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EXECUTIVE SUMMARY

THIS RESEARCH REPORT EXAMINES HOW ORGANIZATIONS ADOPT ARTIFICIAL INTELLIGENCE (AI) AND WHY SIMILAR LEVELS OF AI INVESTMENT CAN LEAD TO MARKEDLY DIFFERENT VALUE CREATION OUTCOMES.

Despite widespread experimentation with AI across industries, most organizations have not yet translated adoption into sustained organizational transformation. In many cases, AI initiatives remain limited to pilots or isolated applications, delivering incremental efficiency improvements but failing to meaningfully influence core processes, decision-making practices, or long-term strategic direction. For example, a company might use AI to automatically process invoices faster, but still make strategic decisions in the same old way, using the same data silos and approval structures – thus limiting the systemic value creation potential of the technology.

We argue that this **"AI adoption paradox"** cannot be explained by technological immaturity alone. Rather, it reflects a mismatch between how AI is introduced and how value from AI is structurally generated, governed, and scaled within organizations. Moving beyond a use-case or maturity-based view, the report advances a macro-level framework that conceptualizes AI adoption as a problem of organizational transformation rather than technology deployment.

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The AI Transformation Logics Framework

Building on and extending prior research on digital transformation, the study introduces the **AI Transformation Logics Framework**, which organizes AI initiatives along two fundamental dimensions:

1. **VALUE CREATION MECHANISM** – i.e., how AI creates value:
   - **Automation**, where AI substitutes for human effort in routine, well-defined tasks, generating efficiency and cost reductions.
   - **Enhancement**, where AI augments human judgment and decision-making through insights, predictions, or generative capabilities.
   - **Reconfiguration**, where AI enables fundamentally new ways of organizing work, coordinating activities, or creating value, often reshaping processes, roles, or business models.

2. **IMPACT SCOPE** – i.e., where AI creates value:
   - **Localized**, affecting specific roles, teams, or functions.
   - **Integrated**, spanning multiple functions or business units within the firm.
   - **Systemic**, extending across organizational boundaries to partners, customers, or broader ecosystems.

Combining these dimensions yields the **AI Transformation Logics Matrix**, which maps distinct logics of AI-driven change. Crucially, the framework positions **individual AI initiatives**, not organizations as a whole, recognizing that firms typically pursue heterogeneous portfolios of AI efforts.

Organizational AI Footprints and Transformation Outcomes

The report draws on five in-depth case studies of large organizations operating in different industries. By mapping each organization's AI initiatives onto the matrix, the analysis reconstructs what the study refers to as an **AI footprint** *(see Figure 1)* – the overall pattern created by the organization's portfolio of AI initiatives. By mapping initiatives onto the matrix, the analysis reconstructs each organization's AI footprint *(see Figure 1)* – the aggregate pattern formed by its portfolio of AI initiatives.

As highlighted by the "**Common**" **AI Footprint Area**, when looking across the different cases and companies, AI initiatives are currently concentrated in the areas of automation / enhancement, predominantly at the single business unit level. This means that most of current AI applications are designed to improve the efficiency or effectiveness of (pre-existing) specific tasks, roles, or functions, rather than to support integrated or organization-wide change. But what are the implications for organizations?

Figure 1
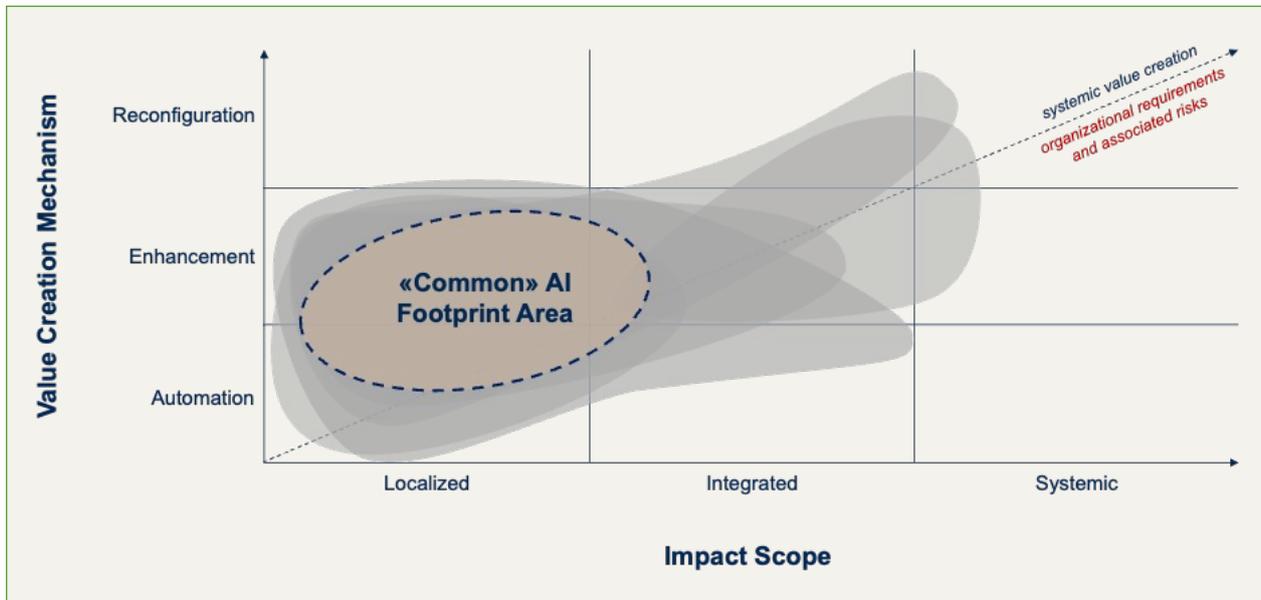
Key Insights

Overall, the matrix highlights an important pattern: the closer an AI initiative is to the upper-right area of the matrix, the greater its potential to **generate systemic value** – that is, **value that reshapes how the organization operates or how it interacts with its broader ecosystem**. This does not imply, however, that more limited AI initiatives are inherently ineffective, **nor that every organization should aim for that part of the matrix as an ultimate goal**.

Localized AI initiatives focused on automation or enhancement **can and do create value**. They often improve efficiency, reduce costs, or support better decisions within specific functions or roles. What they typically **do not deliver is the kind of disruptive or transformative impact** that is often associated with AI in strategic discussions. The value generated remains bounded. Whether such initiatives succeed nonetheless depends largely on the degree of internal consistency between the organization's strategic intent and the logic through which AI creates value.

This links to **Insight #1**: **there is no single optimal AI configuration**. Organizations that align their AI initiatives around a clear transformation logic – and reinforce this alignment through appropriate data infrastructures, governance arrangements, and organizational design – are better positioned to scale value over time. For example, two companies may both deploy AI to support demand forecasting. In one case, the tool is implemented locally within a single function, using isolated data and producing limited efficiency gains. In the other, the same capability is embedded in shared planning processes across functions, supported by common data standards and governance. While the underlying technology may be similar, the second configuration is far more likely to generate sustained and scalable impact.

Secondly, a critical challenge emerges when AI initiatives are spread across a multitude of systems and standalone solutions. While each initiative may deliver short-term benefits on its own, the cases show a significant risk associated with the uncontrolled accumulation of isolated AI use cases. As the number of local projects grows, organizational complexity and maintenance costs increase, often without corresponding gains in strategic impact. This observation underpins **Insight #2: platform-oriented AI architectures are more likely to produce positive outcomes over time than purely project-based approaches.**

The analysis also shows that organizations start recognizing the potential value of moving toward more integrated and systemic forms of AI and are actively attempting to do so. In this context, three additional insights emerge.

Insight #3: data governance and architecture are critical enablers of scalability. Progressing from localized automation to more integrated or reconfiguration-oriented AI depends less on algorithmic advances than on shared data foundations, standardized interfaces, and robust governance mechanisms. Consider an organization that initially deploys AI to automate invoice processing within the finance function. The solution performs well locally but relies on function-specific data definitions and manually curated datasets. When the organization later attempts to extend similar AI capabilities to procurement, compliance, or supplier management, it encounters significant friction: data formats differ, ownership is unclear, and integration costs rise sharply.

Insight #4: AI transformation is fundamentally an organizational design challenge. Moving beyond automation requires deliberate changes to roles, decision rights, and coordination mechanisms. More advanced forms of AI value creation cannot be separated from changes in how organizations work and govern themselves. Back to the demand forecasting example: while the technical solution may be accurate, its impact remains limited if decision rights, incentives, and workflows remain unchanged. Managers may continue to rely on established practices, using AI outputs selectively or ignoring them altogether.

Insight #5: reconfiguration typically requires openness and co-innovation. The evidence indicates that achieving systemic AI impact is rarely possible within organizational boundaries alone. Reconfiguration – understood as the redesign of processes, value chains, or business models – often requires collaboration with partners, suppliers, customers, and, in some cases, regulators. An organization seeking to use AI to optimize its supply chain may quickly reach the limits of what can be achieved using only internal data. Forecast accuracy, inventory optimization, or sustainability outcomes depend heavily on information held by suppliers, logistics partners, or customers. Without access to these external data sources, AI-driven improvements remain incremental.

That is why AI Transformation does not appear to be a linear maturity path: as the scope and ambition of AI initiatives expand, so do the organizational requirements and the associated risks. **Moving toward more integrated or systemic configurations typically demands stronger data governance, more sophisticated coordination mechanisms, clearer accountability structures, and greater exposure to operational, regulatory, and reputational risk.** In many contexts, these additional requirements may outweigh the potential benefits, at least in the short to medium term. As a result, the matrix should be interpreted **as a strategic design space** rather than a maturity ladder, helping organizations assess trade-offs between potential impact, complexity, and risk when defining their AI strategy.

Contribution and Implications

This research contributes to the management literature by offering an integrative framework that connects micro-level AI initiatives to macro-level transformation outcomes. Rather than prescribing a linear maturity path, it conceptualizes **AI adoption as a strategic design space characterized by trade-offs between value creation mechanisms, impact scope, complexity, and risk.**

For researchers, the framework provides a foundation for comparative analysis of AI strategies across firms and sectors. **For executives, it reframes the central question of AI strategy: not how fast or how advanced AI adoption should be, but how to ensure coherence between AI initiatives, organizational structures, and strategic priorities.** AI creates lasting value when treated as a catalyst for organizational alignment, not as a collection of isolated technological experiments.

1.

INTRODUCTION: FROM AI ADOPTION TO AI TRANSFORMATION

1.1 The AI Adoption Paradox

Artificial Intelligence (AI) has rapidly transitioned from a peripheral technological curiosity to a central pillar of organizational strategy. Over the past decade, breakthroughs in machine learning, the diffusion of cloud computing, and the exponential growth of data availability have significantly lowered the barriers to AI adoption. As a result, organizations across different industries now invest heavily in AI capabilities, experimenting with use cases ranging from predictive maintenance and fraud detection to generative content creation and decision support systems[1].

Despite this momentum, a striking paradox characterizes the current state of AI in organizations. **While AI adoption is widespread, its transformative impact remains limited.** Numerous surveys and empirical studies report that **most AI initiatives fail to progress beyond pilot stages, producing localized efficiency gains but rarely reshaping core business processes or strategic trajectories**[2]. Executives often describe AI as a strategic priority, yet the realized value frequently falls short of expectations.

This paradox is not merely a consequence of immature technology. On the contrary, many AI tools have reached a level of technical sophistication sufficient to support large-scale deployment. Instead, **the challenge lies in the organizational conditions under which AI is introduced, governed, and integrated. AI initiatives are frequently pursued as isolated projects, disconnected from broader transformation agendas, and evaluated primarily through short-term efficiency metrics. As a result, organizations accumulate a growing number of fragmented AI solutions without developing the capabilities required to scale and sustain their impact.**

Understanding this gap between AI's promise and its realized outcomes requires moving beyond questions of technical feasibility toward a deeper examination of how AI creates value within organizations.

