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# The Dual-Framework AI Maturity Model

Aligning Internal Organisational Readiness with External Product Strategy

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**TIIVISTELMÄ:**

Tekoälyn nopea käyttöönotto merkitsee suurta strategista muutosta nykyaikaisille yrityksille, mutta monet organisaatiot jäävät jumiin niin sanottuun pilottikiirastuleen. Tämä johtuu siitä, ettei yrityksen sisäisen valmiuden sekä markkinoille tuotavien tekoälytuotteiden ja -palveluiden välillä ole selkeää linjausta. Tekoälymallien suorituskyky noin kaksinkertaistuu 4–6 kuukauden välein, ja tämä kiivas kehitystahti tekee mukana pysymisestä poikkeuksellisen haastavaa. Olemassa olevan kirjallisuuden tarkastelu osoittaa, että nykyiset kypsyysmallit käsittelevät sisäistä organisaatiokyvykkyyttä ja ulkoista tuotestrategiaa toisistaan erillisinä siiloina.

Tämän puutteen ratkaisemiseksi tutkielmassa kehitetään, arvioidaan ja jalostetaan uutta tekoälyn kypsyysmallia Design Science Research -lähestymistavan (DSR) avulla. Kehitetty malli perustuu sosioteknisten järjestelmien teoriaan sekä dynaamisten kyvykkyyksien näkökulmaan, ja sen ulottuvuudet on johdettu seitsemän vakiintuneen kypsyysmallin jäsennellystä vertailusta. Alkuperäinen rakenne pohjautuu kirjoittajan käytännön kokemukseen pohjoismaisen SaaS-yrityksen tutkimus- ja kehitysyksiköstä, jossa hän on vastannut yli 400 yritystason tekoälytoimeksiannosta. Näissä järjestelmissä tietoturva ja datan hallintatapa on suunniteltu suoraan osaksi järjestelmäarkkitehtuuria. Kehystä arvioitiin lopuksi haastattelemalla seitsemää monitoimialaista asiantuntijaa puolistrukturoidusti.

Arviointi vahvisti, että tekoälyn onnistunutta käyttöönottoa rajoittavat enemmän organisaatiotekijät ja psykologiset tekijät kuin itse teknologia. Temaattinen analyysi johti useisiin rakenteellisiin muutoksiin mallissa. Se toi esiin tietohallinnon perustavan roolin EU:n tekoälyasetuksen kaltaisen sääntelyn puitteissa sekä loppukäyttäjien vastustuksen äkillisiä, käyttöliittymättömiä agenttirajapintoja (zero-UI) kohtaan. Tämän muutosvastarinnan taustalla vaikuttaa usein huoli oman työpaikan kohtalosta. Lisäksi analyysi osoitti tarpeen määrittää konkreettiset, narratiiviset persoonat kuvaamaan kutakin kypsyystasoa.

Lopullinen kaksoiskehys tarjoaa organisaation johdolle diagnostisen työkalun, joka yhdistää sisäisen operatiivisen valmiuden ulkoiseen tuotekypsyyteen. Kun nämä kaksi ulottuvuutta asetetaan rinnakkain, johtajat voivat tunnistaa strategisia epätasapainoja. Tästä esimerkkinä on niin sanottu Vaporware-riski, jossa korkean tason tuotetta yritetään rakentaa liian heikon sisäisen perustan päälle. Kehys esitetään teoreettisena väittämänä, ja seuraavassa tutkimusvaiheessa näitä keskinäisriippuvuuksia on tarkoitus testata määrällisellä tutkimuksella laajemman organisaatiootoksen avulla.



**AVAINSANAT:** Tekoäly, Kypsyysmalli, Design Science Research, Sosiotekninen linjaus, Tuotestrategia, Tekoälyn hallinto

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**ABSTRACT:**
Artificial Intelligence (AI) is becoming an integral part of how companies operate, and the fast pace of adoption represents a major strategic shift. Many organisations risk getting stuck in pilot projects rather than turning AI into a real competitive advantage. The core issue is the lack of clear alignment between internal capabilities and the AI products and services brought to market. Capabilities do not appear on their own. AI model performance roughly doubles every four to six months, and that pace makes keeping up especially difficult. A review of the existing literature shows that current maturity models treat internal organisational capability and external product or service strategy as disconnected silos.

This thesis uses the Design Science Research (DSR) method to develop, evaluate, and refine a Dual-Framework AI Maturity Model that addresses this gap. The resulting framework is grounded in the theory of Socio-Technical Systems and in the perspective of dynamic capabilities. The dimensions of this newly built maturity framework are based on a structured comparative review of seven other maturity models already in established use, combined with the author's own practitioner experience from working in the research and development function of a Nordic SaaS company that has deployed AI capabilities in production for over 400 enterprise customers, with security and data governance designed into the system architecture. The first version of the framework was validated through semi-structured interviews with seven cross-functional industry experts. The model was then updated based on those interviews to serve the real needs of business even better.

The study confirmed that successful AI adoption is held back more by organisational and psychological factors than by the technology itself. The theme-based analysis carried out in this study brought to light the need for several structural changes to the model. The findings highlighted for example the critical need to act according to the rules and regulations set by the EU for data management and security and the end-user resistance to sudden zero-UI agentic interfaces changes.

The resulting Dual-Framework provides organisational leaders with a practical diagnostic tool for strategic planning. It links an organisation's internal operational readiness with the capability to produce external AI-based products and services. With this two-dimensional view, leadership can identify areas where AI strategy and its execution are out of balance and plan an executable path toward the target state. Despite the interviews, the scope of this study remains limited. Due to that limitation, the model can be considered a theoretical proposition. The next research step is to test and validate further the resulting maturity model with a larger sample of organisations.

**KEYWORDS:** Artificial Intelligence, Maturity Model, Design Science Research, Socio-Technical Alignment, Product Strategy, AI Governance

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## Abbreviations

**AI: Artificial Intelligence**

**API: Application Programming Interface**

**AX: Agent Experience**

**CMM: Capability Maturity Model**

**CMMI: Capability Maturity Model Integration**

**DSR: Design Science Research**

**EU: European Union**

**GDPR: General Data Protection Regulation**

**HR: Human Resources**

**IT: Information Technology**

**KPI: Key Performance Indicator**

**LLM: Large Language Model**

**MLOps: Machine Learning Operations**

**ROI: Return on Investment**

**SaaS: Software as a Service**

**UI: User Interface**

**UX: User Experience**

# 1 Introduction

## 1.1 Background and Context

The rapid adoption of Artificial Intelligence (AI) is changing how organisations operate, the business models they aim to pursue, and the strategies they need to win (Wang, 2025; Åström, Reim, & Parida, 2022). It is also embedded in the daily work of many knowledge workers, and ways of managing have had to adapt (Williams & Samtani, 2024). For senior leaders the transition has become a central strategic challenge (Saha et al., 2023). Global AI spending is on track to pass $300 billion by 2026 (McKinsey & Company, 2025). Industry reports place the failure rate of AI projects as high as 85%, the phenomenon now commonly called “pilot purgatory”, where promising AI experiments never scale beyond isolated pilots (McKinsey & Company, 2025; Woerner et al., 2025). The reason is structural as Brynjolfsson, Rock, and Syverson (2021) describe in the productivity J-curve. This shows that spending money on AI does not immediately pay off and so companies first need to build up supporting intangible assets. Mikalef and Gupta (2021) back this up by proving that AI capabilities only improve business performance when they are paired with the right organizational resources and are properly integrated.

Davenport and Ronanki (2018) and EY (2025) highlighted that AI helps with improving operational efficiency, supporting better decision making and changing how organisations engage with their customers. It turns out that acting on AI’s potential is harder than seeing it (Keding, 2021). Many organisations get stuck in ad-hoc experimentation with pilot projects accumulating without ever being used organisation-wide or realising their value (BCG, 2025). The result of this is wasted resources and AI spend that fails to translate into actual value (Kahan, 2024). A more structured approach to adoption is needed (Business Finland, 2025). The maturity model developed in this thesis is meant to serve as both a diagnostic tool and a roadmap for AI development.

## 1.2 Problem Statement

Despite the clear potential of AI, organisations face a wide range of challenges with their attempts to adopt AI. These challenges go beyond technological capabilities into organisational, human, and process development areas (AI Finland, 2025). Without a structured framework on how to operate, the costs are significant. Financial investment does not yield returns, competitive standing is weakened, and promising experiments fail to scale or reach usage.

A close reading of the existing literature reveals a basic flaw in current AI maturity models. Those treat internal organisational capability and external product strategy as disconnected silos (Rittman, 2023). Existing frameworks tend to focus on either one of the aspects: how to do things internally inside the organisation, or what we can offer customers in our services. This siloed approach contributes significantly to this problem by preventing organisations from creating the continuous cycle of development where internal capabilities fuel better external products, and insights from those products then help improve the internal capabilities (Emerald Publishing, n.d.).

This leaves a relevant research gap. Leaders currently lack a dual framework that lets them diagnose internal readiness and assess the maturity of their external, AI-powered product or services portfolio at the same time. Without such a model companies risk one of two outcomes. They may build strong internal processes that never translate into market-differentiating products or real value for the business. Or they may launch AI-native products without the stable, scalable, and well-governed internal capabilities required to sustain them (Cui et al., 2024). This research addresses the problem directly by developing and providing initial validation for a dual-framework AI maturity model that bridges the gap between internal capability and external product execution.

## 1.3 Research Objectives and Research Questions

The primary objective of this thesis is to conceptualise, develop, and provide initial validation for a strategic framework, namely an AI maturity model, that guides organisations through the levels of AI adoption. To support this primary objective, three main objectives are set:

1. To identify from existing literature the key categories of AI capabilities within an organisation.
2. To define clear and progressive stages of AI maturity.
3. To map common challenges and governance structures to each stage of the model.

This thesis is guided by this Research Question (RQ):

- **RQ:** What are the core components and developmental levels of a maturity model that can effectively guide organisations in their strategic adoption of Artificial Intelligence?

To provide a complete answer, the following Sub-Questions (SQ) are investigated:

- **SQ1:** What are the key organisational areas (for example strategy, data, technology, people, governance) that help determine AI maturity?
- **SQ2:** What are the characteristics and activities that separate one level of AI maturity in an organisation from the next?
- **SQ3:** What are the primary ethical and organisational challenges that emerge at the different levels of AI maturity?
- **SQ4:** How can a dual-framework model effectively integrate an organisation's internal capabilities with the external capabilities to give a big picture on the potential?

## 1.4 Scope and Delimitations of the Research

The scope of this research is the development of a strategic framework applicable to business organisations seeking to integrate AI. The study takes a cross-industry perspective so that the resulting model is broadly relevant. To be more specific the focus is primarily on mid- and large-sized companies. These companies share enough common challenges around scale, legacy systems, complex governance structures, and organisational change that a single maturity model can describe them commonly. On the other hand, small startups, vary so widely in their structure and constraints that a single model would struggle to capture their reality. For this reason, mid- and large-sized companies are the more suitable target for the framework developed here. This boundary is consistent with the organisational-theory literature on companies growth, which identifies established mid- and large-sized companies as the target of analysis whose administrative structure can sustain repeated capability to invest in projects (Penrose, 1959; Aldrich & Auster, 1986), and with the digital-transformation literature, which concentrates empirical work on this same segment (Vial, 2019).

The research is limited in several ways. First, this thesis uses a qualitative, exploratory research design based on the Design Science Research (DSR) paradigm. It relies on in-depth expert interviews to evaluate and refine a pre-designed framework rather than on a large-scale quantitative survey. Second, the research does not cover the technical implementation details of specific AI algorithms (such as the mathematics of training Large Language Models). The emphasis is on organisational strategy, readiness, and product management. Third, while the model highlights regulatory compliance, in particular the European Union Artificial Intelligence Act (EU AI Act), it focuses on the implementation of governance structures rather than providing an extensive legal framework on AI ethics (Samarawickrama, 2022).

## 1.5 Thesis Outline

The structure of this thesis is as follows:

- **Chapter 1: Introduction**
  This chapter provides the background and context for the research, defines the research gap and problem statement, and outlines the research objectives and questions that guide the research.
- **Chapter 2: Theoretical Background**
  This chapter presents a review of the existing academic and industry literature. It covers theories on AI in business, organisational readiness, implementation frameworks, and existing maturity models to build the theoretical foundation for the research.
- **Chapter 3: Research Methods**
  This chapter showcases the qualitative research methodology chosen for the research. It opens the expert interview process used for data collection and explains the directed analysis approach applied to the interview data.
- **Chapter 4: Results**
  This chapter presents the findings gotten from the analysis of the expert interviews. The results are highlighted thematically to answer the research questions, and show the dimensions, levels, and challenges associated with AI adoption.
- **Chapter 5: Refined Maturity Model**
  This chapter presents the refined version of the AI Maturity Model. It details the levels of the model, explains the capabilities and criteria for each level, and provides a framework for practical application.
- **Chapter 6: Discussion**
  This chapter highlights the implications of the findings and the developed model in relation to the theoretical background.
- **Chapter 7: Limitations and Future Research**
  This chapter talks on the limitations of the current research and proposes concrete directions for future research to build on from there onwards.
- **Chapter 8: Conclusion**

This chapter draws the final conclusions of the study, summarises the main contributions, and reflects on the broader significance of the dual-framework for AI adoption.

# 2 Theoretical Background

This chapter reviews the academic literature that forms the theoretical foundation for this thesis. It synthesises existing knowledge to set the context, justify the research gap, and informs on the development of the AI maturity model. The chapter begins with the strategic importance of AI in modern enterprises. It then touches on the maturity models as a tool for managing complex technological transformations. It identifies and details the core organisational dimensions that constitute AI capability. It closes by proposing the Dual-Framework AI Maturity Model and identifying the specific gaps in the literature that the framework addresses.

## 2.1 The Strategic Imperative of AI in Modern Enterprises

The contemporary business environment is being restructured at a basic level, often described as the Fourth Industrial Revolution, in which digital transformation is the primary catalyst for competitive advantage (Williams & Samtani, 2024). With this restructuring, Artificial Intelligence (AI) has emerged as a general-purpose technology set to become the central driver of organisational evolution and economic value creation (Kitsios & Kamariotou, 2021; Åström, Reim, & Parida, 2022; Mikalef et al., 2019). The strategic question for organisations is therefore no longer whether to adopt AI, but how to integrate it effectively to redefine value propositions, streamline operations, and renew their business models (Saha et al., 2023; Wang, 2025).

The arrival of AI is comparable to the arrival of the internet and the graphical user interface. Both of those earlier waves redefined the basic mechanics of how companies operate and stay competitive. Only a minority of the organisations that ignored the change survived it. AI represents a wave of similar magnitude. It cannot be skipped, and it cannot be jumped on carelessly. Also, on the other hand, it has more risks and so cannot be jumped on without planning. The strategic task for leaders is to find the best way to act on its opportunities while remaining cautious of its threats. This duality is something any maturity model in this space must highlight.

Recent studies show that firms that successfully scale AI initiatives report large performance gains, and the global AI market is overall projected to grow exponentially. This highlights the economic stakes (Mikalef & Gupta, 2021; OECD, 2023). The impact of AI extends far beyond simple automation. It enables a large scale of capabilities. These range from process automation to increase efficiency, insights that help human decision-making and engagement systems that change the customer experience (Davenport & Ronanki, 2018). Acting on these capabilities requires organisations to develop specific organisational capabilities, often referred to in the strategic management literature as "dynamic capabilities" (a capacity to purposefully create, grow, or modify the company's resources) and "absorptive capacity" (the ability to recognise the value of new information and apply it to commercial gains). In the context of AI, these capabilities are what enable a company to move beyond the adoption phase to achieve real strategic agility and a sustainable competitive advantage (Keding, 2021).

