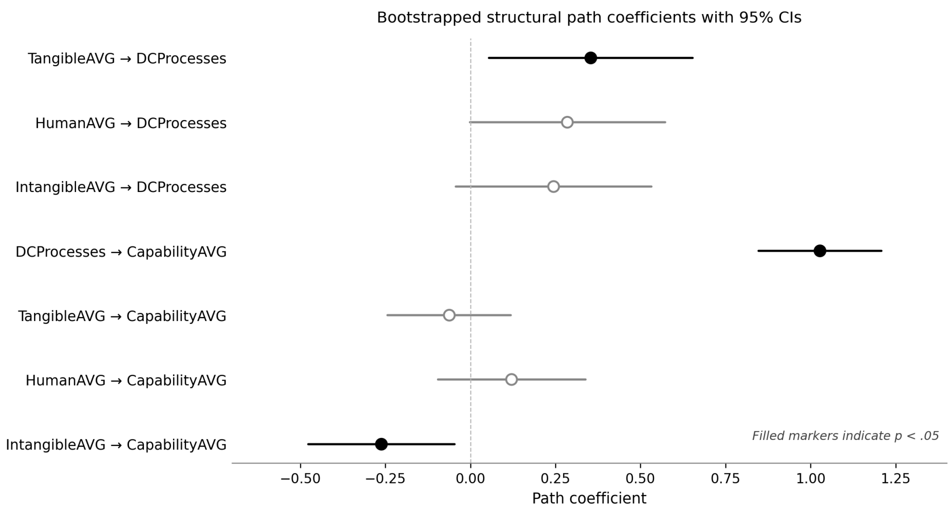


Table 5.5. Cohen's f-squared effect sizes (benchmarks: 0.02 small, 0.15 medium, 0.35 large).

Path	f-squared	Size
TangibleAVG -> DCProcesses	0.146	Small
HumanAVG -> DCProcesses	0.089	Small
IntangibleAVG -> DCProcesses	0.081	Small
TangibleAVG -> CapabilityAVG	0.012	Negligible
HumanAVG -> CapabilityAVG	0.039	Small
IntangibleAVG -> CapabilityAVG	0.183	Medium
DCProcesses -> CapabilityAVG	2.546	Large

Effect sizes are small for the resource-to-process paths and negligible to small for the direct resource-to-capability paths. The *DCProcesses → CapabilityAVG* path shows a large effect size ($f^2 = 2.546$).

5.6 Predictive Metrics

PLS prediction was used as supplementary evidence. Out-of-sample RMSE values were lower than the linear model benchmark for all predicted indicators. At the construct level, out-of-sample MSE was 0.470 for *DCProcesses* and 0.206 for *CapabilityAVG*; MAE was 0.569 and 0.359 respectively. These metrics do not remove the HTMT caveat from Section 5.3.

5.7 Mediation Assessment

The mediation assessment used bootstrapped component paths and calculated indirect effects. Specific indirect-effect confidence intervals were not estimated separately; the evidence is exploratory.

For *TangibleAVG*, both the a-path (*TangibleAVG → DCProcesses*) and the b-path (*DCProcesses → CapabilityAVG*) were significant (Table 5.4), while the direct path was not. The calculated indirect effect was 0.363, consistent with mediation through *DCProcesses*.

For *HumanAVG*, neither the path to *DCProcesses* nor the direct path to *CapabilityAVG* was significant (Table 5.4). The calculated indirect effect was 0.292. Mediation was not supported.

For *IntangibleAVG*, the path to *DCProcesses* was not significant. The direct path to *CapabilityAVG* was significant and negative (Table 5.4). The calculated indirect effect was 0.250. Mediation was not supported.

Table 5.6 summarizes the hypothesis results.

Table 5.6. Hypothesis testing summary (decision criterion: bootstrapped p < .05 for H1 paths and a-path / b-path / direct-path pattern for H2).