A central limitation of much of the existing discourse on AI lies in the implicit assumption that adoption leads naturally to a significant improvement in the company's performance. This assumption reflects a legacy view inherited from earlier waves of information technology, where digital tools were largely deterministic, rule-based, and embedded within stable organizational processes. In such contexts, implementation challenges could often be resolved through process redesign, training, and incremental optimization.

AI fundamentally departs from this model. Rather than executing predefined instructions, AI systems operate probabilistically, learn from data, and generate outputs that may evolve over time. These characteristics introduce a level of uncertainty and (potentially) openness that distinguishes AI from previous digital technologies. As a result, **AI does not simply support existing processes; it actively reshapes how work is performed, how decisions are made, and how responsibility is distributed between humans and machines. It involves a complete transformation of the**

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1   *Further data on AI usage and adoption in Europe (as of 2024) can be found in the following report:*
    AI Adoption in Europe: State of the Art.

2   *See for example:*
    Beware the AI Experimentation Trap (Harvard Business Review, 2025),
    State of AI in Business 2025 (MIT Project NANDA, 2025),
    The AI Adoption Puzzle: Why Usage Is Up But Impact Is Not (Boston Consulting Group, 2025).

organizing and strategic processes, and accordingly of the value logics of the organization, being it an evolution of, and extreme manifestation, of an organization's digital transformation[3].

From this perspective, **AI adoption is not about deploying algorithms, but about reconfiguring sociotechnical systems** – like many other contemporary digital technologies. It affects roles, skills, coordination mechanisms, and governance structures. In some cases, it also extends beyond organizational boundaries, requiring new forms of collaboration with suppliers, partners, customers, and regulators. Treating AI adoption as a purely technological challenge therefore obscures the deeper organizational changes required to unlock its potential.

This distinction helps explain why many organizations experience diminishing returns from AI investments. **When AI is introduced without rethinking workflows, decision rights, or data governance, it tends to reinforce existing structures rather than transform them. Consequently, AI remains confined to narrow domains of automation instead of becoming a lever for broader organizational renewal.**

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3 See Cennamo et al. (2020) of the shifting of the management paradigm that digital transformation leads to.

1.2 Introducing the Concept of AI Transformation

A common response to uncertainty surrounding AI adoption has been to focus on individual use cases. Organizations often pursue a portfolio of AI initiatives designed to demonstrate quick wins, validate technical feasibility, or showcase innovation to internal and external stakeholders. While this approach can generate valuable learning, it also carries significant risks.

First, **a use-case-centric approach tends to privilege local optimization over systemic impact**. Individual teams may deploy AI solutions tailored to their specific needs, leading to a proliferation of heterogeneous tools, models, and data pipelines. Over time, this fragmentation increases complexity, raises maintenance costs, and limits the potential for reuse and integration, as we find in our research.

Second, **evaluating AI initiatives primarily through isolated business cases obscures their cumulative effects and transformative impact on organizational capabilities**. An organization may report dozens of successful pilots while lacking a coherent understanding of how these initiatives interact, whether they reinforce strategic objectives, or whether they build shared capabilities. In such contexts, AI portfolios grow in volume but not in strategic depth.

Finally, **a narrow focus on use cases makes it difficult to assess alignment between declared strategic ambition and operational reality**. Organizations may articulate aspirations of radical transformation or ecosystem leadership while their AI investments remain concentrated in localized automation. Without a framework to interpret these patterns, misalignment often goes unnoticed until it manifests as stalled scaling efforts or unmet expectations.

These limitations suggest the need for a higher-level perspective capable of capturing the underlying logics through which AI initiatives generate value and interact across the organization.

This research adopts a macro perspective on AI, grounded in the premise that value creation from AI depends on two fundamental questions: how AI creates value and where that value materializes. In this sense, the adoption of AI implies an AI transformation, just like the adoption of modern digital technologies gave rise to the phenomenon of digital transformation[4]. Rather than cataloging technologies or applications, building on and extending the digital transformation framework developed by Cennamo et al. (2020), **we develop here an AI Transformation framework that identifies the dominant logics that shape AI-driven change**.

The first transformation dimension concerns the **value creation mechanisms**. AI can generate value by automating routine tasks, enhancing human judgment through data-driven insights, or enabling fundamentally new ways of working and organizing. These mechanisms differ not only in their economic impact but also in their implications for skills, governance, and change management.

The second dimension concerns the **impact scope** of AI initiatives. Some applications remain localized within individual roles or functions, while others span multiple business units or extend across organizational boundaries into broader ecosystems. The scope of impact shapes both the complexity of implementation and the nature of the organizational capabilities required.

By combining these two dimensions, it becomes possible to map the landscape of AI transformation in a structured yet flexible way.

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4   *See Cennamo et al. (2020)*

Building on these premises, the objective of this research is to develop and empirically ground a framework that helps organizations make sense of AI transformation beyond isolated use cases. Specifically, the study seeks to:

1. Identify the core dimensions that structure AI-driven value creation in organizations.

2. Analyze how different AI initiatives combine into organizational footprints.

3. Explain why certain initiatives support scalable transformation while others lead to fragmentation or misalignment.

4. Derive actionable insights for executives navigating AI transformation in large, complex organizations.

The remainder of the report is structured as follows.

Section **2** reviews the academic and practitioner literature relevant to AI, productivity, organizational transformation, and ecosystems, establishing the theoretical foundations for the analysis.

Section **3** outlines the research design and methodology.

Section **4** introduces the AI Transformation Logics Matrix at a macro level, focusing on its two core dimensions.

Section **5** presents five case studies and maps their AI footprints.

Section **6** derives explanatory sub-variables from the cross-case analysis.

Section **7** discusses the key insights and managerial implications,

Section **8** concludes with limitations and directions for future research.

2.
LITERATURE REVIEW

2.1 Artificial Intelligence and Productivity

Early economic and managerial discussions of artificial intelligence framed AI primarily as an advanced form of automation. In this view, AI extends previous waves of mechanization and digitalization by enabling machines to perform tasks that were once considered uniquely human, such as pattern recognition, language processing, and complex classification[5]. From this perspective, AI-driven productivity gains stem largely from labor substitution, cost reduction, and efficiency improvements in standardized and repetitive activities[6].

This interpretation emphasizes continuity with earlier technological paradigms. AI is treated as a general-purpose technology that reduces the marginal cost of executing tasks, increases speed and consistency, and minimizes human error[7]. Empirical studies documenting the deployment of AI in areas such as document processing, customer service chatbots, and fraud detection support this view, showing measurable efficiency gains in well-defined domains[8].

However, scholars increasingly question whether this automation-centric framing adequately captures the distinctive nature of AI. Unlike traditional automation technologies, AI systems do not rely solely on explicit rules but learn from data, adapt to new conditions, and produce probabilistic outputs[9]. This introduces forms of uncertainty and variability that complicate direct substitution of human labor. As a result, **AI automation often requires ongoing human oversight, retraining, and contextual interpretation, blurring the boundary between automated and non-automated work**[10].

A second strand of literature shifts the focus **from substitution to augmentation**. Rather than replacing human workers, AI systems are seen as tools that enhance human cognitive capabilities by processing vast amounts of information, identifying patterns, and generating recommendations[11]. In this view, AI complements human judgment, enabling individuals and teams to make better, faster, or more informed decisions[12].

This perspective emphasizes task recomposition rather than task elimination[13]. As AI takes over analytical or repetitive components of work, human effort is redirected toward interpretation, contextualization, and decision-making. Examples include clinical decision support systems that assist physicians, AI-assisted programming tools that support software developers, and predictive models that inform managerial planning[14].

Importantly, **augmentation is not automatic. Its effectiveness depends on how tasks are redesigned and how AI outputs are integrated into workflows**. Poorly designed systems

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5   See Autor (2015) and Brynjolfsson & McAfee (2014) for early formulations of this automation view.

6   See Acemoglu and Restrepo (2020) for formal and empirical treatment of AI-driven task substitution.

7   See Bresnahan and Trajtenberg (1995) and Cockburn, Henderson and Stern (2018) for the General Purpose Technology framing of AI.

8   See Brynjolfsson, Hui and Liu (2019) and Raj and Seamans (2019) for examples of firm-level evidence of such gains.

9   See Jordan and Mitchell (2015) and Agrawal, Gans and Goldfarb (2018) for foundational discussions of learning-based AI.

10 See Rai, Constantinides and Sarker (2019) and Shrestha, Ben-Menahem and von Krogh (2019) for sociotechnical analyses of these dynamics.

11 See Davenport and Kirby (2016) and Brynjolfsson and Mitchell (2017) for examples of augmentation framing.

12 See Panico, Murtinu and Cennamo (2023) for a formal model of this co-intelligence and Jarrahi (2018) for empirical evidence of human–AI collaboration.

13 See Raisch and Krakowski (2021).

14 To read more about these examples, see Topol (2019) and Faraj, Pachidi and Sayegh (2018).

may overwhelm users with information, reinforce cognitive biases, or create new sources of error[15]. Imagine an AI system that supports credit officers in a bank. For each loan application, the model produces a risk score, but also dozens of additional indicators, confidence intervals, feature weights, and technical explanations. Every case arrives on the officer's screen with dense tables, graphs, and probability distributions. In theory, this provides transparency; in practice, it overwhelms the user. Under time pressure, the officer cannot tell which information really matters and ends up focusing either only on the final score or on the few variables they already trust. Instead of improving judgment, the AI narrows attention and reinforces existing biases. Errors occur not because the model is wrong, but because the human–AI interface makes it difficult to use the model well. Consequently, productivity gains from augmentation are contingent on organizational choices regarding role design, training, and governance[16].

Despite compelling micro-level evidence of AI-enabled efficiency and augmentation, aggregate productivity effects remain elusive. This discrepancy has given rise to what is often referred to as the **"AI productivity paradox[17]." While firms report localized improvements, macroeconomic indicators show modest or inconsistent gains.**

Several explanations have been proposed[18]. First, productivity statistics may fail to capture quality improvements, customization, or new forms of value enabled by AI. Let's imagine a company using AI to personalize its online store. Two customers both buy one item, so in productivity statistics the firm produced "two units." But one customer receives a generic offer while the other gets a product perfectly tailored to their preferences, which in the future will likely create more retention. The second transaction creates much more value, but this shows up nowhere in standard productivity measures.

Second, productivity gains may be offset by adjustment costs associated with organizational change, learning, and coordination. Let's imagine a logistics firm introducing AI to optimize delivery routes. In the long run, routes become faster and cheaper. But in the first year, managers spend months cleaning data, drivers need training, planners must change routines, and mistakes occur while people learn to trust the system. The short-term disruption absorbs much of the efficiency gain, so measured productivity barely moves.

Third, benefits may be unevenly distributed, accruing to a subset of firms or functions rather than diffusing broadly. Let's imagine a large tech-savvy retailer using AI to improve demand forecasting and inventory management. Its profits and efficiency rise sharply. Smaller competitors, lacking data and skills, see little improvement. At the industry level, the leader gets much more productive, but the average firm does not – so overall productivity growth looks weak even though AI is working for some.

At the organizational level, this paradox suggests that productivity gains from AI are not self-sustaining. Without complementary investments in data infrastructure, governance, and skills, early gains may plateau[19]. Moreover, scaling localized productivity improvements does not necessarily translate into strategic advantage, particularly if competitors can replicate similar use cases[20].

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15 See Parasuraman and Riley (1997) for a foundational discussion on the misuse of automation.

16 See Raisch and Krakowski (2021).

17 See Brynjolfsson, Rock and Syverson (2019) and McElheran et al. (2025).

18 See Brynjolfsson, Rock and Syverson (2019) and Autor, Mindell and Reynolds (2020).

19 See for example Tambe, Cappelli and Yakubovich's (2019) work about AI use in Human Resources Management.

20 See Porter and Heppelmann (2015).

This insight reinforces the **need to distinguish between short-term efficiency gains and deeper forms of organizational transformation.**

Beyond average productivity effects, the literature increasingly examines the distributional consequences of AI adoption. Studies suggest that AI may disproportionately benefit high-skilled workers, managers, and capital owners, while placing downward pressure on routine roles[21]. Within organizations, this can exacerbate inequality, reshape power dynamics, and generate resistance to change[22].