The potential for disruption is large. When AI technologies mature, they will change the nature of management by moving organisations from hierarchical, experience-based decision-making structures to faster, data-driven, and decentralised decision making (Raisch & Krakowski, 2021). The path to becoming an AI-driven enterprise is complex and risky. There is a widely acknowledged gap between recognising the strategic importance of AI and successfully embedding it into the day-to-day operation of the organisation (Korherr & Kantere, 2022). Many companies are stuck with a state of "pilot purgatory", which meant that promising but isolated AI experiments fail to scale or deliver company-wide impact or usage. This is a disconnect between ambition and operational reality, which calls for a structured framework to guide AI adoption. The aim is to help organisations move from ad-hoc experiments to strategic and systemic integrations (Shah & Ladhani, 2023).

There is a growing amount of criticism towards the actual productivity and other benefits related to the use of AI. Acemoglu (2024) estimates that the realistic productivity contribution of generative AI over the next decade is far smaller than what consulting forecasts imply, on the order of a few tenths of a percentage point per year. Brynjolfsson and McElheran (2019) show, using U.S. Census Bureau data, that the diffusion of predictive analytics is concentrated on the small number of large, digitally mature firms, with the median firm capturing little measurable benefit. Cockburn, Henderson, and Stern (2018) treat AI as a general-purpose method of invention whose impact depends on the capacity for companies to develop around it. These studies do not contradict the strategic case for AI. They make explicit that the value AI generates is conditional on complementary organisational change. This is the conditional logic the maturity model in this thesis is designed to surface.

## 2.2 Maturity Models as a Framework for Technological Transformation

To manage the complexity of adopting transformative technologies, the concept of the maturity model has proven to be a useful strategic tool. The concept originated in software engineering with the Capability Maturity Model (CMM), and it provides a framework for describing the evolutionary stages of an organisation's capability in a specific domain. Conceptually, the frameworks discussed in this thesis describe a many-sided evolution. They do not only measure technological capability, but a complex mix of organisational change, decentralised decision-making practices, and ongoing governance evaluation.

A maturity model serves as an evaluative and comparative basis. It defines a structured path of development from an initial, often chaotic state (Level 1) to a disciplined, optimised, and innovative state (Level 5) (Butler, 2021). Its primary purpose is to give organisations a clear roadmap. The roadmap helps them assess their current capabilities (the "as-is" state) and define a desired and realistic future state (the "to-be" state). It also helps identify the specific process improvements, resource allocations, and strategic actions needed to bridge the gap.

CMM is the historical predecessor in software engineering, but the broader idea of a maturity model has since become a versatile organisational tool used across many domains. The literature usually splits maturity models into three types by design intent. Descriptive models outline the as-is stages of evolution. Prescriptive models give strategic guidelines for reaching a desired to-be state. Diagnostic models work as assessment tools for identifying operational gaps and misalignments. The AI maturity framework proposed in this thesis is designed to integrate all three functions.

For AI the maturity model is a strong fit for the multiple sided challenges of adopting it because it shifts the focus from technical implementation to a wider view of organisational capability (Jöhnk et al., 2021).

AI capability can only be realised if the entire organisation adapts alongside the technology. AI is not a tool that can be bolted onto an unchanged operating model. It is a change in how people work and operate. Repetitive tasks move to AI-enabled automation, while humans shift into supervisory and improvement-oriented roles. This is known as Human-in-the-Loop (HITL). In HITL, the human is no longer the executor of routine work but the supervisor who verifies that the result is acceptable and who continually seeks to improve the result and the process getting there. This shift is as much a management challenge as it is a technological one, and it requires development of organisational capabilities and leadership practices at the same time with necessary technical investments.

Several researchers have already applied the maturity-model idea to AI. Butler, Espinoza-Limón, and Seppälä (2023), for example, propose a five-level AI Capability Assessment Model (AI-CAM) that gives organisations a way to think about readiness across multiple dimensions. Mahaur (2024) offers a four-level framework focused on strategic AI integration, with a progression that runs from a Disconnected state, where AI is purely tactical, to an Integrative state, where AI is part of corporate strategy. Both of these researchers underline that AI maturity is a path of learning and adaptation rather than a one-time technology project. Improving processes and capabilities step by step across different dimensions increases the likelihood of AI investments delivering a return and creating competitive advantages.

This thesis is based on the Socio-Technical Systems (STS) theory. The STS theory originates from Trist and Bamforth (1951) and their studies on mechanised coal mining at the Tavistock Institute. The principal idea is that any working system contains two sides both of which must be looked at together. The technical side refers to the tools, the machines, and the processes that connect them. The social side refers to the people performing the work, the roles they hold, and the norms that shape how they treat each other. Both sides need to be considered when designing systems. Focusing on solely one side of the puzzle would lead the system to underperform.

Cherns (1976) introduced the idea of joint optimisation. He claimed that if the technical side moves faster, or at different paces in general, than the social side, the intended benefits remain uncaptured. The same happens the other way around. A better tool that a team is unable or I use is not significantly better than having no tools in the first place. In the same way, a highly skilled team without the right tools at hand cannot deliver value either.

A more recent research has adopted this idea into digital and AI work. Sony and Naik (2020) discovered that projects that pushed the technology forward without bringing the people along failed in the same way as Trist and Bamforth (1951) saw in the coal mines decades earlier. Pasmore et al. (2019) argued that this gets worse with algorithmic systems as they scale faster than the social practices around them, leading to the gap between the two widening faster than before. Makarius et al. (2020) built a socio-technical framework specifically for AI. They treat algorithms as new participants in the workplace. Whether those algorithms get accepted depends on the social setup around them.

The dual-framework in this thesis applies this idea to AI maturity. The Internal model covers the social side so people, roles, governance, and culture. The External model covers the technical side. The two are designed to be assessed and developed together.

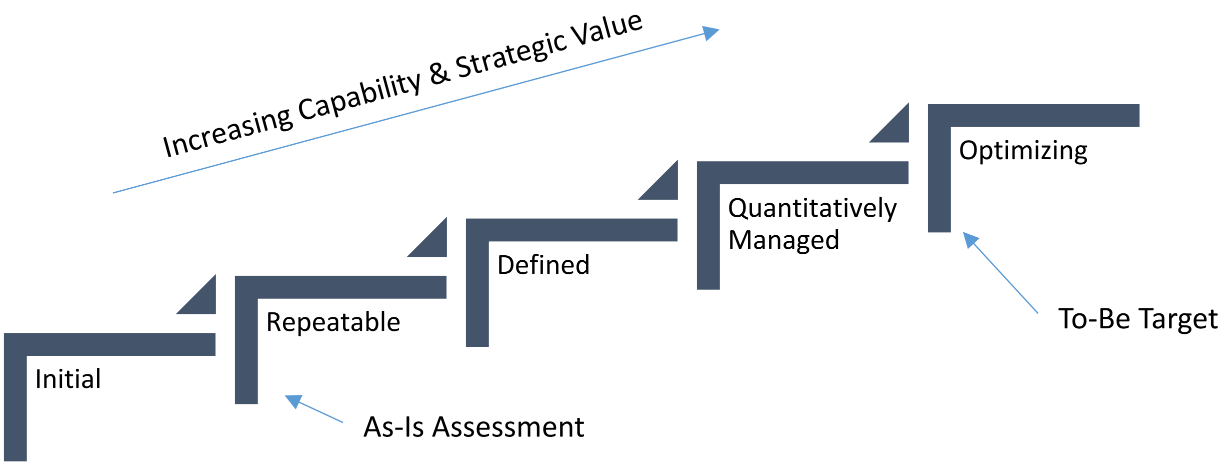


**Figure 2-1 Conceptual Purpose of a Maturity Model (Adapted from Butler, 2021).**

The stages refer to organisational capability. Different organisations move through them at different speeds. The CMM stage names (Initial, Repeatable, Defined, Quantitatively Managed, Optimizing) are kept here as Paulk et al. (1993) defined them.

## 2.3 A Brief History of Maturity Models

The history of maturity models is most famously traced back to the Capability Maturity Model (CMM), developed by the Software Engineering Institute (SEI) at Carnegie Mellon University in the late 1980s. CMM was designed to help the U.S. Department of Defense assess the capability of software development contractors. It introduced the seminal five-level structure that has become the de facto standard for most subsequent models:

1. **Initial**: Processes are chaotic, ad-hoc, and success depends on individual heroics.

2. **Repeatable (or Managed)**: Basic project management processes are established to track cost, schedule, and functionality.
3. **Defined**: The software process for both management and engineering activities is documented, standardized, and integrated into a standard organisational process.
4. **Quantitatively Managed**: The organisation establishes quantitative objectives for quality and process performance and uses data to control them.

5. **Optimizing**: The organisation focuses on continuous process improvement through quantitative feedback and the piloting of innovative ideas and technologies.

The success of CMM led to its evolution into the Capability Maturity Model Integration (CMMI), which sought to integrate models for different organisational functions (for example systems engineering and software engineering). The core idea remained the same: organisational maturity is a path of increasing process control, predictability, and effectiveness. This staged approach to capability development has since been adapted to many other domains, including data management and project management, and now to Artificial Intelligence (Gama, Tyskbo, & Svedberg, 2022; Mikalef et al., 2019). Two examples worth noting are the Data Management Body of Knowledge (DAMA-DMBOK), the reference framework maintained by the Data Management Association International, and the Organisational Project Management Maturity Model (OPM3) published by the Project Management Institute. Both adapt the CMM logic to their respective domains and confirm the broad portability of the maturity-model concept.

## 2.4 Scholarly Criticisms of Maturity Models

While maturity models are useful and widely used strategic tools, they are still subject to scholarly criticism that must be acknowledged. Critics frequently argue that these frameworks assume a perfectly linear and sequential progression that rarely reflects the complex real-world organisational dynamics (Wendler, 2012; de Bruin et al., 2005).

Traditional models often fall into the "plug-and-play" thinking fallacy. This includes an assumption that simply having new technology available would automatically lift an organisation to the next level of maturity. This assumption, to a large extent, ignores the complex, non-linear and iterative nature of human adoption and cultural change that cannot be entirely controlled upfront.

Any rigid stage-gate based models also struggle to properly and accurately represent organisations that are advanced in one department but immature in others. The Dual-Framework AI Maturity Model proposed here is built to answer those academic criticisms. It rejects pure technological determinism and works instead from the principle of socio-technical alignment. The framework couples an internal capability engine with an external product matrix. With AI the maturity is not given but has to be earned through coordinated efforts in culture, governance and strategic intent.

## 2.5 The Foundations of AI Readiness: Organisational Learning and Data Culture

AI integration is a modern software requirement, but successful adoption is not a technology problem. The literature points to two cultural attributes that determine whether an organisation can transform itself. Those are its maturity as a learning organisation and the strength of its data-driven culture (Palade & Carutasu, 2021; Emerald Publishing, n.d.). An organisation that does not have the capability to learn new things cannot apply AI correctly in the first place.

The learning-organisation concept is most closely associated with Senge (2006), who describes a firm where “people continually expand their capacity to create the results they truly desire, where new and expansive patterns of thinking are nurtured, where collective aspiration is set free, and where people are continually learning how to learn together.” Such firms are good at creating and transferring knowledge, and at adjusting their behaviour as that knowledge changes. The framing dates to the 1990s, but the underlying claim is independent of any particular technology. Recent AI-readiness research replays it in current language (Jöhnk et al., 2021; Ransbotham et al., 2023). The same logic carries straight into AI adoption.

AI implementation is not a one-off event. It is an ongoing cycle of experimentation and adaptation. Organisations with a mature learning culture have an advantage as experimentation needs psychological safety and process flexibility. They can pilot new AI tools and learn quickly from both the wins and the failures. This leads to integrating the tools into core workflows in a shorter time span. Rigid structures and a fear of the unknown are not slowing down such companies (Jöhnk et al., 2021).

A data-driven culture is the modern day learning organisation in the digital era. The basic idea is to make decisions based on evidence rather than intuition (Raisch & Krakowski, 2021). It is important to highlight that this does not mean an organisation needs a perfect, company-wide data culture before it can start trying out AI. The first AI pilots usually showcase where the company's data is messy or inaccessible. That pain pushes the organisation to clean up its data and invest in better data systems. This means a data-driven mindset and organisational learning are not milestones you check off before you start working with AI. They form the baseline requirements which keep growing stronger as an organisation advances in the journey.

## 2.6 Illustrative Frameworks for AI Maturity

The maturity model concept has been widely adapted to AI, often using visual metaphors to illustrate the progression. The S-Curve (Figure 2-2), popularised by industry analysts such as Gartner, is a common visualisation tool to show how business value increases as an organisation moves through stages of awareness and experimentation toward systemic change. Other frameworks visualise capability as a pyramid (Figure 2-3), emphasising the need for a solid data and skills base level before higher-level innovation can be achieved. It is also possible to see maturity as a series of expanding concentric circles (Figure 2-4), where the impact of AI grows from a single project to throughout the entire business ecosystem.

A complementary lens, useful for understanding how AI spreads inside any single organisation, is Rogers' classic technology adoption curve. This framework groups adopters into five segments, namely innovators, early adopters, early majority, late majority, and laggards. It shows that any new technology reaches different parts of an organisation at different speeds. The curve helps explain why maturity rarely advances at the same speed. A small minority of innovators and early adopters typically experiment first, while the larger early and late majorities require proof of value and active change management process before adopting new tools. The laggards may resist the change altogether. A maturity model that ignores this distribution risks mischaracterising a company as a unified actor when in practice it contains many different segments moving at very different paces.