Hypothesis	Decision	Empirical basis
H1a: TangibleAVG -> DCProcesses	Supported	$\beta = 0.353$, $p = .008$, $f^2 = 0.146$
H1b: HumanAVG -> DCProcesses	Not supported	$\beta = 0.285$, $p = .101$, $f^2 = 0.089$
H1c: IntangibleAVG -> DCProcesses	Not supported	$\beta = 0.244$, $p = .088$, $f^2 = 0.081$
H2: Resources -> DCProcesses -> CapabilityAVG	Partially supported	Mediation pattern matches for tangible resources only; no separate bootstrapped indirect-effect confidence intervals were estimated

H1a is supported; H1b and H1c are not supported at the 5% level although both coefficients are positive and in the predicted direction. H2 is partially supported, with the mediation pattern matching only for *TangibleAVG*.

6. Analysis

6.1 Resource Paths to Dynamic Capability Processes

Tangible resources

H1a says that tangible AI resources are associated positively with dynamic capability processes. The data supports this prediction as follows: *TangibleAVG → DCProcesses* was significant (β = 0.353, $p = .008$, $f^2 = 0.146$), and the direct path *TangibleAVG → CapabilityAVG* was not (β = -0.063, $p = .442$). As evidenced by the theory in Section 3.2.1, this pattern is backed by the dynamic capabilities theory, predicting that material resources do have an influence on the capability outcomes indirectly, through organizational coordination and orchestration, rather than having a direct effect themselves. For dynamic capabilities theory in relation to AI, the result hints at a similar claim; even the most material resources do not seem to go beyond the processes that convert them into a capability.

Human and intangible resources

The hypothesis H1b and H1c assumed a positive relationship between human and intangible assets of the artificial intelligence system and dynamic capability processes. While both the coefficients show positive values (HumanAVG → DCProcesses: $\beta = 0.285$, $p = .101$, $f^2 = 0.089$; IntangibleAVG → DCProcesses: $\beta = 0.244$, $p = .088$, $f^2 = 0.081$).

The sample is also concentrated in firms that are still early in their AI adoption journey (52.2% reporting just 1–2 years of AI experience), as well as in consulting and professional services (43.5%). This might reduce the variation in resource categories where strategic differences take longer to emerge. In addition, Intangible_3 loaded at 0.595, suggesting some measurement noise within the IntangibleAVG construct.

Furthermore, the engagement quality argument raised in Section 3.2.2 (Lebovitz et al., 2022) could also help explain the findings. The argument suggests that the value of human resources in relation to AI depends less on skill availability and more on how professionals actually use and interpret AI-generated outputs. Therefore, a broader resource-level construct might struggle to fully capture these effects.

From a dynamic capabilities lens, the non-significant findings should not necessarily be interpreted as evidence against the predicted relationships. Instead, the current sample may simply not provide a strong enough signal to clearly detect the effects. Importantly, all three resource categories still display directional consistency with the proposed theory. While this is only tentative evidence, it suggests that the resource-to-process pathway may operate broadly as theorized. Whether the human and intangible resource paths would reach significance in a larger and more heterogeneous sample remains an open question.

6.2 Dynamic Capability Processes and AI Capability Maturity

The b-path in the mediation chain is running from dynamic capability processes to AI capability maturity. With *DCProcesses* being the main predictor of *CapabilityAVG* ($\beta = 1.027$, $p < .001$, f^2

= 2.546), and explaining 83.3% of the variance. This can be further substantiated based on the logic developed in the discussion of Section 3.2.4 where capabilities are enforced through organizational processes but are not obtained as assets in their pure form.

Additionally, the path coefficient higher than 1.0 has to be approached with some caution. High HTMT values (DCProcesses-CapabilityAVG = 1.094; CapabilityAVG-TransformingAVG = 1.145) might suggest that participants were unable to distinguish whether they are involved in activities involving dynamic capabilities processes or they achieved capability maturity, which might represent a limitation of this survey study design. But it can also be explained by the conceptualization of artificial intelligence capability presented in Section 3.2.4, which is indeed close to the above empirical findings. If the notions of capability and capability development processes are inseparable from a conceptual point of view, they are also unlikely to be separated empirically in surveys.