From a managerial perspective, these distributional effects have important implications. AI initiatives that focus narrowly on cost reduction may undermine trust, morale, and long-term capability building. Conversely, **strategies that emphasize augmentation and skill development may foster broader engagement but require greater upfront investment**[23].

These tensions underscore that productivity is not a purely technical outcome, but a socially mediated one. How organizations choose to deploy AI reflects underlying values, priorities, and strategic intent.

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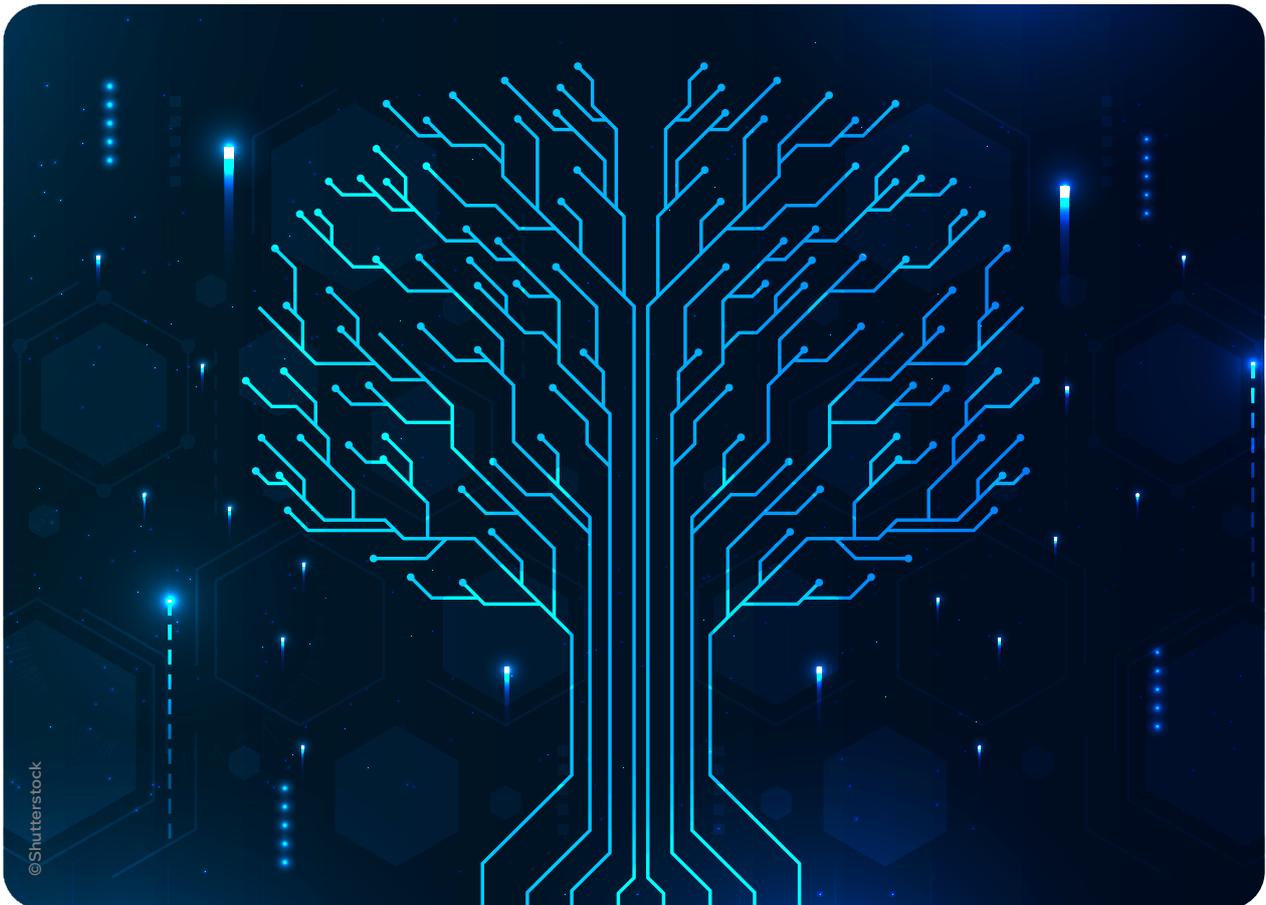
21 *See Acemoglu and Restrepo (2020) and Autor, Mindell and Reynolds (2020).*
22 *See Kellogg, Valentine and Christin (2020).*
23 *See Raisch and Krakowski (2021).*

2.2 Artificial Intelligence as a Sociotechnical System

A foundational distinction in the literature on artificial intelligence concerns the shift from deterministic information technologies to probabilistic, learning-based systems. Traditional enterprise IT systems operate through predefined rules and stable logic: given a specific input, the system produces a predictable output. Organizational processes, control mechanisms, and accountability structures were historically designed around this determinism[24].

AI systems, by contrast, generate outputs based on statistical inference, learned representations, and evolving data distributions. Their behavior is inherently probabilistic and may change over time as models are retrained or exposed to new data[25]. This characteristic challenges long-standing assumptions about reliability, predictability, and control in organizational systems.

From an organizational perspective, this shift introduces a new class of uncertainty. Managers can no longer rely solely on ex ante specification and testing; instead, they must manage AI systems as dynamic entities whose performance depends on context, data quality, and ongoing human intervention. As a result, AI adoption requires new forms of monitoring, validation, and governance that extend beyond traditional IT management practices[26].

This distinction is critical for understanding why AI adoption often triggers organizational frictions. When probabilistic systems are embedded into structures designed for deterministic technologies, misalignment emerge, leading to distrust, underutilization, or overreliance on AI outputs[27].

Another distinctive feature of AI systems is their capacity to learn from data, either through explicit retraining or through continuous feedback loops.

From an organizational perspective, learning does not occur automatically. AI systems may improve model performance while organizations fail to adapt processes, roles, or decision criteria accordingly. Conversely, organizations may change practices in response to AI outputs without fully understanding their limitations or biases[28].

A central theme in sociotechnical research on AI thus concerns the allocation of decision authority between humans and machines. AI systems increasingly generate predictions, classifications, and recommendations that inform or partially automate decisions previously made by humans. This raises fundamental questions about who decides, who is accountable, and how responsibility is distributed.

The literature distinguishes between **different modes of human–AI interaction**, ranging from decision support, where humans retain full authority, to decision automation, where AI systems act autonomously within predefined boundaries. Between these extremes lie hybrid configurations in which humans supervise, validate, or override AI outputs[29].

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24 See Zuboff (1988), who showed how early information systems reinforced formal monitoring, standardization, and predictability.

25 See Jordan and Mitchell (2015), who define machine learning systems as adaptive systems that generalize from data rather than execute fixed rules, and Agrawal, Gans and Goldfarb (2018), who emphasize that AI replaces prediction under certainty with prediction under statistical uncertainty.

26 See for example Rai, Constantinides and Sarker (2019).

27 See Faraj, Pachidi and Sayegh (2018).

28 Rai et al. (2019) emphasize that without structured feedback loops, such co-adaptation can degrade rather than improve performance.

29 Shrestha, Ben-Menahem and von Krogh (2019) show that most organizations converge on hybrid arrangements in which humans and algorithms jointly perform tasks, rather than replacing one with the other.

Importantly, decision authority is not merely a technical parameter but a social and political one. Shifting decision rights can alter power relations within organizations, redistribute expertise, and challenge professional identities. Resistance to AI adoption often stems less from technical limitations than from perceived threats to autonomy, status, or accountability[30].

Taken together, sociotechnical perspectives (see Table 1 for a recap) highlight that AI adoption challenges foundational elements of organizational design. Probabilistic behavior, shifting decision authority, and dynamic learning require organizations to rethink control mechanisms, accountability structures, and coordination practices.

Table 1.
Key differences between Traditional IT systems and AI systems
(source: authors' elaboration).

Technical Dimension	Traditional IT systems	AI systems
Logic of operation	Rule-based and explicitly programmed; the system follows predefined if–then logic	Data-driven and learned; the system infers patterns from data
Relationship between input and output	Deterministic; the same input always produces the same output	Probabilistic; the same input may produce different outputs depending on model state
Predictability	High; behavior can be specified and tested in advance	Limited; behavior depends on training data and model updates
Source of errors	Coding mistakes or incorrect rules	Data bias, model drift, statistical uncertainty, or misalignment with context
Socio-Technical Dimension	**Traditional IT systems**	**AI systems**
Uncertainty	Low and mainly technical (bugs, system failures)	High and structural (uncertain predictions, confidence levels, changing accuracy)
Control mechanisms	Ex ante control through specifications, testing, and validation before deployment	Ongoing control through monitoring, retraining, and performance management
Role of humans	Humans design the rules and then supervise execution	Humans must continuously interpret, validate, and adjust outputs
Accountability	Clear; responsibility can be traced to rules and designers	Ambiguous; outcomes depend on data, models, and human–AI interaction

30 For example, Kellogg, Valentine and Christin (2020) demonstrate how algorithmic systems reshape power and control in organizations, often provoking resistance when they encroach on professional judgment or autonomy.

2.3 Scaling AI in Organizations

A recurring theme in both academic and practitioner literature is **the difficulty organizations face in scaling AI initiatives beyond early experimentation**. While many firms report a growing number of pilots, proofs of concept, and exploratory projects, relatively few manage to transition these initiatives into stable, production-level systems embedded in core operations[31].

This reflects a structural tension between exploration and exploitation. Early AI projects are frequently designed to test technical feasibility, generate quick wins, or build internal momentum. These projects are typically localized, limited in scope, and shielded from broader organizational constraints. While such conditions foster experimentation, they also create dependencies on specific teams, datasets, or tools, making subsequent scaling difficult.

Centralization is another critical determinant of AI scalability. Decentralized models are often praised for their flexibility and responsiveness to local needs. By allowing business units to pursue AI initiatives autonomously, organizations can surface diverse use cases and foster innovation. However, without coordination, fragmentation emerges as organizations accumulate multiple AI initiatives developed in parallel by different units. Each project may optimize locally, but together they form a heterogeneous landscape of models, platforms, and data pipelines. Over time, **this fragmentation increases coordination costs, complicates maintenance, and undermines the ability to reuse or integrate AI capabilities across the organization**[32]. Centralized models aim to address these challenges by standardizing tools, platforms, and development practices. Central units can also concentrate scarce AI talent, enforce compliance, and prioritize initiatives aligned with strategic objectives. Yet excessive centralization may slow experimentation, distance AI development from business realities, and generate resistance among local teams[14].

Regarding data availability and quality, these are widely recognized as critical enablers of AI. Data is embedded in business processes, ownership structures, and power relations, making its governance a central concern for AI scalability. Organizations often operate with fragmented data landscapes shaped by historical silos, mergers, and legacy systems. In such contexts, data access is negotiated rather than standardized, and data quality varies widely across domains. AI initiatives developed within one unit may rely on datasets that are inaccessible or unusable elsewhere, limiting their portability[33].

The literature highlights the importance of shared data governance frameworks that define standards for data quality, access, security, and accountability[34]. Such frameworks enable AI

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31 *This pattern is documented by Davenport and Ronanki (2018), who show that most firms remain stuck at the pilot stage, and by Iansiti and Lakhani (2020), who argue that AI requires organizational redesign rather than isolated projects.*

32 *See Mikalef et al. (2020), that propose that decentralized AI development may lead to duplication, incompatible data assets, and rising coordination costs.*

33 *For example, Faraj, Pachidi and Sayegh (2018) studied a large hospital that introduced a machine-learning system to predict patient flow and allocate beds, staff, and equipment more efficiently. The AI model was built using high-quality data from one department that had invested heavily in digitizing its clinical and administrative processes. Within that unit, the system worked well and significantly improved planning and throughput. However, when hospital management tried to extend the system to other departments, scaling failed. Each department recorded patient data differently, used different software systems, and followed different coding practices. Some units stored key information in free-text notes, others in structured databases; some updated records in real time, others only at the end of shifts. In addition, different professional groups (doctors, nurses, administrators) controlled different parts of the data and were reluctant to change their routines. As a result, the AI model that worked well in one part of the hospital could not be transferred elsewhere without extensive data cleaning, renegotiation of data ownership, and redesign of workflows.*

34 *As van den Broek, Sergeeva and Huysman (2021) demonstrate, the practices around how data is generated and interpreted shape what AI systems can do in each unit.*

initiatives to move beyond local contexts by creating a common foundation for integration and reuse. However, establishing these frameworks requires organizational alignment and executive support, as data governance often challenges entrenched interests[35].