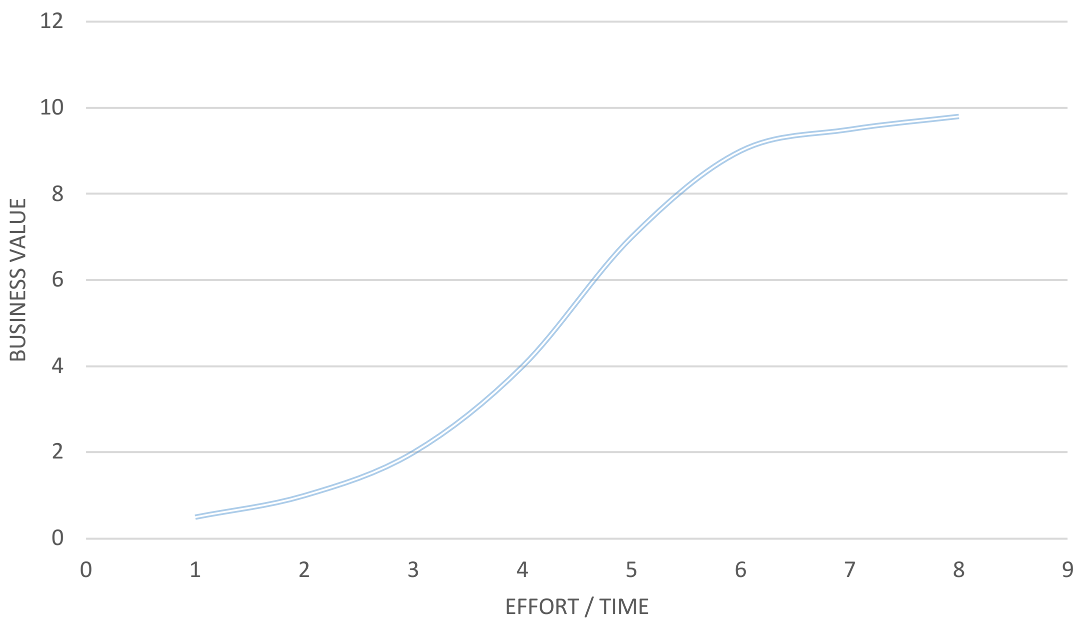


**Figure 2-2: S-Curve of AI Business Value (Derived from Mahaur, 2024).**

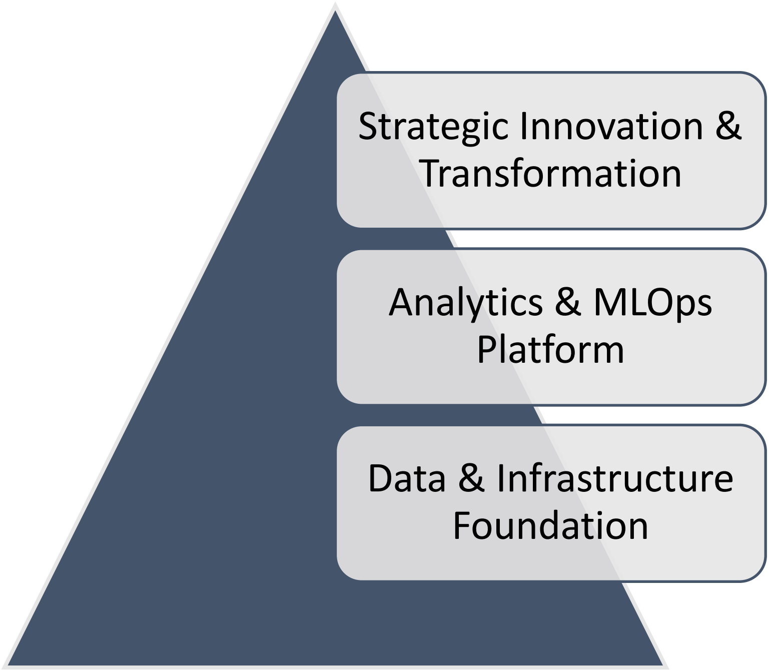


**Figure 2-3: The AI Capabilities Pyramid (Adapted from Mikalef et al., 2019)**

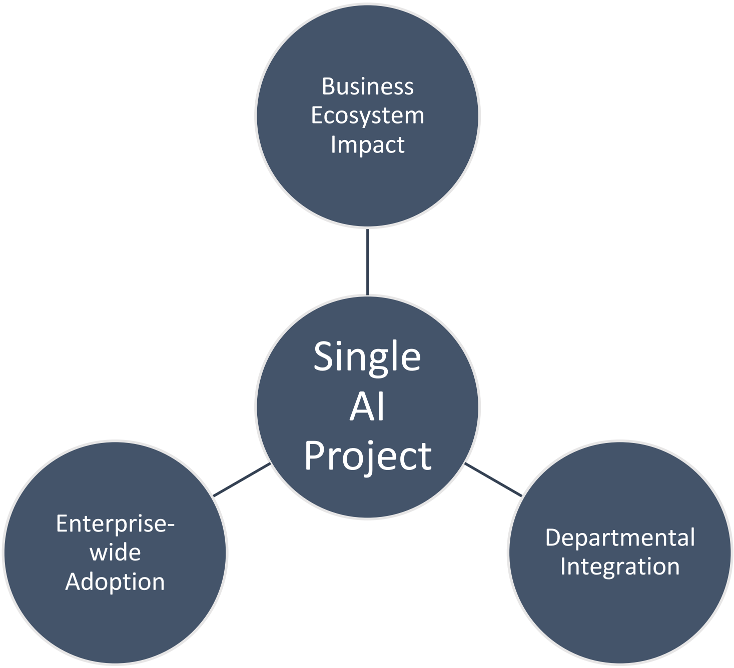


**Figure 2-4: Organisational Impact of AI (Derived from Korherr & Kantere, 2022).**

Beyond the illustrative metaphors above, this thesis is built on a structured comparison of seven established maturity models found from the AI, digital-transformation, and process-engineering literature. The comparison covers two AI-specific staged models (Butler, 2021; Mahaur, 2024), two peer-reviewed AI readiness frameworks that specify dimensions without staged levels (Mikalef & Gupta, 2021; Jöhnk et al., 2021), one broader digital-transformation maturity framework (Saldanha, 2019, as discussed in Vial, 2019), one recent industry-research model of AI value capture (Woerner et al., 2025), and the original CMMI model as the historical reference point (CMMI Institute, 2018).

| Maturity model (source) | Primary scope | Dimensions | Level structure | Validation method |
|---|---|---|---|---|
| AI-CAM (Butler, 2021; Butler et al., 2023) | Internal AI readiness | Strategy, data, technology, people, governance (5) | 5 levels (Initial → Optimising) | Case-based; no longitudinal validation |
| Strategic Enterprise AI (Mahaur, 2024) | Strategic AI integration | Strategy, operations, talent (3) | 4 levels (Disconnected → Integrative) | Conceptual synthesis |
| AI capability conceptualisation (Mikalef & Gupta, 2021) | Firm-level AI capability | Tangible, human, intangible resources (8 sub-dimensions) | No staged levels; resource-based view | Quantitative survey; PLS-SEM with firm-performance link |
| AI readiness factors (Jöhnk et al., 2021) | Pre-adoption readiness | Strategic, resource, knowledge, culture, data (18 items) | No staged levels; readiness factor list | Delphi study with practitioners |
| Digital transformation maturity (Saldanha, 2019, in Vial, 2019) | Broader digital transformation | Customer experience, operations, business model (3) | 5 stages (Foundation → Living) | Conceptual and case-based |
| AI maturity for bottom-line impact (Woerner et al., 2025) | Enterprise AI value capture | Data, talent, governance, operating model (4) | 4 stages | Large-N practitioner survey (industry research) |
| CMMI (CMMI Institute, 2018) | Generic process capability | Process areas grouped into categories | 5 levels (Initial → Optimising) | Formal appraisal and assessment scheme |
| Proposed Dual-Framework (this thesis) | Internal capability and external product, with explicit interdependence | 9 internal + 8 external dimensions | 5 levels in each model, with theoretically supported progression | DSR; qualitative expert evaluation; quantitative validation called for |

**Table 1: Comparative review of existing AI and digital maturity models.**

None of the reviewed models diagnoses internal organisational capability and external product strategy together, either combining them into a single axis or treating them as separate research streams. Only Mikalef and Gupta (2021), Jöhnk et al. (2021), and Woerner et al. (2025) report formal empirical validation. The AI-specific staged models have been validated conceptually rather than over time, which is why this thesis evaluates its framework through expert interviews. The dimensions across all the reviewed models focus around five recurring areas (strategy and leadership, data and analytics, technology and tools, people and culture, and governance and risk), and the Dual-Framework's internal model uses these five dimensions for analytical compatibility with the existing literature.

## 2.7 Key Dimensions of AI Capability

Achieving AI maturity requires balanced and coordinated development across several related organisational areas. Existing literature offers fragmented taxonomies of AI readiness. Some models focus heavily on IT infrastructure while others place most of the weight on human resources (Mikalef & Gupta, 2021; Jöhnk et al., 2021). To create a usable Design Science Research (DSR) framework that solves a real organisational problem, this thesis intentionally synthesises those fragmented approaches into five core capability dimensions. This specific five-pillar structure has been deliberately chosen over a larger, six- or seven-dimension model to avoid conceptual overlap and keep the framework easy to use. The author of this thesis has selected these five dimensions as a synthesis based on the maturity-model literature reviewed in the Section 2.6. The theoretical background for these dimensions is presented in the Sections 2.7.1–2.7.5.

Within the selected structure, "ROI and Business Impact" sit underneath "Strategy and Leadership" rather than each of them standing on their own. That is because ROI is a direct result of a well-aligned strategy and not an independent operational skill. "Ethics and Governance" also include the internal and external perspectives, because they focus on very different practical issues. The internal governance lays primary attention to employee data privacy and managing operational risk, while the external ethics covers algorithmic transparency, user trust, and how to make the AI in the product easier to explain.

This five-pillar structure covers all the organisational layers needed for socio-technical alignment, connecting high-level strategy and laying foundational structures for better workforce dynamics and regulatory compliance.

### 2.7.1 Strategy and Leadership

The reason strategy and leadership are a core dimension comes from two main theories. These are the dynamic capabilities theory (Teece, Pisano, & Shuen, 1997; Teece, 2007) and the upper echelons theory (Hambrick & Mason, 1984) both prove that any strategic change depends on top management noticing new opportunities and driving the interest within an organisation. This dimension measures how deeply AI is built into the corporate strategy and how actively leadership champions it. At low maturity levels, AI projects are merely isolated experiments, with no backing from leadership backing or no clear link to the business results sought after. Highly mature organizations have a clear, company-wide AI vision driven straight from the C-suite. The AI strategy is explicitly linked to business goals, investment is focused, and a culture of data-driven decision-making is built from the top down (Mahaur, 2024). This includes approving budgets, communicating the vision, managing the organisational change, and holding the enterprise accountable for AI objectives (Ransbotham et al., 2023; Lakshman & Sunkara, 2024).

### 2.7.2 Data and Analytics Infrastructure

The theoretical basis for the data dimension comes from resource-based theory applied to information resources, and specifically from the DAMA Data Management Body of Knowledge (DAMA International, 2017). This defines the maturity stages of data quality, governance, architecture, and accessibility. Data is the foundational element of any AI system. This dimension measures the maturity of an organisation's data ecosystem, covering not only the volume and variety of data but also its quality, accessibility, and governance. Low-maturity firms often struggle with fragmented, siloed, and low-quality data. High-maturity organisations, by contrast, have invested in a modern data architecture (such as a data lake or a federated data mesh), strong data governance policies, and clear data lineage (AI Finland, 2025). This means their AI systems are given reliable, accessible, and ethically sourced information. This is an important precursor to developing trustworthy and effective models.

### 2.7.3 Technology and Tools

The technology dimension is extracted from IT architecture and platform literature, particularly Sambamurthy, Bharadwaj, and Grover’s (2003) work on digital agility, and on the MLOps literature. This defines a clear progression from ad-hoc model deployment to standardised, scalable model operations (Kreuzberger, Kühl, & Hirschl, 2023). This dimension refers to the technological stack that enables AI development and deployment. The progression of maturity moves from using basic, off-the-shelf AI tools to building a scalable Machine Learning Operations (MLOps) platform. An MLOps platform is an internal platform that standardises how AI models are developed, deployed, monitored, and retired across the organisation. Still important to remember that trendy functionalities (such as generative AI or autonomous agents) quickly become outdated. In the context of a strategic maturity model, this dimension does not simply track software trends. It reflects the organisational capability to integrate advanced AI architectures with legacy enterprise systems and scale them securely.

For example, while the current technological frontier points toward multi-agent architectures that run workflows autonomously, the word "autonomous" in an enterprise context does not imply a total absence of legal or human oversight. High technical maturity requires the structural capability to build highly automated, generative workflows that still retain the mandatory Human-in-the-Loop (HITL) governance checkpoints. These HITL checkpoints ensure safety, legal compliance, and reliable product outputs. The HITL is the current best practice that ensures the organisation avoids costly mistakes caused by blindly trusting the output of AI and lacking control.

### 2.7.4 People, Skills, and Culture

The dimension of people in this study is based on theorganisational learning theory (Senge, 2006; Crossan, Lane, & White, 1999) and on Edmondson's (1999) work on psychological safety within teams. The skills side is taken from absorptive capacity (Cohen & Levinthal, 1990). Technology alone is not sufficient to create value. It requires skilled people working within a supportive culture. This dimension evaluates an organisation's human capital. It includes the availability of technical talent to make the systems work. This remains a major bottleneck for many firms (OECD, 2023). It also extends to the broader "AI literacy" of business and management staff. This is very much needed for effective human-AI collaboration. A mature organisational culture supports psychological safety for experimentation, encourages cross-functional teamwork between technical and other units, and reframes AI as a tool that helps with people's work rather than simply replacing them (Raisch & Krakowski, 2021).

#### 2.7.5 Governance, Ethics, and Trust

Governance, ethics, and trust draws on institutional theory (DiMaggio & Powell, 1983) and on the AI ethics governance literature, particularly Fjeld et al. (2020), Novelli et al. (2024), and Lee et al. (2023). This is used to assess the structures in place to manage risks such as algorithmic bias and data privacy concerns. In the current regulatory environment, governance is no longer just an internal ethical choice. It is a strict legal mandate with severe financial penalties. This is seen, for example, with the GDPR in the European Union.

The regulatory environment, shaped by frameworks such as the European Union Artificial Intelligence Act (EU AI Act) shapes this dimension. Regulatory compliance is therefore best treated as a core organisational capability rather than a one-off legal hurdle. Mature organisations translate these shifting legal requirements into a day-to-day operating practice of "Compliance by Design" (Fjeld et al., 2022). Low-maturity firms are more reactive and that exposes them to severe legal risk. High-maturity firms encapsulate the governance into the engineering work and product architecture. Also structures such as internal AI Governance Committees are set in place so that scalable models are secure and transparent by default (Lee et al., 2023).

It is also good to note that the responsibilities in this dimension overlap meaningfully with the broader corporate-responsibility agenda represented by the Environmental, Social, and Governance (ESG) framework. The "S" and "G" of ESG, namely social impact and governance, are directly engaged by AI adoption, as algorithmic decisions affect employees, customers, and wider society. It is important to treat AI governance as part of an organisation's ESG posture, rather than as a narrow technical compliance task. This helps anchor it in the same accountability structures already used for sustainability reporting and ethical conduct.

The EU AI Act sorts AI systems into four risk tiers, and each tier maps onto a specific level of the framework's governance dimension. At the strictest end, unacceptable-risk systems such as social-scoring applications are banned outright. The framework treats recognising and refusing to build such systems as a baseline Level 1 capability. High-risk category of systems are those used in employment, credit, education, and critical infrastructure. The Act requires conformity assessment, technical documentation, monitoring, and human oversight for them. The framework treats meeting these obligations as a Level 3 capability. Limited-risk systems such as customer-facing chatbots require only transparency disclosures and sit at Level 2 in the model. Minimal-risk systems are largely unregulated and form the baseline on which most internal experimentation can easily take place.

How strict the Act is as a binding constraint on companies remains a question mark. The Commission's Omnibus simplification package (European Commission, 2025) has been seen as a softening of certain reporting requirements, and some commentators argue that the Act's main practical effect falls on individual rights protection rather than on commercial conduct. The framework's value does not depend on which side is right. Mature organisations will anyway need the capability to classify, document, and oversee their AI systems.