On the other hand, when we consider dynamic capability theory with respect to AI capability, the two-way reasoning is applicable. The high empirical association confirms the theoretical claim that the dynamic capability process is the immediate cause of capability effects. Nonetheless, the discriminant validity overlaps suggest there could be an evaluation limit in adopting the entity approach with respect to AI capability. In practice, the processes of sensing, seizing, and transforming might have been the capability itself.

For the higher-order construct, the weight of TransformingAVG was highest (0.518), then SensingAVG (0.379), and lastly, SeizingAVG (0.255). This follows the theoretical stress on structural reconfiguration discussed in Sections 3.1.3 and 3.2.4. Formative weights, like all measurement weights, are specific only to a particular sample and must not be generalized to other contexts.

6.3 Mediation Assessment

While H2 posits that processes of dynamic capability mediate the relationship between AI-specific resources and AI capability maturity, the evidence provided for the mediation is exploratory as there was no estimation of separate bootstrapped indirect effect confidence intervals.

For TangibleAVG, the criteria indicated the existence of a mediation relationship, as a significant a-path ($\beta = 0.353$, $p = .008$), significant b-path ($\beta = 1.027$, $p < .001$), non-significant direct path ($\beta = -0.063$, $p = .442$), and an indirect effect value of 0.363. In line with the precedent set by Mikalef et al. (2020), in the case of big data analytics, although with the consideration of the calculated and not bootstrapped indirect effect, a smaller sample, and the HTMT problem.

In the case of HumanAVG and IntangibleAVG, the a-path to DCProcesses was insignificant and hence the mediation criteria were not fulfilled. However, the above does not necessarily exclude the existence of mediation, since, in all likelihood, the sample size was simply not enough to reveal it.

For dynamic capabilities theory with applications to AI, the partial finding is noteworthy as it represents an expansion of the theoretical framework into the context of AI.

6.4 The Negative Direct Path from Intangible Resources

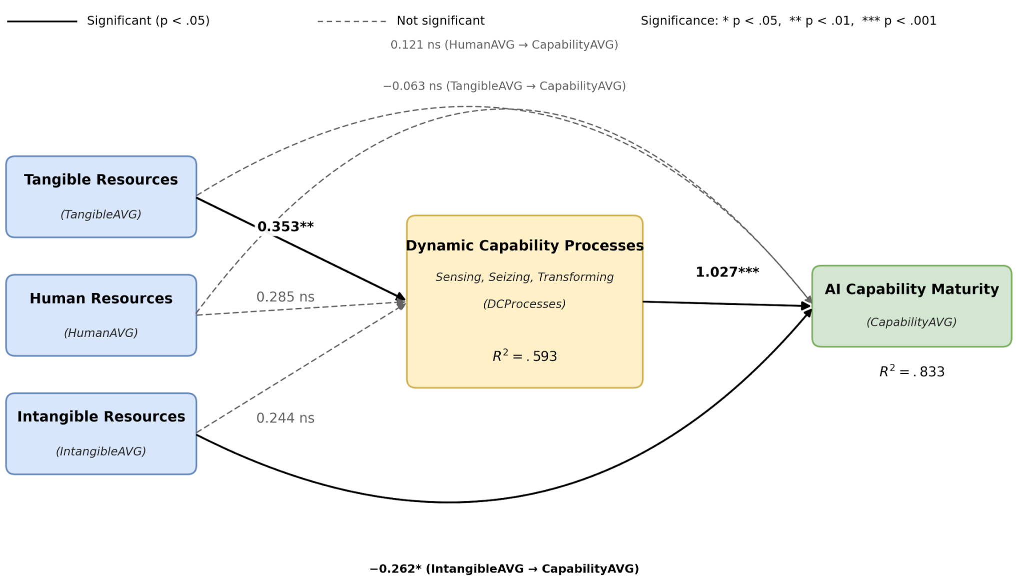
IntangibleAVG was significantly and negatively associated with *CapabilityAVG* (= -0.262, p = .025, $f^2 = 0.183$). This contradicts the theoretical justification proposed in Section 3.2.3, which considered intangible resources to be positively linked to capability effects both directly and dynamically.