Importantly, **data governance also intersects with ethical and regulatory considerations**. As AI systems increasingly rely on sensitive or cross-functional data, organizations must balance innovation with compliance, transparency, and risk management. These trade-offs shape not only what can be scaled, but also how AI systems are designed and deployed[36].

Architectural choices also play a crucial role in shaping the scalability of AI initiatives[37]. The literature emphasizes that architectural decisions create path dependence. Early choices regarding platforms, vendors, or data models influence subsequent development trajectories, shaping what can be scaled and how easily new capabilities can be integrated. Organizations that prioritize speed over coherence in early AI initiatives may inadvertently lock themselves into suboptimal architectures.

Finally, a critical yet underexplored question in the literature concerns what organizations are actually scaling. Much research treats scalability as an inherently positive outcome, without interrogating the nature of the AI initiatives being scaled. However, scaling localized automation may increase efficiency without contributing to strategic differentiation or organizational transformation.

This observation highlights the **distinction between scaling activity and scaling impact**. Recognizing this distinction **shifts attention from the quantity of AI initiatives to their underlying value creation logic**[38]. It also reinforces the need for frameworks that help organizations assess whether their AI portfolios support their strategic objectives, rather than merely expanding operational capacity.

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35 See Kellogg, Valentine and Christin (2020).

36 For example, in studies of AI deployment in hiring, van den Broek, Sergeeva and Huysman (2025) find that the introduction and use of AI resulted in crowding out expert practices of performing fairness, favouring instead the version performed by HR.

37 This is not exclusive to AI and represents a well-known phenomenon in the Information Systems discipline: already in 2000, Baldwin and Clark (2000) showed how modular architectures enable recombination and scaling, while Tilson, Lyytinen and Sørensen (2010) demonstrated that early digital infrastructure choices lock organizations into specific development trajectories.

38 As emphasized by Berente et al. (2021).

2.4 Artificial Intelligence and Organizational Transformation

A substantial body of research examines how artificial intelligence reshapes work within organizations[39]. Contrary to early narratives predicting widespread job displacement, empirical studies increasingly show that AI adoption leads to a reconfiguration rather than a simple elimination of work[14]. Tasks are decomposed, redistributed, and recombined, altering the content of jobs and the skills required to perform them[40]. AI systems often assume responsibility for analytical, repetitive, or data-intensive components of work, while humans focus on interpretation, judgment, and relational activities. This redistribution changes not only task execution but also the cognitive demands placed on workers. Employees are expected to interact with AI outputs, assess their relevance, and integrate them into broader decision contexts.

The reconfiguration of work is uneven across functions and industries. Knowledge-intensive domains such as finance, engineering, and professional services tend to experience deeper changes, as AI penetrates core analytical activities. In contrast, other domains may see more incremental adjustments. These variations complicate organizational transformation efforts, as different parts of the organization move at different speeds and face distinct challenges[41]. As AI becomes embedded in organizational processes, new hybrid roles emerge at the intersection of business, technology, and data. These roles include AI product owners, data stewards, model risk managers, among others. Their function is to translate organizational needs into technical requirements, oversee AI system behavior, and ensure alignment with strategic and regulatory constraints[42].

The emergence of such roles reflects a broader shift in organizational capabilities. Rather than concentrating expertise in isolated technical teams, **effective AI transformation requires distributed capabilities that span functions and hierarchical levels**[43]. Organizations must develop the capacity to frame AI problems, evaluate AI outputs, and adapt processes accordingly.

The literature emphasizes that building these capabilities is a gradual process. It involves training, experimentation, and changes in career paths and incentive structures. Organizations that underestimate the time and effort required to develop hybrid capabilities often struggle to move beyond superficial AI adoption[44].

Organizational transformation driven by digital technologies is rarely frictionless. This is particularly true for AI, as resistance may additionally arise from concerns about job security, loss of autonomy, or erosion of professional identity, as already stated in section 2.3.

Institutional frictions also emerge from misalignment between formal structures and informal practices. Even when AI systems are technically sound, they may be ignored or subverted if they conflict with entrenched routines or norms[45]. The literature highlights the importance of sensemaking and narrative framing in addressing these challenges.

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39 See for example Acemoglu and Restrepo (2020) and Autor (2024).

40 See Jarrahi et al. (2021), who show that knowledge workers increasingly function as supervisors and sense-makers of algorithmic output.

41 See Faraj, Pachidi and Sayegh (2018) and Kellogg, Valentine and Christin (2020).

42 See Kellogg, Valentine and Christin (2020).

43 See Mikalef et al. (2021).

44 See Faraj, Pachidi and Sayegh (2018) and Kellogg, Valentine and Christin (2020).

45 See Lebovitz, Lifshitz-Assaf and Levina (2022), whose study depicts departments where professionals do not incorporate AI outputs into final judgments ("unengaged augmentation"), due to clashes with professional routines and meaning systems.

How AI is communicated – as a tool for empowerment or as a mechanism of control – shapes employee responses and adoption outcomes[46].

A key insight from organizational research is that transformation unfolds over time and is shaped by historical choices. The adoption of digital technologies does not follow a linear trajectory from experimentation to maturity. Instead, organizations move through phases characterized by learning, adjustment, and occasional setbacks.

Early AI initiatives influence subsequent developments by shaping expectations, capabilities, and architectural choices[47]. Successful pilots can generate momentum and legitimacy, while failed experiments may foster skepticism and risk aversion. These dynamics create path dependence, constraining the range of future options.

Temporal considerations also affect how transformation is evaluated. Short-term performance metrics may undervalue investments in capability building or organizational learning, leading to premature abandonment of promising initiatives. Conversely, long-term transformation requires sustained commitment and tolerance for uncertainty[48].

Recognizing AI transformation as a temporal process highlights the limitations of static maturity models. It reinforces the need for frameworks that capture movement, coherence, and evolution over time.

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46 *See Benbya, Pachidi and Jarvenpaa (2020), who show how organizational narratives about AI influence adoption trajectories.*

47 *See Rai, Constantinides and Sarker (2019).*

48 *This tension is well documented by Brynjolfsson, Rock and Syverson (2021).*

2.5 Artificial Intelligence Beyond the Firm

As AI systems increasingly rely on large volumes of heterogeneous data and complex computational infrastructures, their **development and deployment often extend beyond the boundaries of a single organization**[49]. A growing body of literature therefore examines AI through an ecosystem lens, emphasizing inter-organizational coordination as a key driver of value creation[50].

In many industries, AI-enabled processes depend on data flows that span suppliers, partners, customers, and third-party service providers. Examples include supply chain optimization, predictive maintenance across asset networks, financial risk monitoring, and personalized customer experiences. In such contexts, AI systems are embedded in networks of actors whose incentives, capabilities, and constraints must be aligned[51].

The literature highlights that coordination challenges increase significantly as AI initiatives move from localized to cross-organizational settings. Differences in data standards, governance practices, and technological maturity can limit interoperability and undermine system performance. Moreover, issues of trust and data sharing become central, as organizations must balance collaboration with concerns about competitive advantage and intellectual property[52].

These challenges suggest that AI transformation at scale cannot be understood solely as an intra-organizational phenomenon. Ecosystem-oriented research emphasizes the role of platforms and standards in enabling AI-driven value creation. Platforms provide shared technological foundations – such as data infrastructures, APIs, and development tools – that facilitate interaction among multiple actors. In AI contexts, platforms can accelerate innovation by lowering entry barriers and enabling reuse of models, data, and capabilities. Network effects may arise as more participants contribute data or applications, enhancing system performance and value for other participants. However, platform dynamics also introduce new forms of dependency and power asymmetry. Platform owners may exert control over access, pricing, and governance, shaping how value is distributed within the ecosystem[53].

The literature underscores that participation in AI platforms involves strategic trade-offs. While openness can foster ecosystem growth, excessive openness may dilute differentiation. Conversely, closed systems may preserve control but limit scalability and learning. Organizations must therefore navigate complex decisions about openness, standardization, and partnership models when pursuing AI initiatives with systemic impact[54].

Regulation represents another critical dimension of any AI ecosystems, particularly in sectors such as finance, healthcare, transportation, and energy. **Regulatory frameworks governing data protection, algorithmic transparency, fairness, and accountability directly influence how AI systems can be designed and deployed**. Rather than treating regulation as an external constraint, recent research conceptualizes it as an integral component of AI system design.

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49 As for many other forms of digital transformation initatives: see Cennamo and Gawer (2018) and Helfat and Raubitschek (2020) that show that competitive advantage in digital technologies increasingly depends on ecosystem positioning and coordination rather than firm-level assets alone.

50 See Constantinides, Henfridsson and Parker (2018), that extend this logic to platformized digital and AI infrastructures.

51 See Adner (2017), that shows how misalignment among complementors constrains system-level value.

52 See Jarrahi et al. (2021).

53 See Kenney and Zysman (2020), that document how digital platforms concentrate control over data and access; and Jacobides, Cennamo and Gawer (2024) that analyze how platform governance redistributes power and value in digital and AI ecosystems.

54 See Veale and Borgesius (2021) that analyze how data protection, explainability, and fairness requirements constrain and shape AI system design.

Compliance requirements shape architectural choices, governance structures, and operational practices. Demands for auditability and explainability may favor certain model types or limit the use of fully autonomous systems. Consider a bank that uses AI to decide whether to approve or reject loan applications. Financial regulation requires the bank to be able to explain to customers and regulators why a credit decision was made and to demonstrate that the decision was not discriminatory. Because of these auditability and explainability requirements, the bank may not be able to deploy a highly complex deep-learning model that produces accurate predictions but offers no clear rationale for individual decisions. Instead, it would be forced to adopt a more interpretable model, such as a gradient-boosted tree or a logistic regression with explainable features, even if this slightly reduces predictive accuracy. The system could be also designed so that a human credit officer must review and confirm borderline cases, rather than allowing the model to make fully autonomous decisions. Here, regulation directly shapes both the choice of model and the degree of automation: legal requirements for explanation and accountability rule out certain AI architectures and prevent the organization from moving to full automation, even when technically feasible.

At the same time, regulation can enable AI adoption by providing clarity and legitimacy. Clear rules reduce uncertainty for organizations and stakeholders, facilitating investment and collaboration. In ecosystem settings, regulatory alignment becomes particularly important, as inconsistent rules across jurisdictions can hinder cross-border AI initiatives[55].

This perspective highlights that regulatory exposure is not uniform across AI initiatives. The degree to which an AI system interacts with customers, affects rights, or operates across organizational boundaries influences both risk and governance requirements.

2.6 Synthesis and Research Gap

The literature reviewed in this section provides a rich but fragmented understanding of artificial intelligence and organizational change. Economic perspectives emphasize productivity effects but often abstract from organizational and institutional context. Sociotechnical research illuminates human–AI interaction and decision-making but tends to focus on localized settings. Organizational studies highlight challenges related to governance, scaling, and transformation over time, while ecosystem research draws attention to coordination, platforms, and regulation.

Taken together, these streams converge on a critical insight: **AI transformation is not a singular or uniform process. Instead, it unfolds through diverse logics of value creation and impact, shaped by organizational choices, governance structures, and external dependencies.** However, existing research lacks an integrative framework capable of connecting these insights in a way that is both analytically rigorous and operationally meaningful for large organizations.

Most existing approaches either catalog individual use cases or assess AI maturity along predefined dimensions. While valuable, these perspectives offer limited guidance for understanding how multiple AI initiatives combine into coherent—or incoherent—organizational strategies. They also struggle to explain why organizations with similar technologies and resources experience vastly different outcomes from AI adoption. This research addresses these limitations by introducing a macro-level framework that focuses on two fundamental dimensions distilled from the literature: how AI creates value and where that value materializes.