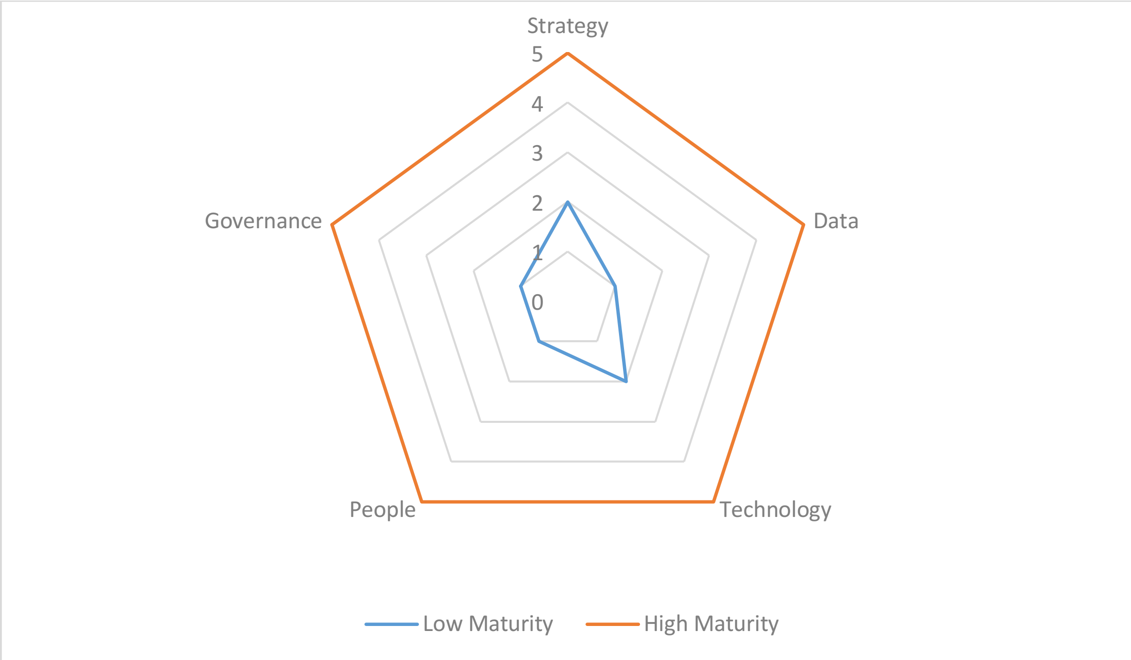


**Figure 2-5: The Five Dimensions of AI Capabilities (Derived from Mikalef & Gupta, 2021; Butler, 2021).**

## 2.8 A Proposed Dual-Framework for AI Maturity

The existing literature on AI and digital maturity in general, reviewed in Section 2.6, revealed a profound gap. The established frameworks, such as the AI-CAM strategic model (Butler, 2021) and Mahaur's (2024), mainly focus on operational processes. They treat internal organisational readiness and external product strategies as two separate entities, failing to form an explicit link between a well-running internal operational engine and competitive customer-facing AI products.

To address the above-mentioned gap, this thesis presents a Dual-Framework for AI maturity, grounded in Socio-Technical Systems Theory and Dynamic Capabilities. From a socio-technical perspective, an organisation cannot achieve alignment if its technical output (a highly advanced external AI product) is developing faster than its social infrastructure (internal culture, skills, and governance). The dual-framework visually and conceptually combine these two sides. It brings proof points that the socio-technical alignment of mature internal capabilities is the fundamental requirement to successfully fuel and scale external product innovation. Also, the market data and user feedback loop from the external product must be fluid to ensure rapid iteration and refinement. The path to a perfect solution is experimental, iterative and, all in all, an interactive process.

The framework derives from the established AI readiness research (e.g., Mikalef & Gupta, 2021; Butler, 2021; Jöhnk et al., 2021) alongside the author's own hands-on experience implementing enterprise AI and developing data secure AI powered SaaS solutions. Combining academic theory with real-world experience ensures that the model is grounded in operational reality right from the start. As organisations move up through the maturity levels, AI management shifts from temporary, ad-hoc fixes to more reliable and consistent data-driven decision-making, embedded in every department.

The above-mentioned approaches aligns well with Teece's (2007) framework. According to him, internal capabilities drive external product maturity through three phases: sensing, seizing, and reconfiguring. To sense an opportunity, a company requires clean data and AI-literate workforce to be able to recognize what is actually possible. Seizing that opportunity then requires a leadership team willing to fund the project, a tech platform that can handle the workload, and a functional governance process. After launching, with the product running and evolving, this phase is what Teece defines as reconfiguring. This depends a lot on internal capabilities like model monitoring, compliance review, and feedback handling. Customer use of the live product then gives new data back into the organisation. That new data helps with future decisions about which products to build next and which risks have shown up in practical use. The fully developed models, including their detailed dimensions, levels, and descriptive tables, are presented in Chapter 5 as the primary artifact resulting from this research.

The progression between levels is drawn from Crossan, Lane and White's (1999) 4I model of organisational learning, which describes how a new practice moves through four stages. The steps are intuiting it as an individual, interpreting it in conversation with others, integrating it across the team, and institutionalising it as a standard part of the organisation. The transition from Level 2 to Level 3 in the framework is the hardest one because it requires the move from individual interpretation to organisational integration. That move requires shared understanding, and shared understanding requires central coordination. This is why the model treats Level 3 as a centralisation step rather than a scaling step. Cohen and Levinthal's (1990) work on absorptive capacity makes the same point from a different angle. An organisation can only absorb new knowledge once it has built up enough related prior knowledge to recognise what the new data provides. Jöhnk et al. (2021) find that this same transition is empirically the most common point at which AI adoption stalls.

### 2.8.1 Model 1: Internal AI Capability Model

| *Capability Dimension* | Level 1: Unaware / Ad-Hoc | Level 2: Exploring / Foundational | Level 3: Practicing / Systematic | Level 4: Scaling / Managed | Level 5: Leading / Optimizing |
|---|---|---|---|---|---|
| ***Strategy & Vision*** | No formal AI strategy exists. | AI is mentioned in some discussions, but no official strategy is in place. | A formal AI strategy is drafted, aligned with specific business unit goals. | AI is a core pillar of the overall corporate strategy. | AI drives the corporate strategy and creates new business opportunities. |
| ***Leadership & Sponsorship*** | No executive awareness or interest. | A few managers show interest; sponsorship is limited to small pilot projects. | C-suite sponsorship is secured for key, funded initiatives. | A central AI leader (e.g., Head of AI) coordinates efforts across the enterprise. | The entire executive team is AI-literate and champions an AI-first culture. |
| ***ROI & Business Impact*** | AI impact is zero or unmeasured. | ROI is not formally tracked; focus is on learning, not financial return. | Success is measured by project completion and specific, local KPIs. | ROI is systematically measured and linked to enterprise-level efficiency gains. | AI creates new revenue streams or demonstrably autonomous operational efficiencies. |
| ***Data Governance*** | No data governance. Data is a wild west. | Basic discussions about data ownership begin for pilot projects. | Formal data governance policies are implemented and enforced. | A mature, enterprise-wide data governance model is fully operational. | Data governance is automated and seamlessly integrated into all data workflows. |
| ***Data Infrastructure*** | Data is siloed, inaccessible, and often of poor quality. | Point-to-point data connections are made for specific projects. | A centralised data warehouse or data lake is established. | A scalable, real-time data platform serves the entire organisation. | A federated data mesh architecture provides clean, accessible data everywhere. |
| ***Technology & Architecture*** | Standard IT infrastructure with no AI-specific components. | Experimentation with cloud-based, off-the-shelf AI services and APIs. | A rudimentary, centralised AI/ML framework is being built in-house. | A secure, scalable, and robust internal MLOps platform is operational. | The organisation contributes to open-source AI architecture and frameworks. |

| | | | | | |
|---|---|---|---|---|---|
| ***Skills & Roles*** | No dedicated AI roles exist. | One or two AI champions or data-savvy individuals drive efforts. | Formal roles like Data Scientist and ML Engineer are hired into a central team. | Dedicated AI teams are embedded within multiple business units. | AI expertise is deeply integrated across all functions, not just in technical roles. |
| ***Culture & Collaboration*** | Siloed departments; fear or ignorance of AI is common. | Collaboration occurs on a project-by-project basis. | Cross-functional teams (business, tech, data) are formed for AI projects. | A culture of data-driven decision-making is spreading across the organisation. | A culture of continuous learning and safe experimentation is the norm. |
| ***Ethics & Risk Management*** | No awareness of AI-specific risks. | Risks are considered informally on a case-by-case basis. | An initial AI risk framework is developed, often driven by the legal team. | A mature, proactive AI ethics board and review process are operational. | The organisation is seen as an industry leader in responsible and ethical AI. |

**Table 2: Preliminary Internal AI Capability Model (Author's creation, synthesized from literature review)**

### 2.8.2 Model 2: External AI Product Maturity Model

| ***Product Dimension*** | **Level 1: No AI Integration** | **Level 2: Feature-Driven / "Bolt-on"** | **Level 3: Experience-Aware / Rethought** | **Level 4: AI-Native / Core Value** | **Level 5: Ecosystem-Orchestrating** |
|---|---|---|---|---|---|
| ***Product Strategy*** | The product roadmap does not include AI. | AI is used to add “checklist” features to achieve competitive parity. | AI is used strategically to improve the core user experience and increase retention. | AI is the core differentiator and value proposition of the product. | The product becomes a platform, enabling others to build AI-powered value. |
| ***Business Model*** | Traditional (e.g., license fee, one-time sale). | No change to the business model; AI is an included feature. | AI features may justify a new pricing tier (e.g., “Pro” version). | The business model is intrinsically linked to AI (e.g., pay-per-prediction, outcome-based). | The business model is based on platform usage and ecosystem participation. |
| ***User Experience (UX)*** | Static, one-size-fits-all experience. | AI features feel like distinct add-ons, separate from the core product flow. | The product feels “smarter” and begins to anticipate user needs within existing workflows. | The experience feels predictive and deeply personalised; it “just works.” | The user transitions from a consumer to a creator, using generative AI to create new things. |
| ***Agent Experience (AX)*** | Does not exist. | The experience is limited to manual, one-off prompting of a simple tool, such as a side-panel chatbot. The user must initiate every interaction. | The system begins to anticipate simple user needs within existing workflows. The user starts to trust the AI for basic, predictive suggestions. | This marks the clear transition to Agent Experience. The user's role shifts from a director to a supervisor, overseeing AI agents that perform complex, multi-step tasks. | The experience is defined by "zero-UI" environments where the user governs autonomous agents that work in the background. The interaction is highly predictive and multimodal, happening with minimal friction. |

| | | | | | |
|---|---|---|---|---|---|
| ***Core Product Logic*** | The user must do all the work and make all the decisions. | The core product logic is unchanged; AI is a "sidecar" | Core user flows are rethought to remove steps and automate decisions. | The product could not exist or deliver its value without AI at its core. | The product logic becomes generative, creating entirely new outputs, not just predictions. |
| ***Technology Integration*** | Monolithic architecture not built for AI. | Heavy reliance on integrating third-party APIs for quick deployment. | A mix of APIs and custom-built models for specific, high-value tasks. | A proprietary, secure, and scalable AI architecture is the product foundation. | The proprietary architecture is opened up as a platform for third-party developers. |
| ***Data & Personalisation*** | No user data is leveraged for in-product experience. | Basic data (e.g., user segment) is used to trigger simple AI features. | A feedback loop is created; user interactions are used to improve the AI models over time. | Rich, real-time user data fuels a deeply personalized, 1:1 experience. | User and ecosystem data create powerful network effects, making the platform smarter. |

**Table 3: Preliminary External AI Capability Model (Author's creation, synthesized from literature review).**

## 2.9 Overcoming the Challenges and Risks in AI Adoption

The multidimensional capabilities outlined in Section 2.7 do not develop by themselves. The progression is frequently stalled by barriers inside the organisation. An effective maturity model must therefore act as a diagnostic guide for anticipating and mitigating these friction points. A synthesis of the literature reveals a clear taxonomy of these obstacles, which often arise from organisational problems rather than technical deficits (Korherr & Kantere, 2022). While technical hurdles are substantial, still the most stubborn barriers are coming from the socio-technical friction of people, processes, and strategy.

Key organisational challenges identified in the literature include the lack of a clear strategy and business case. Many organisations initiate AI projects based on technological hype rather than a clear connection to business value and this is leading to a failure to secure long-term funding and an inability to demonstrate ROI. The continuous skills gap is another primary constraint on growth as the demand for top talent with advanced AI and data science skills surpasses the supply. Organisational and cultural resistance also creates a hurdle, as AI initiatives often set new requirements for major changes to existing business processes and job roles. This is prone to trigger resistance by employees who fear for job losses and distrust algorithmic decision-making. The advancement of many companies is stalled by wrongly implemented, over protective data governance and technology related availability issues even when their actual strategy is clear. They are struggling with a lack of high-quality, accessible, and well-governed data that makes their AI ambitions technically infeasible. Ethical and regulatory uncertainty also creates reputational and legal risks. A lack of clear internal governance frameworks for this complex area can lead to barriers and a reluctance to deploy AI in high-stakes applications.

Working through these challenges successfully is a hallmark of increasing maturity. A well-designed maturity model should therefore define both the capabilities needed at each stage and how to overcome the specific challenges associated with that stage. Three sources from the change-management literature inform how the framework treats the transition between levels. Kotter (1996) describes organisational change as an eight-step sequence that begins with establishing urgency and ends with anchoring new practices in the culture, and his sequence maps onto the level progression of the Internal AI Capability Model. The Prosci ADKAR model (Hiatt, 2006) operates at the individual level. It explains why a top-down mandate alone is not enough. Each person must want the change before they can be expected to learn it, do it, and stick with it. Vial's (2019) peer-reviewed synthesis of the digital transformation literature finds that the absence of structured change-management practice is one of the most cited causes of failure. Each level in the framework therefore carries a corresponding change-management focus, which is set out in the model in Chapter 5.

## 2.10 Summary and Identified Literature Gaps

The review of current literature confirms that Artificial Intelligence has moved beyond experimental use into a strategic role that changes organisational management and value creation. To work through this change and escape "pilot purgatory", maturity models have proven to be useful strategic tools (European Commission, n.d.). The literature shows that successful AI adoption requires a multi-dimensional approach that covers strategy, data infrastructure, technology, human capital, and proactive governance.

However, a careful analysis of the existing frameworks, drawing on the structured comparison set out in Section 2.6, reveals conceptual and practical gaps that this thesis aims to address:

- **The siloing of internal and external capabilities**. The most significant issue in the current academic and industry maturity models is that these models treat internal organisational readiness and external product strategy as isolated silos. Existing frameworks focus either on optimising internal operations for efficiency or on adding AI features to customer-facing products. They fail to create an integrated view that links the two. This leaves leaders without a single tool to diagnose where they are lacking. (Mikalef & Gupta, 2021; Vial, 2019).
- **An over-emphasis on technological milestones**. Many current models heavily rely on advanced technological achievements (for example building custom foundation models) while underrepresenting the organisational blockers. Examples of this could be strict regulatory compliance (EU AI Act) and the psychological resistance of end-users. (Jöhnk et al., 2021; Sony & Naik, 2020).
- **A lack of diagnostic concreteness**. While existing models successfully describe theoretical levels of maturity (for example from "Initial" to "Optimising"), they frequently lack the concrete narrative context and actionable transition steps required for organisations to apply them in practice. (Wendler, 2012; Vial, 2019).
- **A weak link to change management**. Existing maturity models tend to stop at diagnosis. They identify gaps but rarely connect those gaps to the practice of organisational change management, namely the structured discipline of moving people, processes, and culture from one operating state to another. A diagnosis without a path of change leaves leaders aware of the problem but unequipped to act on it. The framework developed in this thesis therefore positions change-management practice as the necessary companion to the maturity diagnosis (Vial, 2019; Kotter, 1996).

This thesis confronts these gaps directly. Using empirical qualitative research, the study goes beyond abstract, technology-centric frameworks to conceptualise and validate a dual-framework AI maturity model. The proposed model bridges the gap between internal capability and external product execution. This is grounded in the practical realities of organisational adoption.