Two explanations are possible based on the model. First, adding a strong mediator would switch the direction of the direct effect, and the nearly significant positive a-effect, along with the highly significant b-effect, fits this expectation. Second, Intangible_3 had a loading of 0.595, while the construct has a very broad meaning (inter-departmental coordination, adaptability, risk-taking, etc.), possibly creating inconsistencies in how the question was understood by respondents.

Neither explanation indicates a practical finding that intangible resources adversely affect AI capability development.

6.5 Synthesis

Figure 6.1. Estimated PLS-SEM model with path coefficients (N = 46). Solid arrows indicate paths significant at the 5% level; dashed arrows indicate non-significant paths. Direct resource-to-capability paths are retained for mediation assessment. R² values are reported for the endogenous constructs.



There is no significant direct link with CapabilityAVG, and TangibleAVG has a positive connection with DCProcesses, thus supporting H1a. Also, there is a failure in supporting hypotheses H1b and H1c at the 5% significance level, which reflects their weak statistical power, as the a-paths of both HumanAVG and IntangibleAVG are positive but insignificant. There is a strong connection between DCProcesses and CapabilityAVG, conditional upon the discriminant validity overlap. Mediation (H2) is only demonstrated for tangible resources, and thus the results must be treated as exploratory. The negative direct path from IntangibleAVG to CapabilityAVG does not reflect any real detrimental influence; rather, it reflects the inadequacies of the theoretical model and measurement framework (see Section 6.4).

In terms of dynamic capabilities theory in the context of AI, the partial-mediation structure confirms some initial quantitative support for one of its core propositions: resources need process orchestration to be converted to capability-based results. The discriminant validity overlap poses an interesting issue for future measurement of the variables in the study, but it can hardly be solved within the current research framework. The following chapter considers the wider implications, practicalities, and limitations, as well as directions for future research.

7. Discussion

7.1 Answer to the Research Question

The research question asked to what extent dynamic capability processes mediate the development of organizational AI capability from AI-specific resources. Based on the findings of this study, the answer is nuanced rather than absolute. The results suggest that dynamic capability processes do appear to act as the main organizational mechanism through which AI capability develops. In the structural model, they showed by far the strongest relationship with AI capability maturity, which is very much in line with the central logic of dynamic capabilities theory.

However, the mediation effect per se exists only for tangible resources in this sample. In regard to human and intangible resources, while the a-path toward dynamic capability processes is significant and goes in the expected direction, it does not meet the 5% level of statistical significance criterion. The collected data thus seem to support the idea of mediation effect in all three resources but lack any evidence that would enable us to prove the existence of such effect with regard to the latter two types of resources.

7.2 Theoretical Implications

The findings carry three implications for how dynamic capabilities theory applies to AI capability improvement.

Firstly, it is evidenced that the theoretical sequence outlined for big data analytics by Mikalef et al. (2020) extends into AI for at least one resource layer, due to the partial-mediation pattern. The result becomes preliminary quantitative evidence for the fact that AI capability stems from organizational processes as opposed to mere accumulation of resources. However, what is not yet confirmed by the data is if this mediation is uniform across different types of resources or if tangible resources specifically play a special role, given that they constitute material preconditions for AI work.

Secondly, the discriminant-validity overlap, i.e. the test measure's distinctiveness, between dynamic capability processes and AI capability maturity becomes a deeper question theoretically.

If each construct is distinct in concept (as discussed in Chapter 3) but not empirically by the survey, then the mere framing of AI capability might need revision when put in relation to earlier IT contexts. Stelmaszak et al. (2025) and Faraj et al. (2018) mention this difficulty; if capability is the activity and not its result, then the survey might just measure the phenomenon labeled in two different ways. Resolving this requires instrument development beyond the scope of this thesis, but the present results highlight it as a measurement priority for quantitative AI capability research.

Thirdly, the formative-weight pattern within dynamic capability processes (*TransformingAVG* > *SensingAVG* > *SeizingAVG*) becomes the clearest empirical support for structural reconfiguration, as mentioned by Warner and Wäger's (2019) in relation to their microfoundations and Raisch and Krakowski's (2021) stance that AI needs continuous refinement organizationally for it to be fruitful.