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55 See Yeung (2022), that argues that regulatory clarity increases investment and cross-organizational collaboration by reducing legal and legitimacy risk, especially in multi-jurisdictional AI ecosystems.

3.

RESEARCH
DESIGN
AND
METHODOLOGY

3.1 Research Objectives and Analytical Approach

The objective of this research is to develop an analytically robust yet practically meaningful **framework for understanding how organizations create value from artificial intelligence and how AI initiatives scale – or fail to scale – into broader transformation**. Rather than evaluating the performance of individual technologies, the study focuses on the underlying logics that shape AI-driven change across organizations.

Given the exploratory nature of this objective, the research adopts a qualitative, theory-building approach. This approach is particularly well suited to phenomena characterized by high uncertainty, rapid technological evolution, and strong context dependence – conditions that clearly apply to AI transformation. The study aims not to test predefined hypotheses, but to **identify recurring patterns, tensions, and mechanisms that explain variation in AI outcomes across organizations**.

The analytical strategy combines insights from academic literature with empirical evidence drawn from in-depth case studies. The resulting framework is intended to bridge theory and practice by offering a structured lens that captures complexity without reducing AI transformation to a checklist or maturity score.

Specifically, the research design follows a multi-stage process integrating theory and empirical analysis. It consists of three main phases:

1. Conceptual grounding through literature analysis
2. Empirical investigation through expert interviews and case studies
3. Iterative framework refinement through cross-case comparison

Each phase informed the next, allowing the framework to evolve through continuous interaction between theory and data.

The first phase involved an extensive review of academic and practitioner literature on artificial intelligence, organizational transformation, and digital innovation. Academic sources were drawn primarily from the fields of economics, management, information systems, and organization studies. Practitioner sources included reports from consulting firms, technology providers, and industry bodies, as well as articles from specialized technology journals.

The purpose of the literature analysis was twofold. First, it provided a theoretical foundation for understanding the multiple ways in which AI can create value and affect organizations. Second, it helped identify recurring themes and unresolved tensions in existing research, such as the gap between AI experimentation and scalable impact, the role of governance and data infrastructure, and the extension of AI beyond firm boundaries.

Importantly, the literature review did not aim to derive a fully specified framework with predefined variables. Instead, it was used to distill two macro-level dimensions that recur across diverse streams of research: the mechanisms through which AI creates value and the scope of its organizational and ecosystem impact. These dimensions served as the initial conceptual backbone of the framework.

The second phase of the research involved a series of semi-structured interviews with experts from large European and global organizations. Interviewees included senior executives, heads of AI and data, digital transformation leaders, and technical experts involved in the design and deployment of AI systems.

The interviews served several purposes. They provided insight into how organizations frame AI strategically, how AI initiatives are prioritized and governed, and which challenges are encountered

when attempting to scale AI beyond pilots. They also helped identify sectors in which AI transformation dynamics were particularly salient, informing case selection.

Interviews followed a flexible guide covering topics such as AI strategy, governance models, data infrastructure, organizational capabilities, and perceived outcomes. This flexibility allowed interviewees to emphasize issues they considered most critical, while ensuring comparability across interviews.

Five organizations were selected for in-depth case analysis. The cases span multiple industries, including manufacturing, finance, travel and leisure, and advanced engineering. All organizations are large, complex entities with international operations and an articulated interest in AI-driven transformation. We followed a theoretical sampling[56] to ensure variance along critically relevant dimensions for the research's objective (eg., different leveraging of AI tools, use cases, and value creation logics and scope) while preserving similarity along other, main organizational dimensions (such as eg., size, resources, multinational operations, financial conditions, strategic focus on AI-driven transformations).

Each case represents a distinct organizational context for AI implementation, characterized by different regulatory environments, technological legacies, and strategic ambitions. Together, the cases provide a rich empirical basis for examining how AI initiatives combine into organizational footprints and how these footprints relate to broader transformation outcomes.

3.2 Unit of Analysis: AI Initiatives and Organizational Footprints

A critical methodological choice in this study concerns the unit of analysis. Rather than treating the organization as a monolithic entity, the analysis focuses on individual AI initiatives – such as specific use cases, platforms, or systems – as the primary units of observation.

Each AI initiative is analyzed in terms of:

• how it creates value,
• where its impact materializes,
• and how it interacts with organizational structures and external actors.

This initiative-level analysis makes it possible to identify heterogeneity within organizations. Organizations rarely pursue a single AI logic; instead, they develop portfolios of initiatives driven by different objectives and constraints. The aggregation of these initiatives forms what the study conceptualizes as an organizational "**AI footprint**."

3.3 Analytical Process and Framework Development

The analytical process unfolded iteratively. In an initial step, AI initiatives identified in each case were mapped onto the two macro dimensions derived from the literature: value creation mechanism and impact scope. At this stage, the framework intentionally remained coarse-grained, focusing only on these macro dimensions.

Subsequently, through within-case analysis, we examined why specific initiatives occupied particular positions in the framework. This involved analyzing governance arrangements, data dependencies, architectural choices, human–AI interaction patterns, and regulatory exposure. These factors were not treated as predefined dimensions but as explanatory elements emerging from the data.

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56 See Glaser and Strauss (1967).

Cross-case analysis then compared patterns across organizations, identifying recurring mechanisms that explained similarities and differences in AI positioning and movement over time. Through this process, a set of sub-variables was systematically refined and articulated. These sub-variables serve as analytical lenses that explain how and why AI initiatives move – or fail to move – across different transformation logics.

As with all qualitative research, this study faces limitations related to generalizability and subjectivity. The findings are not statistically generalizable to all organizations. Instead, they aim for **analytical generalization**, providing concepts and mechanisms that can inform understanding in other contexts.

Several measures were taken to enhance validity and reliability. **Triangulation across literature, interviews, and case materials reduced reliance on single sources. Iterative comparison across cases helped identify robust patterns rather than idiosyncratic observations. Nevertheless, the study focuses primarily on large organizations in advanced economies.** Transformation dynamics may differ in smaller firms or in different institutional contexts. These limitations point to opportunities for future research.

4.

A MACRO FRAMEWORK OF AI TRANSFORMATION LOGICS

4.1 From Use Cases to Transformation Logics

Organizations rarely struggle to identify potential AI use cases. Advances in machine learning, natural language processing, and generative models have made it relatively easy to imagine applications across a wide range of business functions. The more difficult challenge lies in making sense of how these heterogeneous initiatives relate to one another and contribute to broader organizational transformation.

Most existing approaches to AI strategy focus either on cataloging use cases or on assessing technological maturity. While useful for operational planning, these perspectives offer **limited insight into the logic through which AI creates value and scales across the organization**. As a result, organizations may pursue numerous AI initiatives without developing a coherent understanding of how these initiatives interact, reinforce one another, or align with strategic intent.

This research adopts a different perspective. Rather than starting from technologies or applications, it focuses on the transformation logics that underlie AI initiatives. **A transformation logic refers to a recurring pattern through which AI creates value and reshapes organizational activity. Identifying these logics makes it possible to move beyond isolated projects and to analyze AI portfolios in a systematic way.**

To this end, and following similar frameworks on digital transformations[57], the AI Transformation Logics Framework introduces two macro-level dimensions that capture fundamental variation in AI-driven change: value creation mechanism and impact scope. These dimensions are deliberately abstract, allowing them to accommodate a wide range of technologies, industries, and organizational contexts.

4.2 Dimension I: Value Creation Mechanism

The **first dimension of the framework concerns how AI creates business value**. Across the literature and empirical evidence, AI initiatives can be distinguished according to the primary mechanism through which they generate value. While real-world applications often combine multiple mechanisms, one typically dominates in shaping organizational impact.

At a macro level, three ideal-typical value creation mechanisms can be identified: **automation, enhancement**, and **reconfiguration** *(see Figure 2)*. These mechanisms differ not only in economic outcomes, but also in their implications for organizational change, governance, and time horizons.

4.2.1 Automation

Automation refers to AI initiatives that replace or significantly reduce human effort in routine, well-defined tasks. Value is generated primarily through **cost reduction, speed, and consistency**. Examples include automated document processing, standardized customer service interactions, and rule-based decision execution.

Automation-oriented initiatives are often attractive because they **deliver relatively immediate and measurable returns**. Implementation is typically **localized**, and success can be assessed through efficiency metrics such as **time savings or error reduction**. However, **automation tends to reinforce existing process structures rather than transform them**. As a result, **its contribution to long-term strategic differentiation is often limited**.

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57 *See e.g., Cennamo et al. (2020).*

> *Example. A large insurance company uses AI to process simple claims for flight delays. Previously, clerks checked documents, verified flight numbers, and approved reimbursements. Now an AI system automatically extracts information from receipts and airline databases, applies predefined rules, and issues payments without human involvement. Humans are no longer involved in this task. Costs fall and speed increases, but the nature of the work has not changed: it has simply been removed from people and handed to machines.*

4.2.2 Enhancement

Enhancement describes AI initiatives that augment human capabilities rather than replacing them. In these cases, AI systems provide **insights, predictions, or recommendations** that support human judgment. Value arises from **improved decision quality, reduced uncertainty, and better allocation of attention**.

Examples include decision-support systems, predictive analytics for planning, and AI-assisted design or programming tools. Enhancement initiatives often **require deeper integration into workflows** and greater organizational adaptation than automation. They **may also challenge existing roles** and decision rights, as humans and machines jointly shape outcomes.

Compared to automation, enhancement typically delivers value over longer time horizons and depends more heavily on learning, trust, and organizational capability building.

> *Example. A radiology department uses AI to scan medical images and flag suspicious areas that might indicate tumors. The system highlights regions of interest, ranks cases by urgency, and provides probability scores. However, radiologists still make the final diagnosis and decide on treatment. The AI does not replace doctors. It changes how they work: they spend less time searching for abnormalities and more time interpreting findings, explaining results to patients, and deciding on next steps. Human expertise is amplified rather than removed.*

4.2.3 Reconfiguration

Reconfiguration represents the most transformative value creation mechanism. Here, AI enables fundamentally **new ways of working, organizing, or creating value**. Rather than optimizing existing processes, reconfiguration alters their underlying logic, sometimes giving rise to **new business models or ecosystem roles**.
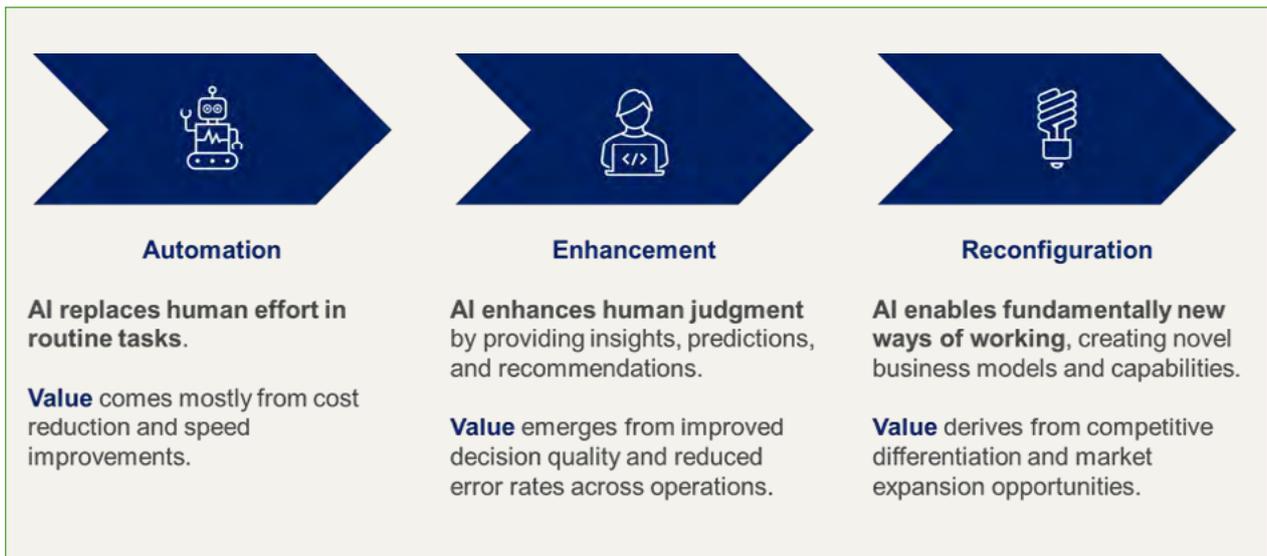
Examples include simulation-driven engineering environments, AI-enabled platforms that reshape customer interaction, or systems that redefine how knowledge is created and shared across organizations. Reconfiguration-oriented initiatives often **require substantial architectural investment and organizational change**. Their value is less easily measured in the short term but may yield durable competitive advantage.