# 3 Research Methods

This chapter sets out and justifies the research methodology of the study. It covers the research paradigm, the initial design of the theoretical framework, the methods used for empirical evaluation, and the process by which the final artifact was refined.

## 3.1 Methodological Approach

This study adopts Design Science Research (DSR) as its foundational methodological paradigm. In information systems and strategic management, qualitative methodologies split into two categories. Behavioural science methodologies aim to observe and explain existing phenomena from scratch. Design science methodologies operate as a prescriptive, problem-solving paradigm (Hevner et al., 2004). DSR explicitly aims to create and evaluate new artifacts (such as models, methods, or frameworks) that solve identified real-world organisational problems.

DSR is a good fit for this thesis. As set out in the problem statement in Chapter 1, organisations are currently failing to scale Artificial Intelligence. This failure is not caused by a lack of available technology. It comes from a strategic misalignment between their internal operational capabilities and their external product strategies. The aim of this study is not to observe this failure passively. The aim is to design a normative artifact (the maturity model) that gives organisations an easy structure to follow. This solution-oriented approach aligns with the nature of DSR.

The creation of the artifact follows the DSR methodology outlined by Peffers et al. (2007). The creation process started with a "Design and Development" phase which preceded any formal testing. During this initial phase, the basic structure of the tool was built. This first version covered both internal capabilities and external product maturity levels. The process followed the previously presented DSR principles, according to which an artifact's initial design must be rooted in both theory and practice (Hevner et al., 2004).

The core capability dimensions on the framework's y-axis were drawn directly from relevant academic literature on AI readiness, dynamic capabilities, and socio-technical alignment. It is worth noting that AI being such a new while rapidly evolving domain, availability of up-to-date documentation is limited. The progressive main criteria defined along the x-axis are based on the author's own practical experience gained from guiding and running over 400 enterprise AI projects.

For clarity, the previously referred enterprise AI engagements do not constitute a formal statistically fully relevant empirical dataset. Instead, they represent the hands-on knowledge used to build the initial framework. The engagements took place mainly between 2021 and 2025 across the Nordic B2B sector. The industries covered finance, manufacturing and technology. All of them are related to a single Nordic technology company where the author has worked, along with his Master's studies, in various roles during the entire period. The clients have been medium- and large-sized European companies.

The patterns and interdependencies built into the maturity model are based on practical rules of thumb learned from hands-on experience. They reflect evidenced recurring bottlenecks and implementation failures rather than findings from a formal quantitative study. Within the DSR paradigm, the practitioner-based design phase forms the initial design cycle. The resulting model was then put through an external empirical validation process.

## 3.2 Data Collection

According to the DSR, data collection took place during the "Demonstration and Evaluation" phase. The aim was not to gather unstructured data and build a theory from a blank page, but rather to collect targeted empirical feedback that provides evidence on the utility, structural logic, and accuracy of the pre-designed artifact. After that, a qualitative data collection strategy was used to capture the different types of insights needed to stress-test the framework..

### 3.2.1 Expert Interviews

The main empirical data used to evaluate the artifact comes from seven semi-structured expert interviews carried out during February and March 2026. When evaluating a socio-technical artifact such as an AI maturity model, a common mistake could be to rely solely on a homogeneous and highly technical sample. Evaluating a model from the perspective of software engineers alone would ignore the cultural, regulatory, and organisational realities that would shape successful enterprise adoption at the end of the day.

Participants were selected from differing backgrounds and expertise so that the maturity model was challenged from multiple perspectives. The full list of participants is shown in Table 4 below.

| Participant ID | Professional Role | Functional Domain Focus | Interview Duration |
|---|---|---|---|
| **P1** | AI Engineer | Technical Architecture & MLOps | 60 mins |
| **P2** | Lead Software Architect | Systems Integration & Development | 60 mins |
| **P3** | Product Owner | Product Strategy & Roadmapping | 60 mins |
| **P4** | Product Designer | UX/UI and Human-Computer Interaction | 60 mins |
| **P5** | Customer Success Lead | Client Onboarding & Value Realization | 60 mins |
| **P6** | Customer Support Lead | End-User Friction & Workflow Automation | 60 mins |
| **P7** | Head of People | Change Management & Organisational Culture | 60 mins |

**Table 4: Overview of interview participants**

This cross-functional mix made a difference as it ensured the framework was tested from all operational angles and evaluated against broader organizational needs rather than just the software stack. The selected participants excluded senior executives like CEOs and board members, because their daily interaction with AI differed significantly from the technical, product, and management roles which were in the scope of this thesis. It is worth noting that future iterations of this research would benefit from including 3-5 business-leader voices, as well. This would test how well the framework works for that sector of roles.

The evaluation interviews, lasting roughly 60 minutes, were conducted via digital meeting platforms in English and Finnish to allow the interviewees to speak in their own language. All interviews were recorded with consent, transcribed, and fully anonymised. During the sessions, participants were explicitly shown the initial theoretical drafts of the maturity models and asked to critique their structure, granularity, blind spots, and practical value.

All seven participants come from the author's broader professional network and share some professional context with the author. This is a methodological limitation rather than an incidental feature of the sample. It is addressed in Section 3.3.

## 3.3 Participant Independence

The seven interviewees in this study come from the author's professional network rather than from an independent sample. Each took part in their capacity as a senior practitioner. The cohort covers different professional backgrounds and roles. The full breakdown is in the participant table in Section 3.2.1. The shared element is that the author knows each of them through prior professional contact. This still creates three risks to evaluation validity that need to be acknowledged. The interviewees may share some background assumptions with the author and therefore not fully challenge taken-forgranted parts of the framework. They may also be reluctant to give strong negative feedback to someone they know professionally. The framework itself was pre-populated from engagements at the company where the author works. It may describe a working reality that is already familiar to participants for that reason.

A few steps were taken to reduce these risks rather than remove them. Interviews were done under anonymisation, recorded, and transcribed word-for-word. Participants understood that critical feedback would be welcomed. The interview protocol asked participants to point out weaknesses, blind spots, and points of disagreement before positive notes on the models were asked for. Constructive feedback was treated as the main input for design iteration. The directed thematic analysis in Section 3.4 specifically prioritised disconfirming evidence. Two of the three design iterations reported in Chapter 4 came from improvement feedback regarding the initial design. None of these steps fully removes the shared-context limitation. The results of this study should therefore be read as confirmatory feedback on the artifact's design from informed practitioners rather than as evidence of generalisability. Section 7.3 reframes this as a priority direction for future research. The framework would be tested with participants who have no relationship to the author.

## 3.4 Data Analysis

In Design Science Research, data analysis is the main mechanism for artifact iteration and improvement. The interview transcripts were not analysed using open coding to find behavioural theories. They were analysed through thematic analysis (Braun & Clarke, 2006) used inside the DSR evaluation framework. The analysis was conducted on the interviewees' critical feedback directly against the existing dimensions and maturity levels of the artifact. This iterative process showed exactly how the model needed structural and contextual change based on practitioner feedback.

To make sure the artifact was tested and not subject to researcher confirmation bias, the analysis focused heavily on "negative cases". These are specific points where the interviewees actively disagreed with the initial matrix. They forced a direct design iteration of the artifact to improve its real-world utility. For example, Design Iteration 1 addressed an ethical blind spot. The initial design of the external product model focused only on user experience, product logic, and data utilisation. Data analysis showed a structural flaw around end-user trust. One interviewee noted this discrepancy. The interviewee stated, "Ethics is included in the internal model but missing from the external model. It should absolutely be added there" (P3). This negative feedback allowed the addition of the "Ethics, Trust & Transparency" dimension into the final external product matrix. The change closed a big compliance gap.

The analytic chain from interview examples to design change can be shown directly. Table 5 shows four examples, the first-cycle codes assigned to them, the categories those codes were grouped into, and the themes that came up across the group of professionals. seven interview transcripts. The themes were not set before coding. They are the result of comparison across all seven interview transcripts.

| Interview excerpt | First-cycle code | Category | Theme |
|---|---|---|---|
| “Ethics is included in the internal model but missing from the external model; it should absolutely be added there.” (P3) | Ethics omitted from external model | Structural gap in product dimensions | Trust and governance must be product-facing |
| “Data-related things can be a bit opaque.” (P5) | Theoretical abstraction in dimensions | Practical usability problem | Need for narrative concreteness |
| “If you had a real-life example or a ‘company persona’ for each level, it would make it much more relatable.” (P5) | Request for concrete personas | Practical usability problem | Need for narrative concreteness |

**Table 5: Example coding of interview excerpts into themes.**

Similarly, Design Iteration 2 mitigated theoretical abstraction. Multiple cross-functional interviewees criticised the initial capability descriptions for being too academic and lacking practical diagnostic utility. Data analysis highlighted a strong consensus that "Data-related things can be a bit opaque" (P5). To solve this, participants suggested that "If you had a real-life example or a 'company persona' for each level, it would make it much more relatable" (P5), with another interviewee agreeing that "adding concrete examples would be great" (P6). This feedback forced a major structural change to the artifact. It made the addition of the "Company Situation" and "Life with AI" narrative rows necessary across both the internal and external models. This iteration made sure the framework worked as an actionable, relatable checklist for corporate leadership.

Design Iteration 3 corrected UX determinism. The initial artifact relied on the thought that organisations would quickly move to "zero-UI" agentic interfaces at higher maturity levels. Analysis of the transcripts showed that interviewees criticised this timeline. They thought that forcing such a transition ignores basic human psychology. They noted that "clicking a button is often still faster" (P3) and that basic users have a "huge resistance to anything new and any change" (P5). This data changed the initial assumption. It allowed to create a revision of the External UX dimension. The artifact was iterated to require a "gradual, almost unnoticeable" interface evolution.

## 3.5 Research Validity and Ethics

In qualitative and Design Science Research, validity is shown through the utility, effectiveness, and reliability of the artifact (Hevner et al., 2004). This was done through the expert evaluation phase. This phase used member checking and cross-functional critique to confirm that the iterated framework addresses the real organisational problems. Transferability is supported by giving detailed descriptions of the artifact's capabilities and the evaluation context. External organisations can then judge the model's fit to their own setting.

Strict ethical protocols were followed throughout the evaluation process. Ethical approval was secured before the expert interviews were done. All participants received information beforehand explaining the purpose of the evaluation. They gave informed consent. They were also guaranteed anonymity and confidentiality. All personal and organisational identifiers were removed from the final transcripts and the published thesis text. Data was stored securely. Participants were told of their right to withdraw at any time.

# 4 Results

The results represent findings from the semi-structured expert interviews. The interviewees were actively working in the areas of AI product development, implementation strategies, and client-facing digital transformations. The goal of these semi-structured discussions was to move from the theoretical level and identify the actual realities of organisational AI adoption.

The discussions gave insights into the friction points on AI integrations that companies were facing. The findings also served as sources to refine the initial theoretical maturity model to better represent the reality that companies were facing. They helped shift from purely technical milestones toward a framework that would be better grounded in organisational psychology, user-experience realities, and regulatory governance.

## 4.1 Artifact Evaluation Feedback

The themes that are presented in this section are not behavioural theories built from a scratch. In line with the Design Science Research (DSR) approach used, they highlight what the interviewees focused on when reviewing the pre-designed framework. During the interviews, the feedback was grouped into four core theme areas.

Experts pointed many times to user resistance to interface change. They flagged the psychological friction that happens when familiar interfaces are changed to AI-driven alternatives. On top of this, they highlighted a "compliance block". This is where data governance and regulatory uncertainty stall AI adoption at the very beginning of the process.

The feedback also confirmed a clear need for top-down strategic mandates. It showed that organic adoption is not enough on its own. There were also discussions on the reality of uneven maturity profiles. Organisations rarely fit into a single capability level. Experts therefore stressed the need for concrete examples. These help leaders see and visualise their current state accurately.

### 4.1.1 User Resistance and the Gradual Evolution of UX

AI maturity models typically focus on autonomous "agentic" systems running in zero-UI environments (Levels 4 and 5) as the final and goal level of maturity. The interviewees warned against forcing this transition to take place too quickly. They also highlighted an existing and real disconnect between the industry hype around AI and the end-user readiness. They noted that people often confuse basic generative tools, which execute actions based on manual prompting, with autonomous agents.

The psychological resistance to giving up control was raised as a major barrier. One interviewee described AI as a "good servant, but a very bad master" (P7). The same interviewee raised concerns that over-reliance on AI could limit human critical thinking and reshape how users search and understand information. This psychological resistance is observable also in daily software usage. As one of the interviewees noted, basic users possess "huge resistance to anything new and any change" (P5). This creates a clear division between early adopters who are willing to deep dive into AI and the more traditional users who want to stay with l the "old button based model" (P3). These traditional users want to maintain the feeling of control over the systems actions.

The interviewees therefore argued that the move toward AI-driven agentic interfaces would have to be introduced smoothly and step by step. If an interface changed entirely and users did not understand the new logic of it and how to use it, they would likely reject it. It was suggested that the shift to an agentic experience should happen "almost unnoticeably, so that everything should not change at once but rather gradually, as that is probably what people fear the most" (P4).

The interviewees also noted there is a basic mental and functional barrier to replacing visual interfaces totally with conversational agents. Human communication has a lot of "vagueness" (P4) and relies heavily on shared understanding. Users (even experienced ones) often struggle to give AI agents the exact instructions needed to run complex tasks properly on the first try. Speech-based interfaces and prompt-driven actions will keep growing in popularity but they still need to be supported by visual interfaces. The main reason for the interfaces is to let users see their options and verify the AI's output.

In the interviews, one concrete example of successful agent use was AI agents that automatically draft detailed bug tickets from customer support conversations. According to the discussion, the AI "makes an insanely good ticket and saves so much time" (P6). It removes the manual bottlenecks. This type of AI action allows the users to focus on the more important aspects of their jobs.

### 4.1.2 Data Security, Governance, and the "Compliance Block"

The interviews highlighted that risk management, data governance, and regulatory compliance cannot be a matter that is only dealt with at the higher levels of the maturity model. They are a genuine concern and blocker for companies operating on lower levels. Experts said that the new data acts from EU and compliance frameworks are currently "hitting like a bit of a bomb" (P5) for clients.

The fear of the unknown leads many to say that "they won't use AI at all" (P5). The specific fear is about where and who can access the sensitive data when they interact with AI models. One participant likened this to a General Data Protection Regulation (GDPR) event that forces everyone to consider how they operate in this environment. The participant noted that the complex legal environment creates frustration and organisational slowness. Companies struggle to figure out "what we are not allowed to do and making sure we don't break the rules" (P2).

Experts warned that "the risk of human error actually grows" (P1). From this aspect data separation and security become necessary for all companies. Vendors or internal IT teams need to be up to date and leading by example on how to exactly meet regulatory requirements (such as the EU AI Act). This helps prevent stakeholders from misunderstanding the risks and from losing trust in the systems entirely. This is why strong governance must be prioritised at the earliest levels.

It was also highlighted that the geopolitical context of AI models makes this compliance more difficult in Europe. Experts noted that leading closed-source model providers are based in the US and often process data there. Many European enterprises therefore cannot guarantee GDPR compliance when using them. Also many companies will have to rely on "security by contract" and not "security by design". It was highlighted also that "other parts of the world do not care about data security as much as Europe does" (P2). This security-conscious mindset is creating a growing demand for local open-source models. For organisations handling highly sensitive data, the future of AI adoption may rely on locally hosted models for the extra safety layer.

### 4.1.3 The Imperative of Clear Ownership and Strategic Mandates

A theme that often was raised was about the repeated failure of organic AI adoption. Leaving AI experimentation to individual departments and treating it as "everyone's job" leads to unclear ownership. With no clear driver or owner, the efforts are fragmented and this creates a general slowness in the adoption.