Needless to say, the weights are specific to the sample, therefore the claims should not be generalized, but observed as a consistency with the reading of dynamic capabilities theory, that states that the transforming dimension holds special importance within technology, given that the underlying technology itself doesn't stand still.

7.3 Practical Implications

For practitioners. Tangible resources, for instance, data infrastructure, computing capacity and adequate and dedicated funding, although obvious, are supported to be preconditions for the core processes related to AI capability maturity. These were the only resource category with a significant path to capability processes in the sample. At the same time, no resource category showed a significant direct path to capability maturity that bypassed dynamic capability processes, which is consistent with the view that AI capability is built through organizational work rather than purchased as a product.

In the dynamic capabilities construct, transforming had the greatest impact of all the formative elements, indicating that perhaps it is the process of structural transformation and role redesign rather than scanning and piloting by themselves that have a more critical impact. In other words, it seems that tangible resources plus processes of activity need to be aligned for dynamic capabilities to be achieved.

For researchers. The HTMT overlap between dynamic capability processes and artificial intelligence capability maturity is an indicator worth considering. In future studies in this field, quantitative research should focus on instrument development in the artificial intelligence setting instead of directly borrowing tools from adjacent information technology domains without modifications. Bigger samples will allow the testing of the human and intangible resources routes, as well as the moderating influence of governance maturity and knowledge intensity, both of which are provided in the current paper's descriptive framework (Section 7.4). Qualitative research supplements using the methodology developed by Warner and Wäger (2019) could shed light on how tangible resource expenditures contribute to the sense-making, opportunity-seeking, and exploitation process, especially in light of the quality engagement reasoning (Lebovitz et al., 2022) that may not be fully covered by resource-based constructs.

Such concerns are made for discussion only and not as research-based recommendations. As the sample is not representative and is concentrated in consulting/professional services, any statements concerning particular managerial practices exceed the scope of our analysis.

7.4 Untested Constructs in Context

AI governance maturity was measured with a mean of 3.700 (SD = 1.091), while AI knowledge intensity was calculated to be 4.717 (SD = 0.616). These are presented as descriptions and not estimates of moderators.

The literature on governance examined in Section 2.3 portrays governance as pertinent to the building of AI capabilities. The need for continued evolution of governance factors is highlighted by Papagiannidis et al. (2023). Also, according to Mikalef et al. (2020), information governance was found to positively influence the connection between analytics and innovation. Furthermore, according to Birkstedt et al. (2023), only three out of the 68 studies reviewed offered empirical proof on AI governance. This indicates that the existing body of literature on governance is one that is characterized by theoretical advances that precede empirical analysis. Nevertheless, the empirical data collected in this study serve to define the maturity level of governance in the surveyed organizations without testing its impact on the pathway from resources to processes.

KnowledgeAVG had the smallest standard deviation among all constructs (SD = 0.616), reflecting the sample composition in consulting and healthcare industries. The characteristics of knowledge-intensive organizations that affect innovation processes have been highlighted by Anand et al. (2007) and Tavoletti et al. (2022). As in the case of governance, the hypothesis regarding whether knowledge intensity could moderate the resource-to-process chain for AI innovation was not investigated in this study, and it was set aside for future research in Section 7.6.

7.5 The Negative Intangible Resources Path

Both explanations of the IntangibleAVG → CapabilityAVG path outlined in Section 6.4 were a matter of statistical suppression and measurement error. A third explanation is also consistent with the results and worth discussing. High scores in the area of intangible resources can point to a particular stage when organizations have a high level of mobilization for AI implementation but low actual capabilities as readiness comes ahead of accomplishment. Holmström (2022) described this gap between readiness and capability achievement, whereas Jöhnk et al. (2021) explained readiness as co-evolution, not an existing condition needed before the implementation process starts. In a static setting, the direct effect left after eliminating the part caused by dynamic capabilities reflects such a transition: high readiness, no capabilities yet. This explanation is conjectural and requires further research to support the idea. Nevertheless, the finding matches the expected importance of intangible resources in capability creation and contradicts the assumption that they prevent capability formation.