Importantly, reconfiguration is not a linear extension of automation or enhancement. It reflects a qualitative shift in how AI is embedded in organizational activity.

> *Example. A logistics company deploys AI to optimize delivery routes in real time based on traffic, weather, and demand. Previously, planners created routes each morning and drivers followed them. Now the AI continuously updates routes throughout the day, and drivers receive dynamic instructions on their devices. This does not simply replace planners or assist drivers. It changes the whole operating model. Planners shift from making daily schedules to supervising the system, resolving exceptions, and coordinating with customers. Drivers interact with the AI as a partner rather than following static plans. Roles, authority, and workflows are reorganized.*

Figure 2.

Value Creation Mechanisms: Automation, Enhancement and Reconfiguration.

Automation

AI replaces human effort in routine tasks.

Value comes mostly from cost reduction and speed improvements.

Enhancement

AI enhances human judgment by providing insights, predictions, and recommendations.

Value emerges from improved decision quality and reduced error rates across operations.

Reconfiguration

AI enables fundamentally new ways of working, creating novel business models and capabilities.

Value derives from competitive differentiation and market expansion opportunities.

4.3 Dimension II: Impact Scope

The second dimension of the framework addresses where AI creates value within and beyond the organization. AI initiatives vary widely in the breadth of their impact, ranging from localized applications affecting individual roles to systemic systems spanning multiple organizations.

This dimension captures the **extent to which AI initiatives reshape coordination, dependencies, and governance across organizational boundaries**. At a macro level, three impact scopes can be distinguished: **localized, integrated, and systemic** *(see Figure 3)*.

4.3.1 Localized Impact

Localized AI initiatives operate within a limited organizational context, such as a specific role, team, or function. Their benefits are contained, and implementation typically requires minimal coordination beyond the immediate domain.

Localized initiatives are often **easier to launch and manage**, making them **common entry points for AI adoption**. However, their limited scope constrains their contribution to broader transformation unless they are deliberately integrated into larger systems.

4.3.2 Integrated Impact

Integrated AI initiatives span multiple functions or business units within a single organization. They enable shared insights, coordinated decision-making, and process alignment across internal boundaries.

Integration increases both potential value and complexity. It **requires alignment on data standards, governance, and workflows, as well as greater organizational commitment**. Integrated initiatives are often central to scaling AI impact, as they move beyond isolated use cases toward shared capabilities.
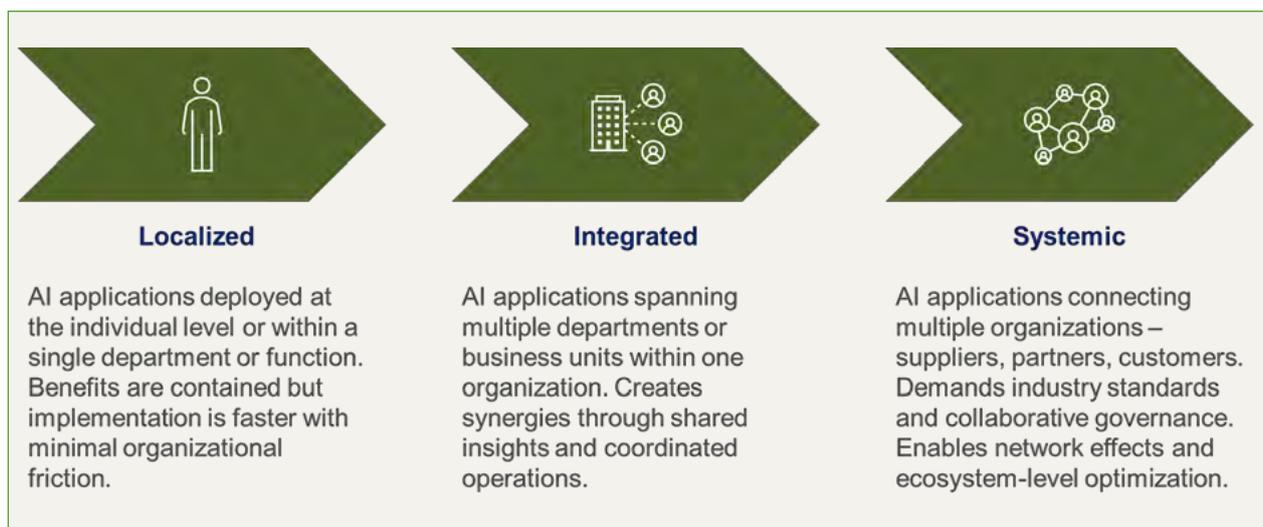
4.3.3 Systemic Impact

Systemic AI initiatives extend beyond organizational boundaries, involving partners, suppliers, customers, or regulators. Their value arises from network effects, ecosystem optimization, or new forms of inter-organizational coordination.

Systemic initiatives are the **most complex to implement**. They **require interoperability, shared governance arrangements, and often engagement with regulatory frameworks**. While not all organizations can or should pursue systemic impact, such initiatives can redefine industry dynamics when successfully deployed, and accordingly the role that the firm plays within the value chain[58].

Figure 3

Impact Scope: Localized, Integrated, Systemic.

Localized

AI applications deployed at the individual level or within a single department or function. Benefits are contained but implementation is faster with minimal organizational friction.

Integrated

AI applications spanning multiple departments or business units within one organization. Creates synergies through shared insights and coordinated operations.

Systemic

AI applications connecting multiple organizations – suppliers, partners, customers. Demands industry standards and collaborative governance. Enables network effects and ecosystem-level optimization.

4.4 The AI Transformation Logics Matrix

Combining the two macro dimensions – value creation mechanism and impact scope – yields the **AI Transformation Logics matrix, a conceptual map of the AI transformation landscape** *(see Figure 4)*. Each cell of the matrix represents a distinct transformation logic characterized by a particular combination of how AI creates value and where that value materializes.

Crucially, the matrix is not designed to position organizations as a whole. Instead, it positions individual AI initiatives. This distinction is essential for understanding real-world AI strategies.

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58 One of our case studies offers a case in point of such industry-level wide transformation in the sports automotive industry.

Figure 4

The AI Transformation Logics matrix.
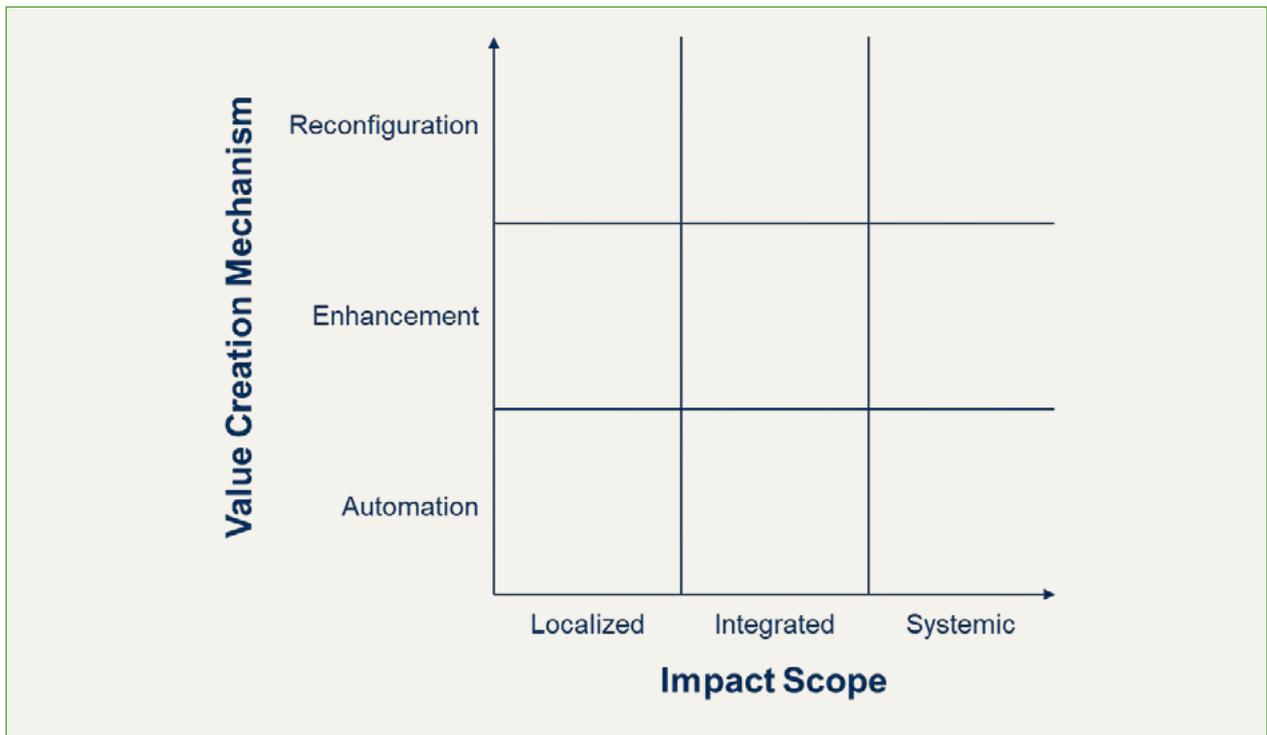
4.4.1 Organizational AI Footprints

Organizations typically pursue multiple **AI initiatives** simultaneously, driven by diverse objectives and constraints. These initiatives **may occupy different positions within the AI Transformation Logics Matrix. The aggregation of these positions constitutes an organization's AI footprint.**

An AI footprint reveals patterns of emphasis, balance, and tension within an organization's AI portfolio. For example, a footprint dominated by localized automation initiatives reflects a different transformation logic than one characterized by integrated enhancement or systemic reconfiguration efforts.

Analyzing footprints rather than single positions enables a more nuanced assessment of AI strategy. It highlights coherence – or lack thereof – between strategic ambition and operational reality.

Footprints also evolve over time. Movement across the matrix reflects changes in governance, capabilities, and strategic priorities. Understanding these dynamics is critical for managing AI transformation as an ongoing process rather than a one-time initiative.

5.
THE CASE STUDIES

Having established the macro framework, the next step is to examine how it applies in practice. The following section analyzes five case studies of large organizations, mapping individual AI initiatives onto the matrix and reconstructing their organizational AI footprints.

Through this empirical analysis, the study explores how different transformation logics manifest in real organizational settings, how footprints reflect strategic coherence or misalignment, and which underlying mechanisms shape AI-driven change.

5.1 Case Study 1 – Protector

5.1.1 Introduction

The first case study concerns Protector[59], a large European industrial group operating across pharmaceuticals, consumer goods, and mechanical manufacturing. The organization's footprint *(see Figure 5)* spans multiple business units, each characterized by different regulatory regimes and operational logics. Against this background of complexity and heterogeneity, the group initiated its Artificial Intelligence journey through a deliberate strategic choice: rather than starting from algorithms or isolated AI experimentation, it **chose to begin with data**.

At the core of this decision was a **shared conviction among senior executives that Artificial Intelligence cannot generate sustainable, scalable, or reliable value without a strong underlying data foundation**. As a result, the company framed AI not as a short-term innovation initiative, but as the natural outcome of a broader transformation toward data discipline and organizational readiness.

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59 For confidentiality reasons, we use pseudonyms to refer to the companies at the center of our case studies.