In the discussions it was highlighted that when tools like ChatGPT were introduced, around "5% of people just went all in and started doing things with it" (P7). On the other hand, a normal employee already has existing ways of working and is likely to adopt new tools very slowly unless actively moved in that direction and shown the value they provide. Companies therefore need internal champions and drivers who can help with the rollout. The role of this champion is to push for change but especially take away concerns and worries.

The interviewees agreed that giving access to technology is not enough on its own. Successful adoption needs a clear culture shift inside the organisation, and this should be driven from the top-down. Leadership must apply pressure and set clear expectations for the teams and lead by example. To successfully integrate AI into the daily operations there needs to be clear guidance and help available. The example that was given was "When you do this task, use this tool" (P3). Once a single tool has been successfully adopted, the organisational friction goes down, and it becomes easier to adopt the next AI tools to help with people's daily work.

This transformation is at its core a change-management problem. For tools to be deployed successfully, the leadership must have a "joint understanding, vision, and desire to do it" (P7). Moving to large experimentation is nearly impossible without this level of alignment. If management is forcing AI tools onto teams without proper upskilling the engagement with the tools is low and in the worst case will create friction with employees. It is important to find motivated individuals on the ground level who can also lead by example and build trust. A good example of this would be an employee in marketing who actively saves time using AI and shares those practices with other people in the team. This creates a so called "carrot and stick" (P7) dynamic. Others then naturally adopt the tools out of fear of falling behind, or a desire to be more efficient. Organisations must also start measuring ROI in a meaningful way. AI initiatives that are eating up resources without delivering clear business value should be killed quickly or fine-tuned to find the value.

#### 4.1.4 Uneven Maturity Profiles and the Need for Concreteness

The interviewees saw the dual-framework approach as the best way to divide the information. They highlighted that dividing the internal capabilities of an organisation and its external product maturity into two different models is smart and to a large extent they should be measured separately. They also pointed a good reality check that organisations rarely sit inside a single maturity level. A company might be running at a high Level 4 in its technological infrastructure but sit at Level 2 in culture and collaboration.

The structure of the model was seen as an "excellent checklist" (P6). It can support strategic thinking and bring transparency to the market. In the discussions it was also highlighted that the academic maturity levels need real-world grounding in order to be believable.

The interviewees suggested also we should move beyond abstract capability dimensions to adding "company personas" (P5) and concrete situational examples. Organisations would find it helpful if there was a clear picture of what life with AI actually looks like at Level 1 compared with Level 4. In that way, organisations can map their current standing and use the framework as a strategic "Blue Ocean" (P3) tool.

## 4.2 Synthesis of Findings

Based on the data gathered from the expert interviews, the initial theoretical maturity model was restructured and updated. The findings led to the following four operational realities that had to be addressed in the final version of the framework.

- **Top-down direction beats bottom-up enthusiasm**. It became evident that moving up the internal maturity scale requires strict governance, dedicated champions inside the organisation, and top-down mandate from the leadership. A successful integration of AI tools cannot solely rely on spontaneous experiments by employees.
- **User experience shapes external maturity**. In product development, you need to gradually introduce an "unnoticeable" shift in user interfaces. It would be a mistake to assume that users would simply drop traditional controls for fully autonomous zero-UI environments. Such an approach would ignore the psychology of the user, including unpredictable and irrational behaviours.
- **Governance is a foundational prerequisite**. From the lowest levels onwards the aspect of security and governance need to be addressed. The General Data Protection Regulation (GDPR), and EU AI Act compliance cannot be overlooked. They are here to stay and evolve.

- **Diagnostic utility depends on narrative context**. The maturity model is as useful a strategic tool as how well it echoes real-life situations and the real life at companies.

The above-mentioned insights lay the foundation for the refined Dual-Framework AI Maturity Model presented in Chapter 5.

# 5 Refined Maturity Model

It is important to acknowledge that real-world organisational progression is rarely perfectly linear. The maturity matrix built is a sequential path. The purpose of the sequential path is to help with diagnosing where you are and having an easy-to-understand logic. Enterprise AI adoption in reality often needs many iterative loops, regressions, and parallel development across many of the matrix’s dimensions at the same time.

Based on the findings from the expert interviews, the initial frameworks shown in Chapter 2 have been rebuilt to match the feedback. The result is a framework made up of the Internal AI Capabilities and the External AI Product Capabilities.

The new model does not lean that much on technological milestones but on actual company dimensions in AI adoption. An example of a removed dimension is the expectation for mid-market companies to build custom foundation models from scratch. Instead, the model for example focuses on organisational realities, what type of role learning plays in AI adoption and how to look at data governance.

The interviewees also gave feedback on making the model actionable and relatable. Each maturity level across both frameworks now has a generic "Company Situation" and a concrete "Life with AI" example. This lets organisational leaders see and reflect on the realities of their companies. They can also clearly see and visualise the steps that are needed to move to the next level.

To handle the complexity of organisational AI adoption, the new framework is also more granular. The main dimensions (the y-axis) come from the synthesis of the theoretical literature reviewed in Chapter 2. The specific progressive criteria inside each cell (the x-axis) come from the author’s practitioner experience. This experience covers over 400 customer AI engagements, as mentioned also earlier. The "Company Situation" and "Life with AI" narratives are built the same way. These matrices are then verified against the data gathered during the expert interview with seven different people from varied backgrounds.

Many academic models tend to favour high-level approaches. The feedback obtained during the interviews underlined the need for  greater granularity. The interviewees noted that a well constructed and detailed enough would also work as a useful practical "checklist" (P6). They also noted that, when the transformation process is properly managed, the company personas help organisations to accurately identify their current state and plan better the path towards the next maturity levels (P7). In other words, a more detailed matrix provides  both more depth and real-life utility.

## 5.1 Refined Maturity Model

The maturity model assesses the organisational readiness, cultural acceptance, and operational infrastructure that are needed to successfully adopt AI inside the company. The levels reflect the organisational readiness of the company.

| ***Capability Dimension*** | **Level 1: Unprepared / Ad-Hoc** | **Level 2: Opportunistic / Siloed** | **Level 3: Coordinated / Centralised** | **Level 4: Integrated / Scaled** | **Level 5: AI-First / Transformative** |
|---|---|---|---|---|---|
| ***Company Situation*** | Operations are heavily manual and rely entirely on traditional IT systems without any AI integration. | AI is explored informally by individual employees seeking efficiency, but without official organisational backing or infrastructure. | The organisation formally recognizes AI's potential, establishing central coordination, budgets, and dedicated task forces to guide adoption. | AI capabilities are scaled enterprise-wide, supported by unified data architectures and dedicated executive leadership. | The organisational structure, daily operations, and business models are fundamentally built around and driven by continuous AI innovation. |
| ***Life with AI (Concrete Example)*** | AI is actively avoided due to a lack of understanding or fears regarding data leaks and regulatory compliance. | Employees use public conversational AI interfaces to write copy or generate ideas but cannot securely input sensitive client data. | Employees safely search internal company wikis via secure AI pipelines; leadership actively tracks the ROI of these pilot projects. | Marketing and sales teams use centralised AI models to instantly analyse customer interactions, automatically generating targeted campaigns and forecasting demand. | AI systems autonomously identify operational bottlenecks, predict market shifts, and propose strategic resource allocations directly to the leadership team. |
| ***Strategy & Vision*** | No formal AI strategy exists. | AI is mentioned in some discussions, but no official strategy is in place. | A formal AI strategy is drafted, aligned with specific business unit goals. | AI is a core pillar of the overall corporate strategy. | AI drives the corporate strategy and creates new business opportunities. |

| | | | | | |
|---|---|---|---|---|---|
| ***Leadership & Sponsorship*** | No executive awareness or interest. | A few managers show interest; support and funding are limited to small, localized pilot projects. | C-suite sponsorship is secured for key, funded initiatives. | A central AI leader (e.g., Head of AI) or a cross-functional steering committee coordinates efforts across the organisation. | The entire executive team is AI-literate and champions an AI-first culture. |
| ***ROI & Business Impact*** | AI impact is zero or unmeasured. | ROI is not formally tracked; focus is on learning, not financial return. | The financial and operational returns of AI projects are actively tracked against clear business objectives. | ROI is systematically measured and linked to enterprise-level efficiency gains. | AI creates new revenue streams or demonstrably autonomous operational efficiencies. |
| ***Data Governance*** | No formal data policies exist; data is scattered, unclassified, and lacks standardized security controls. | Basic discussions about data ownership begin for pilot projects. | Clear rules are established for data access, privacy, and compliance (e.g., GDPR, EU AI Act) for all internal AI tools. | Comprehensive, automated data security protocols govern all AI usage, ensuring sensitive information is never exposed. | Data governance is automated and seamlessly integrated into all data workflows. |
| ***Data Infrastructure*** | Data storage is fragmented across disconnected systems, making it difficult to access or trust for analysis. | Data is manually exported or temporarily connected solely to serve individual, isolated AI projects. | Core business data is centralised into a unified repository, making it reliably accessible for AI applications. | A scalable, real-time data platform serves the entire organisation seamlessly. | A highly dynamic, intelligent data architecture automatically organizes, cleans, and routes data to wherever it is needed in real-time. |
| ***Technology & Architecture*** | Traditional software and hardware setups with no capabilities or integrations designed for AI. | Experimentation with cloud-based, off-the-shelf AI services and APIs. | Standardized enterprise licenses; internal API orchestration. | A robust, scalable internal technical foundation allows teams to rapidly build, deploy, and monitor AI models securely. | The organisation builds highly advanced, proprietary AI architectures that interact autonomously with internal and external software ecosystems. |
| ***Skills & Roles*** | No dedicated AI roles exist. | Individual employees with interest in AI informally drive initial experiments. | Emergence of internal "AI Champions" and AI integration specialists. | Applied AI Engineers and dedicated integration specialists work directly alongside business units. | AI literacy is mandatory across all functions and leadership. |
| ***Culture & Collaboration*** | Siloed departments: fear or ignorance of AI is common. | Knowledge remains within isolated people; there is no formal mechanism to share AI learnings across the company. | Internal AI task forces, knowledge-sharing, and formal training begin. | Top-down mandates to use AI tools for specific workflows. | A culture of continuous learning and safe experimentation is the norm. |
| ***Ethics & Risk Management*** | No awareness of AI-specific risks. | Risks are considered informally on a case-by-case basis. | An initial AI risk framework is developed, often driven by the legal team. | A mature, proactive AI ethics board and review process are operational. | The organisation is seen as an industry leader in responsible and ethical AI. |

**Table 6: Internal AI Capability Model (Author's own creation. Created from literature review and empirical findings).**

### 5.1.1 Core Internal Dimensions Explained

To accurately find their own internal maturity, organisations must evaluate themselves across many different dimensions. The best starting place is strategy and leadership, as it is very difficult to scale AI organically. Treating it as "everyone’s job" leads to a lack of ownership. To get the ball rolling, the company needs to move from isolated curiosity towards a mandated C-suite-driven plan. At this stage it is also important to start recording the financial returns.

Right after that a natural place to continue is data and governance. This is often the main roadblock for companies on the road to adoption. This area measures an organisation’s action on security, privacy, and regulatory compliance. For example, a high maturity organisation needs automated governance and a unified data repository. The role of the data repository is to make sure that sensitive client data is never exposed to parties who should not have access to it.

Following the data and governance is technology and architecture. The progression here is the shift from basic off-the-shelf SaaS experimentation to a scalable internal technical foundation. Such a foundation can assure that an organisation can securely deploy and monitor AI models. It is usually done by using an internally built MLOps platform. The MLOps platform standardises how models are built, deployed and supervised across the enterprise.

The matrix also has an important component on people, skills, and culture. It covers human capital and psychological safety where behaviours are not easy to predict and tend to seem irrational. It tracks the move from isolated AI champions to dedicated applied AI engineers, who are able to make organisation-wide projects happen. It also follows the shift from fear of AI towards a culture of continuous learning and enablement. The ethics and risk management dimensions also cover algorithmic bias. These structures help organisations validate they act as an industry leader in the domain of responsible AI.

### 5.1.2 The Internal Progression Path

Moving through the levels on internal progression usually follows the typical organisational development:

- **Transitioning to Level 2 (Opportunistic)**: The organisation moves from doing nothing to a level where people start exploring the topic and leadership might explicitly let employees explore off-the-shelf tools safely. People are also starting to understand the need for efficiency and value coming from AI.
- **Transitioning to Level 3 (Coordinated)**: The organisation moves from "lone wolf" thinking and experimentation to more coordinated AI development efforts. This level usually needs dedicated internal "AI champions" who can drive the projects. At this level a formal budget also becomes a thing. Compliance guidelines need to be in place so that pilots can be run safely.
- **Transitioning to Level 4 (Integrated)**: Here AI usage becomes an expectation. Leadership formalises the use of AI tools in specific workflows. It builds a strong scalable internal technical foundation around an MLOps platform. The platform is for developing, deploying, and supervising machine-learning models in production.
- **Transitioning to Level 5 (AI-First)**: AI stops being a tool that optimises existing work and starts driving the strategy itself. The business model and daily operations are rebuilt around continual AI innovation.

The boundary between Level 4 and Level 5 is the one that creates most confusion in practice. At Level 4, the organisation is highly integrated and centralised, with a dedicated AI leader and explicit top-down expectations governing enterprise-wide MLOps platforms. AI here is an optimisation layer over the existing corporate strategy. It accelerates and de-risks decisions the strategy already anticipates. This makes existing business units more efficient and strengthens products that are already on the roadmap. It does not yet generate new strategic direction.

Level 5 is a different shape. The system is fully decentralised, agentic, and self-optimising. Autonomous agents manage workflows natively across business units and continual AI innovation actively shapes new strategy rather than merely supporting an existing one. A good example of this is surfacing new market opportunities, proposing new product categories, or restructuring how pricing models work.