7.6 Limitations and Future Research

Each limitation below is paired with the future-research direction it suggests.

Sample size and statistical power. The 46 participants in the sample meet the requirement of 10 times the sample size required in PLS-SEM (Hair et al., 2022) in testing the model presented. The purposive sampling strategy successfully accessed respondents in senior professional positions directly involved in the implementation of organizational artificial intelligence programs, ensuring coverage of respondents from among the intended population, although the limited sample size results in low statistical power in analyzing small effect sizes. In testing the non-significant paths H1b and H1c, effect sizes ($f^2 = 0.089$ and 0.081) were found to be lower than that necessary in achieving sufficient statistical power using the present sample size. Future research recommendation: replication using much larger sample sizes, preferably $N > 200$ based on Mikalef et al. (2020).

Discriminant validity. Values for HTMT of DCProcesses-CapabilityAVG (1.094) and CapabilityAVG-TransformingAVG (1.145) imply a lack of empirical discrimination between mediator and criterion variable. The coefficient for DCProcesses → CapabilityAVG should be overstated, the R2 value reflects excessive model fit to data, and mediation analysis would suffer as well. Directions for further investigation: developing measurement tools to discriminate between process and outcome variables in an AI context, which can rely on the continuously generated framing (Stelmaszak et al., 2025).

Cross-sectional design. The dynamic capabilities theory deals with processes that occur through time (Teece et al., 1997; Teece, 2018), so the cross-sectional approach of surveying cannot follow the dynamics of capabilities, identify path dependence (Helfat & Peteraf, 2003), and determine temporal ordering. The arrows within the conceptual framework symbolize theoretical relationships, but not causality. For further studies: longitudinal frameworks that track the resource-process-capabilities process across time periods, preferably a panel framework.

Sampling and generalizability. Non-probability sampling is concentrated in sectors such as consultancy and professional services (43.5%), and healthcare (21.7%). Also, 52.2% of the participants had 1-2 years of experience in AI (Saunders et al., 2023). Extrapolation beyond this sample would be unjustified. Suggestions for future studies: replication in stratification by industry that enables cross-industry comparison of companies with varying degrees of AI deployment.

Screening items. Two questions for screening purposes were identified but not used as criteria for exclusion, since their interpretations were inconsistent (4.6). Sample selection depends on the recruitment strategy employed, and not on the validated properties of the participants. Recommendations for future studies: develop better screening questions with clear anchors.

Newly developed items. Dynamic capability process items were formulated based on qualitative micro-foundations presented by Warner and Wäger (2019) without any quantitative support beforehand. The problems associated with HTMT could be partially attributed to some items that fail to differentiate between processes and outcomes. Research agenda: psychometric testing of dynamic capability process scales within the AI framework, including exploratory factor analysis and reliability testing of independent samples.

Common method bias. All items are derived from individual respondents. The procedural safeguards and Harman's single factor test were employed (Podsakoff et al., 2003). However, common method variance cannot be ruled out. Future research: Multi-source design, where the sources of resources and processes are collected from different organization respondents, or mediator and outcome measured separately in time.

8. Conclusion

8.1 Summary of Findings

The study examined the possibility that the dynamic capability processes mediate AI capability development from AI-specific resources, through an analysis of a cross-sectional survey of 46 experienced employees and PLS-SEM. The structural model is related to three categories of AI-specific resources (tangible, human, intangible), dynamic capability process as the higher order mediator, and AI capability maturity as the dependent variable.

It was found that tangible resources were the only resource category that showed significant relationship with the dynamic capability process. Human and intangible resources showed positive but statistically insignificant association with the process. Dynamic capability processes were found to be significantly related with AI capability maturity, taking into account the discriminant validity overlap of the two constructs. There was support for the pattern of mediation by tangible resources, which was considered as exploratory evidence. This pattern corresponds to the central claim made by dynamic capability theory: It seems that AI capability arises via processes and not just resource stockpiling. Tangible foundations seem to provide the necessary conditions for this process to take place.