Figure 5

Protector's AI footprint.
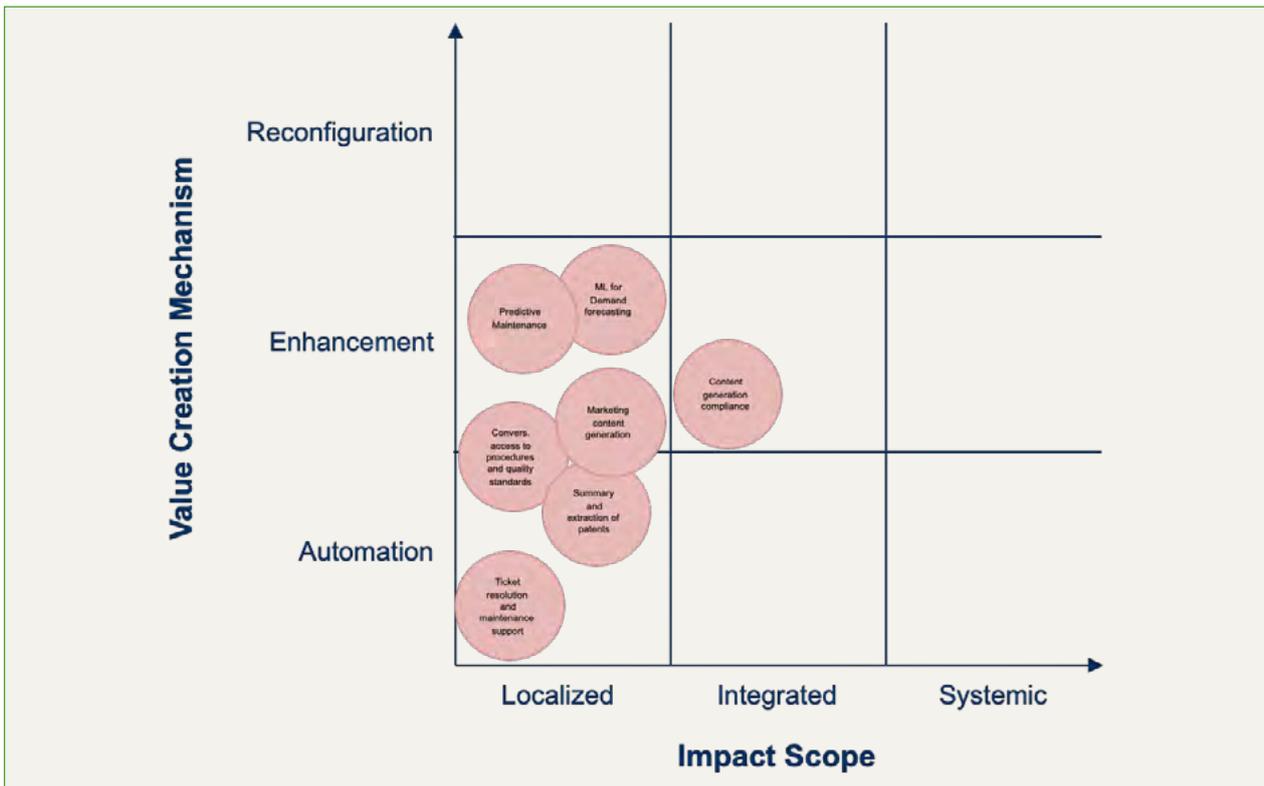
5.1.2 Introduction Strategy and Governance

The first concrete step in this journey was the definition of a corporate-wide data strategy, accompanied by the creation of a dedicated data function. This function was tasked with mapping the organization's information assets, defining common principles for data management, and fostering a shared data culture across business units that had historically operated in silos. The intent was not merely technical, but organizational: data was positioned as a corporate asset rather than a local resource owned by individual functions.

This strategic direction led to the formation of an internal community of practice, bringing together data professionals, IT specialists, and business representatives from different divisions. The community served as a coordination mechanism for sharing standards, lessons learned, and early experimentation, while also helping to diffuse data-related capabilities beyond the central team. In parallel, the company designed and progressively implemented a cloud-based data platform, which has since become a core component of the group's enterprise architecture.

While these foundational elements were being built – a process recognized internally as necessarily slow and complex – the organization deliberately complemented them with a set of short-term pilot initiatives. These pilots were designed to demonstrate tangible business value and to respond to growing demand from business units curious about AI's potential. The result was an explicit **"two-speed" operating logic**: on the one hand, medium- to long-term investments in infrastructure, governance, and capabilities; on the other, fast-moving use cases aimed at solving concrete operational problems.

From a governance perspective, the AI strategy is clearly articulated as data-first and centrally coordinated under the leadership of a Chief Data Officer. **Governance mechanisms include shared guidelines, architectural principles, and ethical standards**. However, at the time of the interviews, data ownership roles and formal accountability structures were still evolving. Security and privacy considerations are treated as non-negotiable design constraints, reflecting the highly regulated nature of several of the group's activities. Increasingly, responsibility for these topics is shared across IT, data, and risk functions, signaling a gradual convergence between technological and governance domains. Ethical considerations are embedded through a formal AI Responsibility Framework and through structured supplier assessment processes aimed at ensuring transparency and accountability across the AI value chain.

5.1.3 Introduction Main AI Use Cases

Within this strategic and governance framework, Protector has developed a broad and heterogeneous portfolio of AI use cases. Rather than targeting radical business model disruption, these initiatives primarily focus on improving efficiency, reliability, and decision quality within existing processes.

In operational domains, machine learning models are used to support demand forecasting and production planning, helping to reduce variability and improve resource allocation. Generative systems have been introduced to assist in technical ticket resolution and maintenance support, enabling faster diagnosis and more consistent handling of recurring issues. In manufacturing environments, AI-driven optimization tools are applied to reduce downtime and improve throughput, often by augmenting rather than replacing human decision-making.

Knowledge-intensive processes represent another major area of application. Conversational interfaces allow employees to access procedures, quality standards, and technical documentation more efficiently, reducing search costs and dependency on informal knowledge networks. In R&D and regulatory functions, AI supports patent documentation through automated text extraction and summarization, as well as the generation of regulatory and scientific content under strict compliance constraints. Marketing teams experiment with AI-enabled media mix modeling and content generation, seeking to improve targeting and effectiveness without compromising brand integrity.

5.1.4 Adoption Drivers

Several drivers explain the organization's decision to experiment with and progressively adopt AI. First, the group operates on top of a **fragmented data landscape** shaped by years of decentralization and acquisitions. AI was seen as a way to extract value from this fragmented environment, provided that sufficient investment was made in data harmonization and governance.

Second, the **rapid diffusion of generative AI tools created a surge of internal demand**, with business units increasingly asking for experimentation and support. This internal "pull" reinforced **the need for a coordinated response** capable of balancing innovation with control. Third, the organization faced growing pressure to respond quickly to business requests while operating within strict regulatory and privacy constraints.

5.1.5 Challenges

Despite early successes, the journey has been marked by **several structural challenges.** The IT landscape remains fragmented, with **multiple legacy systems and overlapping ERP and CRM solutions complicating integration efforts**. Building the data platform proved slower than many business stakeholders initially expected, creating **tensions between long-term architectural goals and short-term performance pressures.**

The **shortage of skilled AI professionals** represents another constraint. **Cultural resistance** also emerged as a non-trivial obstacle: in many parts of the organization, AI continued to be perceived primarily as a technical tool rather than as a driver of organizational change. Finally, **strict data protection and regulatory frameworks** impose additional constraints on experimentation, reinforcing the need for careful governance and staged deployment.

5.1.6 Data and Infrastructure

At the time of analysis, the data platform was operational but still evolving. While core components were in place, full integration across business units had not yet been achieved. Data governance mechanisms were present but not uniformly applied, reflecting different levels of maturity across divisions.

5.1.7 People and Change Management

Recognizing the importance of **the human factor**, the organization launched a series of training and awareness initiatives aimed at demystifying AI and building basic literacy. These initiatives included short educational videos, internal communication campaigns, and open **"AI office hours"** linked to the rollout of a protected internal generative AI environment.

While these efforts increased curiosity and engagement, change management remained relatively loosely structured. Leadership involvement was growing, but AI was still more often framed as a productivity tool than as a catalyst for deep transformation. The introduction of internal generative tools improved individual productivity and confidence without leading to job losses. **HR initiatives focused primarily on technical upskilling, such as prompt engineering, while broader reskilling and role redesign efforts were still in early stages**. Nonetheless, recognition of data and AI roles as strategic assets was beginning to emerge.

5.1.8 Future Outlook

Looking ahead, the organization's priority is to consolidate and scale existing initiatives, moving from proofs of concept to fully embedded business tools. **The long-term vision is to evolve toward an AI-enabled enterprise in which data and intelligence inform decisions end-to-end**. However, executives acknowledge that achieving this vision will require not only technological progress, but also a deeper cultural transformation affecting mindsets, incentives, and organizational structures.

5.2 Case Study 2 – Worldtour

5.2.1 Introduction

The second case study concerns Worldtour, a large multinational group operating in the travel, hospitality, and destination services industry. The company manages a complex portfolio of offerings spanning booking platforms, destination services, customer support, and in-house digital products. The group has **historically maintained strong internal technology capabilities, including a proprietary software factory and centralized digital teams.**

This technological orientation has **significantly shaped the company's approach to artificial intelligence**. Rather than treating AI as a recent innovation triggered by the emergence of generative models, the organization frames its current initiatives as the latest phase of a much longer trajectory. Over more than a decade, the company has progressively integrated machine learning and automation into its core operations, particularly in pricing, demand management, and customer interaction processes *(see Figure 6)*. As a result, **AI is not perceived as an external disruption, but as an endogenous evolution of existing digital competencies.**

Figure 6

Worldtour's AI footprint.
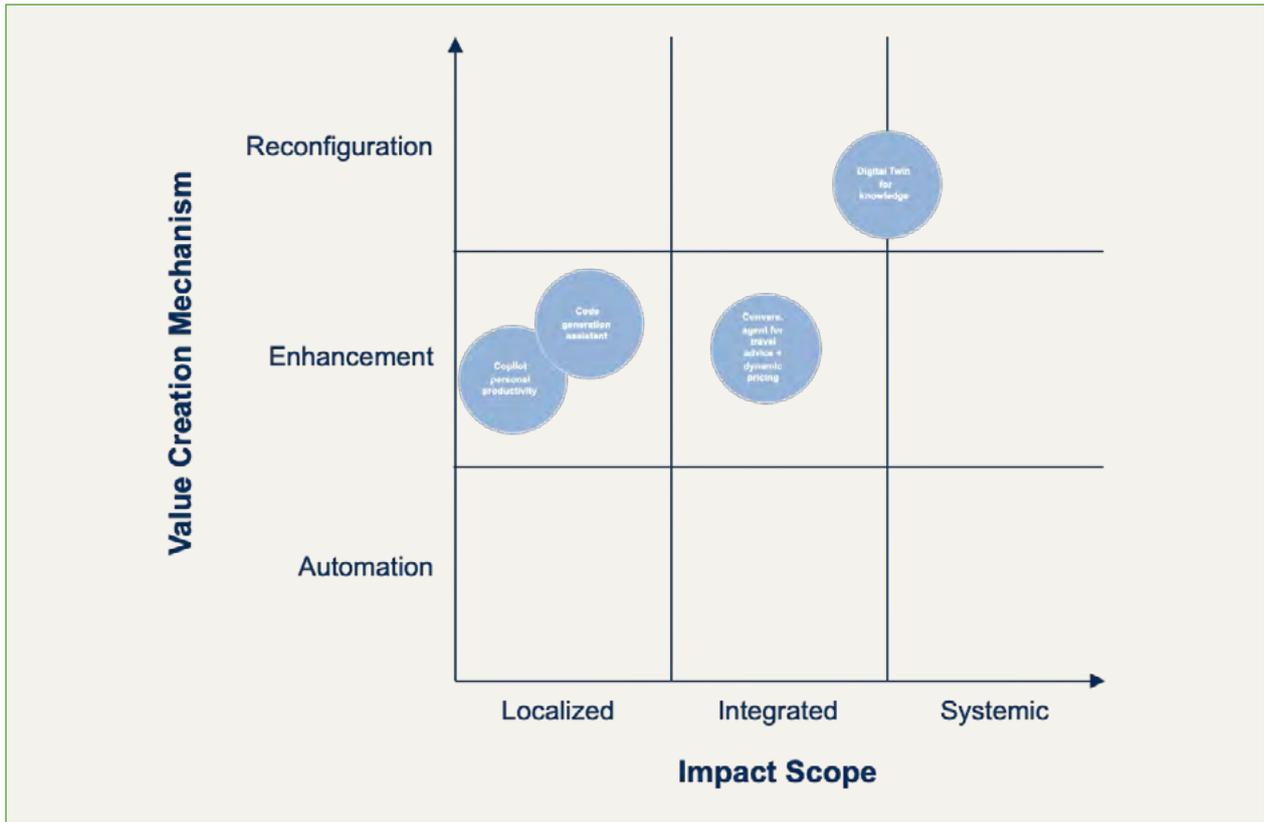
5.2.2 Strategy and Governance

The company's AI strategy is explicitly articulated around the **ambition of becoming an "AI-first" organization**. This ambition does not imply that AI replaces human decision-making across the board, but rather that every major strategic and operational decision is evaluated in light of how AI could contribute to it. Over time, this orientation has translated into increasing investments in proprietary platforms, internal talent, and governance structures designed to support scalability.