## 5.2 Model 2: External AI Product Maturity Model

The external model evaluates how the organisation puts AI into customer-facing products. It also responds directly to expert warnings about user resistance against radical UI changes. The framework focuses on how the user experience with AI is changing and how companies think of different areas of the product on different levels. It also highlights the need for taking baby steps before adopting fully autonomous agentic workflows in the end product.

| ***Product Dimension*** | **Level 1: No AI Integration** | **Level 2: Feature-Driven / Bolt-on** | **Level 3: Experience-Aware / Integrated** | **Level 4: AI-Native / Core Value** | **Level 5: Adaptive Platform / Ecosystem** |
|---|---|---|---|---|---|
| ***Company Situation*** | The product relies entirely on manual user inputs and rigid workflows without any intelligent features. | The product includes isolated, highly visible AI features added on top of the existing architecture, primarily to maintain market competitiveness. | The product intelligently integrates AI into core user workflows to actively reduce friction and automate repetitive tasks. | The core value proposition relies heavily on generative capabilities, shifting the user's role from creator to supervisor. | The product acts as a dynamic, open ecosystem where interfaces and functionalities adapt instantly to user intent via autonomous agents. |
| ***Life with AI (User Reality)*** | A user logging into the software is met with static menus and forms; every single action or data entry must be performed entirely by the user. | Users can trigger a specific AI action, like generating a summary or translating a text block, but the AI forgets the interaction immediately afterward. | As a user navigates their daily tasks, the software proactively surfaces relevant insights and suggests complete drafts based on their past behaviour, requiring only a quick review. | A user provides a high-level goal, and the software autonomously generates the entire project structure, drafts the content, and configures the settings, leaving the user to simply approve the final output. | Traditional interfaces disappear; the user gives a prompt, and the AI agents generate a custom UI and fetch data instantly. |
| ***Product Strategy*** | AI is not on the product roadmap. | AI added primarily to catch up with competitors. | AI is used strategically to reduce user friction. | AI is the primary market differentiator. | The product serves as a foundational AI platform that empowers |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | users to build and deploy their own custom automations. |
| ***Business Model*** | Traditional (e.g., standard license or one-time sale). | The core pricing remains unchanged; AI features are included at no extra cost primarily to demonstrate modernization. | Premium add-ons or AI-powered "Pro" tiers. | Pricing shifts away from flat licenses to value-driven models (e.g., pay-per-successful-resolution, consumption-based billing). | Monetization is driven by platform usage, API consumption, and value generated by user-created autonomous workflows. |
| ***User Experience (UX)*** | Static, one-size-fits-all experience. | Standard UI with distinct, manual AI buttons. | Automated background steps; gradual UI simplification. | Highly predictive; UI anticipates user needs. | Dynamic UI generates tailored views based on current intent. |
| ***Agent Experience (AX)*** | Does not exist. | Micro-assistants for single-action tasks (e.g., a "rewrite text" button). | Embedded AI assistants that work alongside the user within established workflows to handle repetitive actions. | Autonomous agents requiring only human supervision. | Multi-agent orchestration working invisibly in the background. |
| ***Core Product Logic*** | Traditional, step-by-step manual inputs. | The fundamental workflow remains highly manual; AI acts as an optional, isolated tool alongside the main process. | Core flows redesigned to remove manual steps. | Product cannot deliver its core value without AI. | Fully generative and adaptive workflows. |
| ***Technology Integration*** | Standard, deterministic software architecture. | Direct integration of third-party APIs. | Customized integration pipelines that securely connect third-party AI models to the software's proprietary databases. | Proprietary, secure, scalable AI architecture built in-house. | A highly modular, open architecture designed specifically to facilitate interoperability between various AI agents and external systems. |
| ***Data & Personalisation*** | No data leveraged for intelligent features. | Basic prompting without access to deep user history. | AI securely leverages existing client/business data for context. | Deep customization based on continuous user behaviour. | The system continuously learns from the collective behaviours and automations built by its user base, dynamically optimizing the entire platform. |
| **Ethics, Trust & Transparency** | No transparency: users do not know how their data is used in the product. | Basic disclaimers are added (e.g., "This text is AI-generated") to meet minimum compliance. | Users are given clear explanations of how AI features make decisions and can easily opt-out. | "Trust by Design"; the product natively explains its logic (explainable AI) and guarantees user data is not used to train global models. | The ecosystem includes built-in, autonomous guardrails that actively prevent biased or unethical outputs from third-party agents. |

**Table 7: External AI Product Maturity Model (Author's creation, synthesized from literature review and empirical findings).**

### 5.2.1 Core External Dimensions Explained

Product maturity is not about how many AI algorithms have been deployed. It is rather about how deeply those algorithms are part of the user's workflow and the business model. The starting dimension is product strategy and business model. The question to answer here is whether AI is a free, tacked-on marketing tactic used to claim competitive ground, or whether it is the core differentiator that drives value-based monetisation.

The way users interact with these systems is equally critical. The user and agent experience (UX/AX) addresses one of the most important findings from the expert interviews: users have a strong psychological resistance against sudden interface changes. Maturity in this area therefore means moving from static manual forms toward predictive adaptive interfaces.

A mature product also depends on its handling of data context and personalisation. This measures how effectively the product uses historical data to anticipate user needs and tracks the move from generic prompt-based responses to personalised automation. Underneath all of that is ethics, trust and transparency. Based on interviewee feedback, the product needs to actively build end-user trust, from basic legal disclaimers to a full "Trust by Design" approach with autonomous guardrails built in.

### 5.2.2 The External Progression Path

The evolution of external product maturity is marked by the gradual reduction of user friction:

- **Transitioning to Level 2 (Feature-Driven)**: daily manual tasks are seen as easy to bolt on basic "AI-features" to keep up with the competition. While the core UI stays familiar to the user.
- **Transitioning to Level 3 (Experience-Aware)**: the product starts to anticipate needs based on historical data. The AI acts like a "co-pilot" and no manual clicking needed. It prepares drafts or completes tasks in the background. The user's role is to review and approve.
- **Transitioning to Level 4 (AI-Native)**: the user moves from being the creator who creates every step to being the supervisor who manages AI outputs. Also at this level the pricing structure and business model change.

- **Transitioning to Level 5 (Adaptive Platform)**: on this level the product no longer has static user interfaces. The product becomes a dynamic ecosystem where autonomous agents build custom user interfaces in real time based on the user's needs.

## 5.3 Orchestrating the Dual-Framework

The value of the model is using it as a comparative diagnostic tool. A comparative diagnostic tool lets leaders assess two related areas of the organisation side by side. This way they can spot mismatches that any singular dimension model would miss.

In practice, the leadership assesses the organisation on the Internal Capability Model and on the External Product Maturity Model separately. Then to see the points of improvement and mismatch, the two assessments are placed side by side. For example, an organisation aiming for a Level 4 AI-native product will fail if its internal Culture and Collaboration is stuck at Level 2. Possible gaps in the organisation's cross-functional communication practices would block otherwise well-integrated AI experiences. Sustainable AI adoption also requires well coordinated and synchronised parallel efforts on both the internal operational engine and the external product offering.

## 5.4 Managerial Implications and Theoretical Propositions

The Internal and External AI Maturity Models function as evaluated DSR artifacts. Their application also produces insights into the organisation's strategy. The categories and strategy rules listed below are not just random guesses or personal stories, but they are direct results of how the Dual-Framework works.

For organisational leaders, consultants, and product managers, the framework provides a grounded roadmap that enables them to avoid the pitfalls of ad-hoc and uncontrolled experimentation.

**Step 1: Cross-Functional Assessment**

The interviews surfaced that AI progress cannot be assessed nor judged by a single, isolated team. A common mistake would be to let the IT team evaluate the entire company's performance. This would falsely raise the score on tech skills and ignore other areas such as problems in culture or rules. To fix this, an organisation needs to assemble a cross-functional leadership group that includes IT, Product, Legal and Compliance, HR, and Business Operations. Use the matrices to rate the organisation honestly across every individual dimension.

**Step 2: Identifying the "Constraint" Dimension (The Rule of the Weakest Link)**

Organisations rarely advance uniformly. A company may have a Level 4 Data Infrastructure but only a Level 2 capability in Culture and Collaboration. By the Rule of the Weakest Link, an organisation's functionally safe AI maturity is held back by its lowest-rated internal dimension. A company may have a highly advanced technical architecture but no formal Risk Management policies. Deploying advanced models exposes the firm to severe governance risks. The overall maturity then becomes functionally Level 1. Before trying to reach the next overall level, leadership must redirect resources to lift the lowest-rated dimensions. The end goal is a balanced baseline.

**Step 3: Dual-Framework Alignment (The Matrix Analysis)**

One of the main values of the framework comes from its separation of Internal Capability and External Product Maturity. Placing the two positions next to each other helps to see the socio-technical misalignment.

Each type below is a theoretical idea taken from the structure of the framework. It is not a fact from the interview data but a hypothesis for future actual testing.

- **Scenario A, the "Vaporware" Risk (high external, low internal)**: the company is trying to sell a Level 4 AI-native product while running with Level 2 internal capabilities. This poses an extreme operational risk, and the right action is to slow further external feature development. So that the internal compliance and data governance can catch up to avoid future risks.

- **Scenario B, the "Missed Opportunity" (high internal, low external)**: the organisation has strong internal data pipelines and centralised AI governance but offers a product with no AI integration. The priority is to start experimenting with AI on the external product and utilise the data and governance that are nicely in place.
- **Scenario C, the "Balanced Innovator"**: this is the desired state. The internal and external capabilities are aligned and complement each other to succeed as an organisation.

**Step 4: Formulating the Sequential Roadmap**

Both the literature and empirical feedback confirm that maturity is sequential. Trying to jump from Level 1 directly to Level 4 usually leads to the so called "pilot purgatory" phenomenon. When the foundational organisational capabilities have not yet been built up, the success rate of pilot activities is much lower. Organisations can use the "Company Situation" and "Life with AI" examples in the matrix to build a roadmap to use in internal and external development. The roadmaps should focus on matters that progress organisations to the next levels or strengthen their position in the existing one. As an example for a Level 2 organisation, the goal is not to build autonomous agents, but rather to set up a central task force for AI and draft an official strategy. This method lets businesses check their status on a regular basis and carefully guide the shift towards an AI-first company.

To support the practical application of this framework, a companion workbook to help with implementing this scorecard is provided as Appendix 4 of the thesis and is openly available at https://doi.org/10.5281/zenodo.20316329 (Valkama, 2026). The workbook automates a seventeen-question self-assessment test. It also computes the Rule of the Weakest Link on the organisation’s behalf, classifies the organisation into one of the three archetypes, and highlights the actions needed to move to the next level inside each dimension.

# 6 Discussion

This chapter explains what the results really mean. It links the real-world findings from Chapter 4 and the Dual-Framework from Chapter 5 back with the ideas set up in Chapter 2. The goal is to assess bith the usefulness for companies and academic validity of this study.

## 6.1 Why Top-Down Mandates Beat Organic Adoption

The main finding of this research is that the main barriers to AI adoption are not technological. They are organisational. This is also highlighted in the literature by Korherr and Kantere (2022) and Jöhnk et al. (2021). The expert interviews also highlighted that relying on organic AI adoption slows down progress and unsuccessful pilots. Leaving AI as "everyone's job" without clear ownership creates a disconnect between strategy and execution.

The Internal AI Capability Model proposed in Chapter 5 indicates that moving forward in the maturity levels requires true leadership participation and interest. Mature organisations should not just provide access to tools, but they should also guide people on how concretely people can improve their day-to-day work with AI. An example would be "when doing this task, use this specific AI tool". This finding supports the dynamic capabilities view discussed also in Mikalef and Gupta (2021). It highlights that technological resources only generate value when they are rolled out properly and guided to be used. This result also matches the socio-technical view perfectly. The AI tool alone cannot create value until the linked workflow, ownership, and leadership backing are planned with it.

## 6.2 Governance as a Foundational Prerequisite, Not an Afterthought

Existing maturity models treat the regulatory compliance and ethics as advanced topics only dealt on the higher levels of maturity. The interview data contradicted that directly by highlighting that the arrival of new regulatory frameworks, the EU AI Act in particular, is hitting companies "like a bomb". The frameworks create a "cautious paralysis" that is driven by data security fears and the following risks associated with failure to comply.

The framework addresses this by setting Governance as a foundational dimension from Level 1 onwards. Also based on the feedback from the interviews an "Ethics, Trust & Transparency" dimension was also added to the External AI Product Maturity Model to ensure that the end user can trust enough to use the system. This is aligned what is seen as a need in the legal mandates outlined by the European Commission (n.d.) and the "Compliance by Design" principles in Fjeld et al. (2022). These highlight that strong governance is the mechanism that unlocks safe AI experimentation. The human part of the system cannot be an afterthought and must be built directly into the technological design from Level 1 onwards. This human side includes official rules, clear responsibilities, and trust.

## 6.3 The Psychology of User Resistance and Gradual UX Evolution

One of the main research points of this thesis is to link the abstract and unclear "hype" of autonomous AI to the actual expectations of the final user. While technological progress points toward zero-UI, fully autonomous agentic environments, how to get there is not widely discussed. The interviewees warned against forcing this transition too quickly because of inevitable user resistance. Users actively still expect the traditional controls (the so-called "old button model") be sustained due to their fears of losing human oversight on what the system is doing and thus also becoming less relevant for their organisations.

Grounding autonomous-AI rhetoric in these user-level realities directly supports the "automation-augmentation paradox" described by Raisch and Krakowski (2021). In this paradox, AI must be framed as a tool for augmenting human capabilities rather than suddenly replacing them. The External AI Product Maturity Model proposes a gradual, almost unnoticeable UI evolution. It charts a realistic path from manual prompting (Level

2) to contextual co-piloting (Level 3) and finally to architectural supervision (Level 4). Organisations should therefore not run ahead of the psychological readiness of their users.

At first glance, a theoretical tension seems to exist between two findings. Section 4.1.3 calls for strict top-down mandates, while this section calls for gradual UX evolution to reduce user resistance. The two findings operate at different layers and do not contradict. Top-down mandates apply to the expectation of adoption. Leadership must make clear which AI tool is the designated workflow, so that fragmented shadow IT does not take over. Gradual evolution applies to the design of the interaction. The mandated tool must keep enough familiar interface elements to preserve the user's psychological safety. Organisations resolve the tension by mandating the "what" (the process) while easing the "how" (the interface).

## 6.4 Bridging the Gap: The Value of the Dual-Framework

This thesis resolves the main gap in existing literature of siloing of internal operational readiness and external product strategy. Existing models (for example Mahaur, 2024; Butler, 2021) often fail to give a complete view. These do not provide a tool for leaders to diagnose their actual progression and day-to-day operations.

The framework shown in Chapter 5 solves this by linking the two models together. When leaders place their Internal Capability position alongside their External Product position, they can easily spot operational imbalances and what their weakest links are. An example could be the "Vaporware" risk where a company is trying to sell a Level 4 AI-native product while having only Level 2 internal data governance. The Dual-Framework helps identify this and create a roadmap to address the imbalance.

This thesis intends to connect abstract academic theory with practical design strategy. The system is more than just a simple method to categorise ideas. It works as a practical tool for companies to check where they stand and see what steps to take next. The framework also safely guides organisations out of being stuck with pilots and helps them transform into lasting AI-first organisations.

# 7 Limitations and Future Research

This chapter evaluates the scope and limitations of the research. Setting these boundaries is essential for illustrating the findings in a realistic way  and spotting where future academic and practical work should go next.

## 7.1 Methodological and Empirical Limitations

The qualitative and exploratory research approach is the main limitation of this study. The empirical findings and the resulting dual-framework relies largely on a focused cohort of expert interviews. The cohort was selected through purposeful sampling, and the interviewees were chosen deliberately due to their current roles and expertise. In contrast, this approach gave highly relevant insights into the friction points of AI adoption. Examples are the psychology of user resistance and the paralysing effect of data governance. The trade-off is statistical generalisability. The lived experiences of the interviewed AI engineers, product managers, and people leaders reflect a specific cross-section of the industry. Transferability is supported through thick description. Meaning giving detailed contextual accounts of the artifact's capabilities and the evaluation context. Readers can then judge how well the findings apply to their own settings. Universal generalisation needs further quantitative testing (Lincoln & Guba, 1985).

Qualitative thematic analysis also depends on the researcher's interpretation of the transcripts. Clear audit trails were kept supporting dependability, but qualitative coding is never entirely free from subjective interpretation.

The proposed Dual-Framework AI Maturity Model has been conceptually validated by industry interviewees. They confirmed its utility as a strategic benchmarking tool. It has not yet been validated over time. This means it has not been tracked inside a real-world organisation over a long period (Butler, 2021). The model has not been implemented and observed in a real enterprise setting over a multi-year horizon. The specific timeframes, financial resources, and transitional friction needed to move an organisation from Level 1 to Level 5 are then theoretical concepts.