8.2 Closing Remarks

The research problem posed by the thesis is that of how organizations can progress from using AI as just another tool to making it an organizational capability. In this case, the evidence presented is fragmentary and exploratory. What is clear so far is that the process involves more than resource accumulation, and that actual resource foundations may be needed at least to begin with.

The findings suggest that organizational AI capability may ultimately be less about possessing AI-related resources and more about sustaining the organizational conditions through which AI can continuously be interpreted, adapted, and reproduced over time.

Appendix

Appendix A: Structural Model Equations

Notation follows Hair et al. (2022).

Measurement model. All first-order constructs use reflective indicators. For each construct ξ_j with p_j indicators:

$$x_{ij} = \lambda_{ij}\xi_j + \epsilon_{ij}, \quad i = 1, \ldots, p_j$$

where λ_{ij} is the outer loading and ϵ_{ij} is measurement error. First-order constructs: *TangibleAVG* (3 items), *HumanAVG* (3), *IntangibleAVG* (4), *SensingAVG* (3), *SeizingAVG* (3), *TransformingAVG* (3), *CapabilityAVG* (3).

Higher-order construct. Dynamic capability processes (*DCProcesses*) use a disjoint two-stage reflective-formative specification (Hair et al., 2022):

$$DCProcesses = w_1 \widehat{SensingAVG} + w_2 \widehat{SeizingAVG} + w_3 \widehat{TransformingAVG} + \zeta_{DC}$$

where w_k is the formative weight and $\widehat{SensingAVG}$, $\widehat{SeizingAVG}$, $\widehat{TransformingAVG}$ are stage-one construct scores.

Structural equations.

$$DCProcesses = \gamma_1 TangibleAVG + \gamma_2 HumanAVG + \gamma_3 IntangibleAVG + \zeta_1$$

$$CapabilityAVG = \gamma_4 TangibleAVG + \gamma_5 HumanAVG + \gamma_6 IntangibleAVG + \beta_1 DCProcesses + \zeta_2$$

Indirect effects.

$$IE_{TangibleAVG} = \gamma_1 \times \beta_1, \quad IE_{HumanAVG} = \gamma_2 \times \beta_1, \quad IE_{IntangibleAVG} = \gamma_3 \times \beta_1$$

Calculated from component paths; no separate bootstrapped confidence intervals estimated (Section 4.7.2).

Appendix B: Survey Instrument

All Likert-scale items used a 7-point response format: (1) Strongly disagree, (2) Disagree, (3) Somewhat disagree, (4) Neither agree nor disagree, (5) Somewhat agree, (6) Agree, (7) Strongly agree.

AI tangible resources (TangibleAVG)

Item	Wording
Tangible_1	Our organization has the data infrastructure (quality, access, integration) needed to support AI initiatives.
Tangible_2	Our organization has sufficient computing and technology resources (processing power, cloud services, storage) for AI applications.
Tangible_3	Our AI initiatives receive adequate funding, staffing, and time for completion.

AI human resources (HumanAVG)

Item	Wording
Human_1	Our AI specialists have strong technical skills in machine learning, data science, and related AI technologies.
Human_2	Our managers understand business problems well enough to identify valuable AI applications.
Human_3	Our organization is effective at attracting, developing, and retaining AI talent.

AI intangible resources (IntangibleAVG)

Item	Wording
Intangible_1	Different departments in our organization collaborate effectively on AI initiatives.
Intangible_2	Our organization is capable of managing the organizational changes that AI adoption requires.

Item	Wording
Intangible_3	Our organization is willing to invest in AI projects that carry significant uncertainty but also high potential.
Intangible_4	AI initiatives in our organization are well aligned with our overall business strategy.

DC processes: Sensing (SensingAVG)

Item	Wording
Sensing_1	Our organization systematically scans for new AI technologies and trends relevant to our industry.
Sensing_2	Our organization monitors how competitors and other organizations are applying AI.
Sensing_3	Our organization identifies emerging customer or market needs that could be addressed through AI.

DC processes: Seizing (SeizingAVG)

Item	Wording
Seizing_1	Our organization quickly develops pilot projects or prototypes to test promising AI opportunities.
Seizing_2	Our organization commits resources to scale up AI initiatives that demonstrate potential.
Seizing_3	Our organization can rapidly reallocate resources to capitalize on new AI opportunities.

DC processes: Transforming (TransformingAVG)

Item	Wording
Transforming_1	Our organization has restructured roles, teams, or processes to integrate AI into day-to-day operations.

Item	Wording
Transforming_2	Our organization collaborates with external partners (e.g., vendors, startups, universities) to advance AI capabilities.
Transforming_3	Our organization invests in upskilling and reskilling employees to build organization-wide AI readiness.

AI capability maturity (CapabilityAVG)

Item	Wording
Capability_1	AI is systematically embedded in our organization's core processes and decision-making.
Capability_2	Our organization deploys AI in a consistent, replicable way across multiple business areas.
Capability_3	Our AI initiatives consistently generate measurable business value.

AI governance maturity (GovernanceAVG)

Contextual construct; not included in the structural model.

Item	Wording
Governance_1	Our organization has clearly defined roles and responsibilities for AI development and deployment.
Governance_2	Our organization has established formal processes for evaluating and approving AI projects.
Governance_3	There are clear accountability structures for the outcomes of AI systems in our organization.
Governance_4	Our organization has formal processes for identifying and managing risks associated with AI.
Governance_5	Our organization has established ethical guidelines or principles governing AI use.

Knowledge intensity (KnowledgeAVG)

Contextual construct; not included in the structural model.

Item	Wording
Knowledge_1	The expertise and specialist knowledge of our employees is our organization’s most critical asset.
Knowledge_2	Authority in our organization is primarily based on professional expertise rather than formal position.
Knowledge_3	Our work is primarily delivered through projects or client engagements.
Knowledge_4	Professionals in our organization have significant autonomy in how they carry out their work.

Appendix C: Sample Demographics

The full demographic breakdown of the final analysis sample (N = 46) is shown below. Percentages use the final analysis sample. Ten firm-size observations could not be classified and are reported as unclassified.

Characteristic	Category	n	%
Firm size	Fewer than 250 employees	17	37.0
Firm size	250-999 employees	7	15.2
Firm size	1,000-4,999 employees	9	19.6
Firm size	5,000-9,999 employees	0	0.0
Firm size	10,000 or more employees	3	6.5
Firm size	Unclassified	10	21.7
Industry	Consulting and professional services	20	43.5
Industry	Healthcare and life sciences	10	21.7
Industry	Retail and consumer goods	4	8.7

Characteristic	Category	n	%
Industry	Financial services	3	6.5
Industry	Technology and software	3	6.5
Industry	Other	2	4.3
Industry	Energy and utilities	1	2.2
Industry	Manufacturing	1	2.2
Industry	Public sector and government	1	2.2
Industry	Telecommunications	1	2.2
AI experience	Less than 1 year	7	15.2
AI experience	1-2 years	24	52.2
AI experience	3-5 years	10	21.7
AI experience	More than 5 years	5	10.9

Appendix D: Measurement Instruments Overview

The construct, item count, source, and measured dimensions for every construct in the survey are summarized below. Full item wordings appear in Appendix B.

Construct	Items	Dimensions measured
TangibleAVG	3	Data infrastructure, computing capacity, dedicated funding
HumanAVG	3	Technical AI skills, business judgment for AI applications, AI talent management
IntangibleAVG	4	Cross-departmental coordination, change capacity, risk tolerance, strategic alignment
SensingAVG	3	Environmental scanning, AI ecosystem monitoring, competitor evaluation
SeizingAVG	3	AI pilot programs, resource commitment, rapid reallocation
TransformingAVG	3	Structural reconfiguration, partner collaboration, workforce upskilling
CapabilityAVG	3	Institutionalization, systematic deployment, sustained value creation

Construct	Items	Dimensions measured
GovernanceAVG	5	Contextual measure: role clarity, formal evaluation processes, accountability, risk management, ethical guidelines
KnowledgeAVG	4	Contextual measure: expertise as primary asset, expertise-based authority, project-based delivery, professional autonomy
Sample descriptors	3	Firm size, industry, AI experience duration

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