## 7.2 Theoretical and Contextual Limitations

The unprecedented speed of change in the field of AI imposes an important contextual limitation for this research work. Industry observers commonly note that core AI capabilities are roughly doubling or changing every four to six months. This pace of progress is historically unprecedented. The AI capabilities available at the start of a multi-month research project will look different from those available at its end. The technological frontier described in this thesis is the trajectory of the industry as observed in early 2026. The frontier mentioned is the shift toward fully autonomous agentic workflows and zero-UI environments at Level 5. As recent literature notes, a gap remains between industry rhetoric on autonomous agents and the current enterprise reality (Korherr & Kantere, 2022). Specific technological capabilities and user-interface paradigms will keep shifting rapidly. Some of the technical description at the higher maturity levels may therefore need to be updated over time.

The regulatory environment is in a similar state. The European Union Artificial Intelligence Act (EU AI Act) deeply shaped the Governance dimension of the proposed model. Its impacts cannot yet be fully measured. The practical day-to-day compliance reality for mid-sized and large enterprises is still unfolding. The legal specificities of the model's governance and data transparency requirements may need to be adjusted as multilevel governance frameworks mature (Lee et al., 2023).

This study also limited its scope to organisational management, strategy, and product design. It does not cover so deeply the technical computer science architectures required to build large language models (LLMs) from scratch. As a conscious choice, the framework evaluated the application and management of AI rather than its underlying development.

## 7.3 Directions for Future Research

The boundaries of this study open several promising avenues for future academic research and practical development.

### 7.3.1 Quantitative Validation of the Central Interdependence Claim (Priority Direction)

The core empirical claim of this thesis is that internal organisational capability and external AI product maturity are distinct but interdependent. Misalignment between them causes strategic failure. The expert interviews in this study give qualitative support for this claim but do not test it out. The priority direction for future research is therefore a quantitative study. The study would turn each dimension of both models into a measured end product. It would then sample enough organisations to estimate the relationship statistically.

Such a study should test three specific questions. The first is whether the internal and external axes are separable from each other. The alternative is that they turn into a single underlying construct. The second is whether the strength of their alignment predicts organisational outcomes. Examples of outcomes are AI initiative success rates and revenue contribution. The third is whether the relationship holds across industries and company sizes.

Partial least squares structural equation modelling (PLS-SEM) is the standard method for this kind of estimation in the digital-transformation literature (Mikalef & Gupta, 2021). It would be the natural starting point. Until such a study is done, the central claim of this thesis should be read as a theoretical proposition rather than as an empirically demonstrated relationship.

- **Large-scale quantitative validation**. Future studies should convert the dimensions of the dual-framework into a validated quantitative survey instrument and distribute it across a large, multi-national sample. That would make it possible to test the correlation between internal operational readiness and external product maturity directly.

- **Longitudinal case studies**. Future organisational research should run multi-year case studies inside a small number of organisations (a longitudinal design, in contrast to a single snapshot). Embedded researchers can collect direct empirical data on where implementation friction actually lives, and on how much organisational effort each level transition requires in practice.
- **HCI research on the UX-to-AX transition**. Future Human-Computer Interaction (HCI) research should look into the UX-to-AX transition proposed in the External AI Product Maturity Model. Experimental studies could test user acceptance thresholds. The goal is to figure out exactly how "gradual" and "unnoticeable" the shift to zero-UI environments has to be.
- **A scorecard-based diagnostic toolkit**. An initial prototype in this direction has been developed alongside this thesis. It is provided in Appendix 4. The file itself is openly available via Zenodo at https://doi.org/10.5281/zenodo.20316329 (Valkama, 2026). The companion workbook turns the dual-framework into a seventeen-question diagnostic. It scores an organisation across the nine internal and eight external dimensions. It automatically applies the Rule of the Weakest Link. It places the organisation into one of the three socio-technical archetypes set out in Chapter 5. It also surfaces the recommended next-level transition actions per dimension. Future applied research could extend this prototype into a weighted scoring instrument with empirically calibrated dimension weights. The instrument would be validated against the quantitative study proposed earlier in this section. The prototype could also be extended into a standalone web application. The application would give an objective diagnosis of the organisation's exact maturity profile across all linked dimensions.

# 8 Conclusion

Artificial Intelligence (AI) is gaining new and stronger capabilities at an accelerating pace. The latest versions continuously adapt to the new trends and standards. As the speed of AI evolution is incomprehensible for many, organisations remain stuck in "pilot purgatory". In other words, they are held back by a lack of structured processes, fragmented experimentation, siloed strategic thinking as well as organisational resistance due to fear and lack of capabilities. With help of the Dual-Framework AI Maturity Model (referred as “Framework”) developed in this thesis, companies can find a research-backed direction for their next steps in AI adoption.

The expert interviews challenged several common beliefs about how companies adopt AI. The research proved that the biggest hurdles are organisational, psychological, regulatory and rarely only about the technology itself. Issues like data security, lack of clear leadership strategy and employees resisting sudden software changes also represent some of the key reasons for companies remaining stuck. Letting teams experiment with AI on their own is valuable but not sufficient. Making lasting progress requires clear direction from the top leadership, day-to-day supervision, strict governance, and regular training.

The key academic and practical contribution of this study is the Framework and Scorecard Tool built for companies to detect their current position and to obtain insights for their ways forward. The Framework explicitly separates internal capabilities from external ones. Once the two dimensions have been covered, the Framework then consolidates them. In this way, it resolves the flaws identified in the existing literature and provides stakeholders with a real diagnostic tool. AI-native, "top of the game" organisations need to be built on strong internal foundations. In contrast with other models, this Framework ensures that data governance and ethics are covered at all stages, not only at later ones. This is particularly essential with the anticipation of upcoming stricter regulations set by the EU. The recent EU AI Act and Data Act serve as examples of this. Compliance can no longer be an afterthought for organisations.

The path to the next levels of AI maturity is not linear. Instead, it is an ongoing iterative discovery process, filled with elements such as learning, adaptation and socio-technical alignment. The path requires that organisations rethink their strategy, data infrastructure, talent and culture. The attached supplementary Scorecard Tool (see Appendix 4 and https://doi.org/10.5281/zenodo.20316329) helps organisations detect their current status and makes implementing the Framework much easier.

While this study ideally helps companies move forward, it is important to stay conscious and vigilant of the biases that organisations are facing and living in. Any implementation is as good as its weakest link and how the actual execution is carried out. These models and related actionable paths are not flawless, as people understand concepts in significantly different ways. Thus, while organisations thrive through the changes and obtain great results from the Framework, some may fail despite their best efforts. As said, success boils down to relentless execution. A follow-up study on this thesis on the execution perspective would be highly valuable.

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# Appendices

## Appendix 1. Expert Evaluation Interview Protocol

Phase 1: Introduction & Framework Presentation

- (Script): "Thank you for your time. Based on my initial research, I have developed a draft AI Maturity Model. I will share it on the screen now. The goal of this session is to get your feedback on its structure and concepts. I will ask for your thoughts on its key components and then for your overall view. This session will be recorded. All your feedback will stay fully anonymous. Do I have your consent to begin?"

Phase 2: High-Level Structure Validation

- Question 1: "To start, let's look at the overall structure. The model is split into two parts. On one side is 'Internal Capability'. This is about how your company gets ready for AI: your strategy, your people's skills, and your governance. On the other side is 'External Product'. This is about what you actually build and sell to customers. From your perspective, is it important to think about these two things separately? Why or why not?"

- Question 2: " The model proposes five levels of maturity, going from 'Reactive' to fully 'Autonomous'. Does this general five-step journey from simple to complex AI seem realistic and logical to you?”

Phase 3: Thematic Discussion & Expert Insights

- Question 3 (Technology & the Future): “The model's highest level of maturity is defined by 'Agentic AI'. These are autonomous systems that can plan and execute tasks. In your opinion, is this the right direction for the industry, or is it still more hype than reality? What are the biggest hurdles, technical or cultural, to getting there?"

- Question 4 (Governance & Risk): " The framework heavily links governance to compliance with regulations like the EU AI Act. From your perspective, how much of a real, practical concern is this right now for you, your team, or your customers? Is this a topic that comes up in strategic planning, or is it more of an after-thought?"

- Question 5 (Customer & User Experience): " Let's talk about the user experience. The model suggests a big shift. Users move from clicking buttons in a traditional interface to giving goals to an AI and supervising the outcome. Does this shift feel real to you? What's the biggest challenge in getting users to trust and effectively work with an AI agent?"

- Question 6 (Strategy & Culture): " My research suggests a common problem. AI is often 'everyone's job, but no one's clear mandate', which can slow things down. Does this issue of unclear ownership feel familiar to you?"

Phase 4: Expanded Final Evaluation & Refinement

- Question 7: "Having discussed the parts, let's look at the whole model again. What do you see as the single most valuable or insightful part of this frame-work?"

- Question 8: “On the other hand, what do you see as the model's biggest blind spot? Is there a key challenge, role, or stage that you feel is missing?"

- Question 9: "Let's talk about clarity. Are there any terms or concepts in the model, like the names of the levels or the dimensions, that are unclear, confusing, or could be named better?"

- Question 10: "Imagine you are in a leadership meeting tomorrow. Could you see yourself using a diagram like this to justify a project or ask for budget? Why or why not?"

- Question 11: " Finally, on a scale of 1 to 5, where 1 is 'not useful at all' and 5 is 'extremely useful', how valuable would a framework like this be for your organisation? What would it take to make it a 5?”

## Appendix 2. Artifact Evaluation Traceability Matrix

| Artifact Element | Expert Feedback (Negative Cases & Critiques) | Resulting Design Change |
|---|---|---|
| **External Model Dimensions (Ethics)** | Participant (Product Owner) noted: "Ethics is included in the internal model but missing from the external model; it should absolutely be added there". | **Iterated Dimension:** Added the "Ethics, Trust & Transparency" dimension to the External Product Model to ensure holistic compliance representation. |
| **Model Readability & Diagnostic Utility** | Participant (Customer Success Lead) noted that "Data-related things can be a bit opaque". He suggested, "If you had a real-life example or a 'company persona' for each level, it would make it much more relatable". Participant (Product Owner) agreed: "Having descriptive examples or product personas for each level would be highly useful". Participant (Customer Support Lead) also affirmed that "adding concrete examples would be great". | **Structural Overhaul:** Added the "Company Situation" and "Life with AI" narrative rows across both Internal and External matrices to ground theoretical abstractions in actionable, recognizable organisational realities. |
| **External Model: User & Agent Experience (UX/AX)** | Participant (Product Owner) critiqued the rapid shift to zero-UI, stating: "But clicking a button is often still faster". Participant (AI Engineer) corroborated this: "Clicking the button is faster to do the thing still". Participant (Head of People) added: "We as humans have a lot of contextual understanding... visual support is very important". Participant (Customer Success Lead) noted: "Basic users have a huge resistance to anything new and any change". | **Iterated Trajectory:** Adjusted the UX/AX transition timeline. The model now mandates a "gradual, almost unnoticeable" UI evolution that deliberately maintains legacy visual controls for psychological safety, rather than assuming an immediate leap to fully autonomous agentic environments. |

| | | |
|---|---|---|
| **Internal Model: Skills & Roles** | Participant (AI Engineer) challenged the relevance of certain technical roles at Level 3/4: "Data scientists make sense for product, but for internal teams, I do not believe they are required. I would switch that to Applied AI Engineers". | **Iterated Criteria:** Updated the specific role descriptions in the internal matrix (Levels 3 and 4) to specify "Applied AI Engineers" rather than generic Data Scientists. |
| **Internal Model: Governance & Risk** | Participant (AI Engineer) highlighted that "the number one reason why people would not use a tool is because they are not sure about data security". Participant (Customer Support Lead) echoed that "Many clients are concerned about where their data ends up". | **Iterated Prerequisite:** Restructured the framework's narrative to enforce Data Governance as a strict, foundational roadblock that must be addressed at Levels 1 and 2, rather than an advanced feature reserved for later maturity stages. |
| **Model Nomenclature (Level Titles)** | Participant (Head of People) found the initial naming conventions confusing: "you have two titles for each level... you want them to be as simple as possible". | **Iterated Nomenclature:** Streamlined the titles of the 5 maturity levels to reduce cognitive load and enhance immediate clarity for non-technical stakeholders. |

## Appendix 3. Declaration of Artificial Intelligence Usage

This appendix explains how Artificial Intelligence (AI) was used in this thesis. I only used Google Gemini for two specific tasks: initial planning at the start of the project and final proofreading at the very end.

At the beginning of the project, I used the AI to brainstorm and organize the methodology. I had the model break down the typical stages of Design Science Research so I could map out a realistic timeline for my work. For example, I used a prompt like: "Help me outline a logical chapter structure for a master's thesis using Design Science Research." This helped me map out my workflow, but the AI did not write any of the actual text for the thesis.

When I was working on the maturity matrix, I used Google Gemini to help improve the phrasing of the descriptions. The entire layout of the matrix came from my literature review and the professional experience I talk about in Section 3.1, which includes the five capability dimensions, the five maturity levels, and the logic behind how they progress. Once I built that structure and drafted the cell contents, I used the AI as an editing tool. I asked it to make my drafts clearer and easier to read for people outside of academia. I reviewed all of its suggestions, and I wrote and finalized every single cell myself.

In the final stages, I used the AI to proofread the chapters and fix basic readability issues. I mainly used the model to spot spelling and grammar mistakes. My prompts simply included instructions like: "Please proofread this section for grammar." I went through every single suggestion by hand to make sure the final text stayed true to my original meaning and my own voice.

## Appendix 4. AI Maturity Dual-Framework Scorecard (companion workbook)

A working spreadsheet version of the Dual-Framework AI Maturity Model is available as a companion tool alongside this thesis. It is publicly hosted on Zenodo with a permanent Digital Object Identifier (DOI). This workbook allows easily to apply the framework in practice. They do not have to build their own scoring instrument from the matrices in Chapter 5. It is intended as the immediate first step toward the larger quantitative validation study proposed in Section 7.3.1. It can also be cited on its own using the DOI given below.

DOI: 10.5281/zenodo.20316329
URL: https://doi.org/10.5281/zenodo.20316329
Filename: AI_Maturity_Scorecard.xlsx
Suggested citation: Valkama, O. (2026). AI Maturity Dual-Framework Scorecard (Version 1.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.20316329

The workbook contains five sheets. The Instructions sheet explains the assessment process and the scoring logic. The Assessment sheet holds a seventeen-question instrument. It covers the nine internal capability dimensions (Strategy & Vision, Leadership & Sponsorship, ROI & Business Impact, Data Governance, Data Infrastructure, Technology & Architecture, Skills & Roles, Culture & Collaboration, Ethics & Risk Management). It also covers the eight external product dimensions (Product Strategy, Business Model, User Experience, Agent Experience, Core Product Logic, Technology Integration, Data & Personalisation, Ethics, Trust & Transparency). The Internal Maturity Matrix and External Maturity Matrix sheets reproduce the matrices set out in Chapter 5. They also highlight the assessed position per dimension. The Diagnostic & Recommendations sheet does the rest. It computes the average level per model. It identifies the weakest dimension under the Rule of the Weakest Link. It places the organisation into one of the three socio-technical archetypes set out in Chapter 5 (Balanced Innovator, Vaporware Risk, or Missed Opportunity). It also lists the recommended next-level transition action for every dimension.

The workbook is intended as a structured conversation tool for a cross-functional leadership group. It is not a deterministic single-number verdict. It should be completed jointly by people from IT, Product, Legal and Compliance, HR, and Business Operations. It should also be reassessed quarterly to track movement rather than one-off snapshots. As emphasised in Chapter 5, organisations should not try to leapfrog levels. Each diagnostic cycle should target the very next level only.