Governance has evolved significantly as AI initiatives expanded in scope and impact. Early experimentation was largely decentralized, driven by individual teams seeking to optimize specific processes such as pricing or customer support. As these initiatives demonstrated tangible value, the organization progressively formalized its governance model. By 2024, a **comprehensive AI governance framework had been introduced**, spanning strategy, organization, risk and compliance, ethics, innovation, communication, and data management.

A key feature of this governance model is its **explicit attention to ethical and reputational considerations**. Given the company's high visibility and direct interaction with end customers, leadership recognized early on that AI-related failures could have immediate reputational consequences. As a result, ethical principles, transparency requirements, and accountability mechanisms were embedded into the design and deployment of AI systems.

5.2.3 Main AI Use Cases

The company's portfolio of AI use cases reflects a high level of maturity and spans multiple layers of value creation. At the most basic level, AI tools are used to **enhance individual productivity**. Copilots integrated into office software and development environments support employees in writing documents, producing code, and managing routine tasks, leading to measurable efficiency gains across functions.

Beyond individual productivity, AI plays a **central role in automating and augmenting core business processes**. Dynamic pricing systems continuously adjust offers based on demand signals, competitive context, and inventory constraints. In customer service, conversational agents have evolved from simple rule-based chatbots into more advanced assistants capable of supporting both customers and operators across multiple channels. These systems are increasingly multimodal and integrated with backend systems, allowing them to move beyond information provision toward action execution.

The most distinctive element of the company's approach, however, lies in its development of **proprietary generative AI platforms** based on collaborative agent architectures. These platforms function as **"digital twins of organizational knowledge"**, enabling different agents to specialize in tasks such as IT architecture support, content production, product documentation, and marketing campaign generation. Over time, these agents are being progressively integrated and empowered, creating an ecosystem of digital collaborators that augment human organizational structures.

5.2.4 Adoption Drivers

Several drivers underpin the company's sustained investment in AI. **Competitive intensity** in the travel industry, combined with high price transparency and low switching costs, creates constant pressure to optimize margins and customer experience simultaneously. AI offers a way to manage this tension by enabling more granular pricing, personalization, and service responsiveness.

At the same time, leadership **perceives AI as a structural shift** that will redefine the industry's competitive landscape. Rather than waiting for external disruption, the company has chosen to proactively build internal capabilities that allow it to shape future customer journeys. This forward-looking orientation has been reinforced by a strong innovation culture and by management's willingness to invest in exploratory projects even in the absence of immediate business cases.

5.2.5 Challenges

Despite its relatively advanced positioning, Worldtour faces several challenges. The rapid pace of technological change requires **continuous skill renewal**, particularly as new models, tools, and architectures emerge. Early generative AI pilots exposed **limitations in data quality and knowledge organization**, forcing the company to invest in data cleaning, semantic modeling, and ontology development.

Governance complexity has also increased as AI systems become more autonomous and interconnected. Balancing innovation speed with risk management remains an ongoing tension, particularly in customer-facing applications. Finally, the company must carefully manage **external communication around AI**, as automation in travel services can be perceived as a threat to traditional roles and intermediaries.

5.2.6 Data and Infrastructure

The company's data strategy reflects its long-standing investment in internal digital capabilities. Over time, the organization has consolidated a centralized data office responsible for data governance, analytics, and advanced modeling. This structure supports a data platform that integrates transactional data, customer interaction data, operational data, and content-related assets across multiple business lines.

However, the introduction of generative AI exposed latent weaknesses in data quality, structure, and semantic consistency that had previously remained manageable within traditional analytics and machine learning use cases. Early deployments of large language models revealed inconsistencies in internal documentation, duplication across repositories, and ambiguities in terminology that directly affected model accuracy and reliability.

In response, the organization launched targeted initiatives focused on data cleaning, standardization, and semantic enrichment. Particular emphasis was placed on the development of ontologies and knowledge graphs to structure enterprise knowledge in a way that could be effectively leveraged by generative and agent-based systems.

5.27 People and Change Management

From a people perspective, the organization has approached AI adoption as a **long-term cultural transformation** rather than a short-term efficiency initiative. The presence of a strong internal software factory facilitated early experimentation, but leadership quickly recognized that technical capability alone was insufficient to ensure adoption at scale.

Human Resources has played an active role in redefining roles, competencies, and career paths in response to the growing presence of AI systems. Training initiatives span multiple levels of depth, from basic AI awareness for the broader workforce to advanced programs for engineers, data scientists, and product owners. Communities of practice have been established to enable peer learning and knowledge exchange across functions.

An important dynamic highlighted in the interviews concerns the **gradual normalization of collaboration between humans and digital agents**. Rather than framing AI as a replacement for human judgment, the organization emphasizes the notion of **"AI-augmented professionals"**, where employees are expected to supervise, orchestrate, and refine the outputs of intelligent systems. This framing has helped mitigate resistance and foster a sense of shared ownership over AI initiatives.

5.2.8 Future Outlook

Looking ahead, the company identifies two plausible trajectories for AI-driven transformation. The first is **evolutionary**, focused on continuous improvement in efficiency, personalization, and customer experience. The second is more **radical**, involving a reconfiguration of the customer journey around autonomous or semi-autonomous digital travel assistants capable of managing complex end-to-end interactions.

In both scenarios, **leadership views AI not as a discrete technology, but as an organizing principle shaping future business models, organizational structures, and competitive dynamics**. The ability to orchestrate complex ecosystems of digital agents and human actors is expected to become a key source of differentiation.

5.3 Case Study 3 – Manufacta

5.3.1 Future Outlook

The third case study focuses on Manufacta, a large global manufacturing group operating in the production of industrial components. The organization serves a wide range of end markets and manages a geographically dispersed network of production sites. Over time, the group expanded through acquisitions, which resulted in a highly heterogeneous operational and IT landscape. While this growth strategy strengthened market presence, it also generated significant fragmentation in processes, data structures, and digital capabilities across regions and plants.

For many years, digital initiatives within the organization progressed in a piecemeal fashion. Individual business units and plants introduced local solutions to address specific operational needs, often relying on spreadsheets, bespoke tools, or isolated analytics initiatives. As a result, the organization accumulated technical and organizational debt, limiting its ability to scale digital solutions and extract value at the group level. Against this background, **Artificial Intelligence emerged** not as a natural extension of existing digital capabilities, but **as a potential lever to break organizational inertia** and relaunch a stalled transformation agenda.

A decisive shift occurred following a change in top management in 2023. Under the new leadership, AI was explicitly positioned as a strategic priority and as a catalyst for broader organizational renewal. Rather than framing AI as an incremental efficiency tool, senior executives presented it as an opportunity to question established processes, decision rights, and ways of working across the enterprise *(see Figure 7)*.

Figure 7

Manufacta's AI footprint.
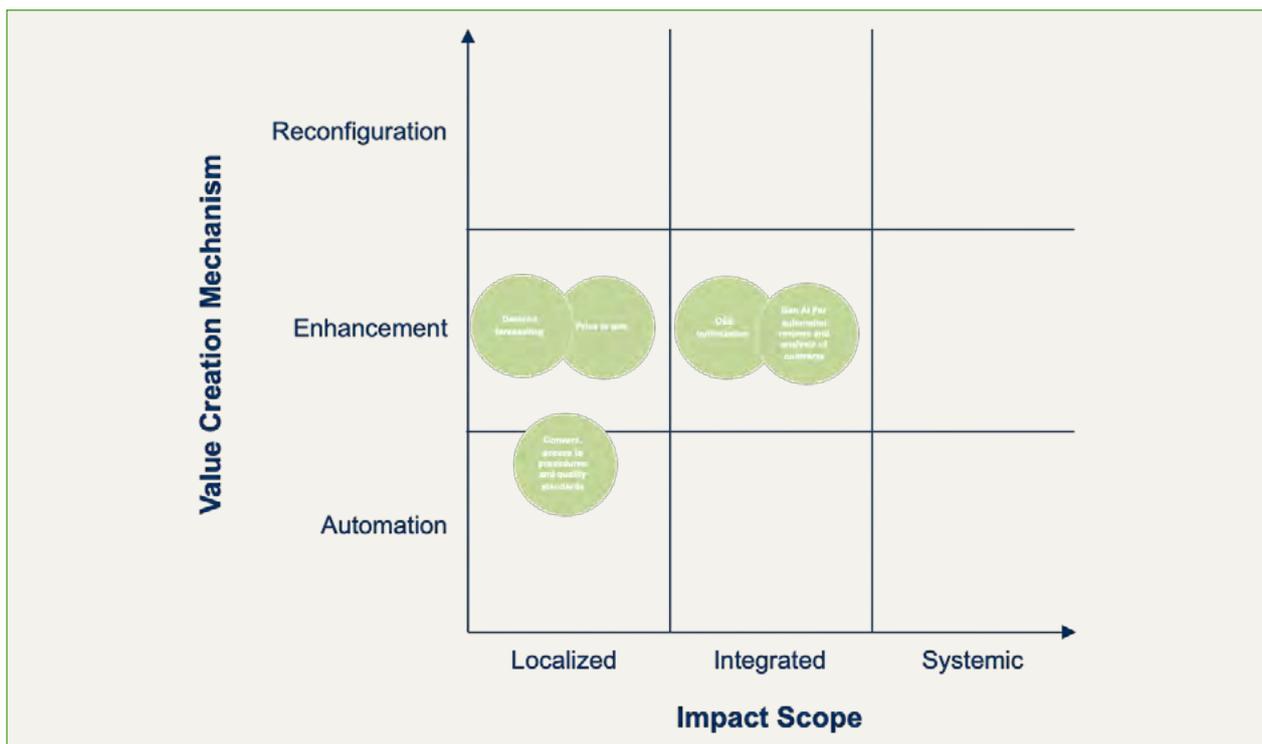
The group's AI strategy was launched through a highly structured and time-bound initiative designed to create alignment at the highest levels of the organization. Over a six-week period, top management, business leaders, and functional heads were involved in an intensive assessment of strategic priorities and operational pain points. This process resulted in the identification of a portfolio of twenty-six AI use cases, spanning manufacturing operations, sales and pricing, R&D, legal functions, and corporate support activities.

From the outset, **governance was deliberately centralized.** Leadership was concerned that decentralized experimentation would reproduce the same fragmentation that had characterized earlier digital initiatives. To address this risk, the organization established a central AI Factory responsible for architectural decisions, methodological standards, and delivery oversight. The AI Factory was positioned as a group-level capability rather than an IT sub-function, reporting directly to the transformation leadership and operating with a clear mandate to prioritize initiatives based on strategic impact.

Delivery was organized around so-called "**fusion teams**," each combining business experts, IT specialists, data professionals, and external partners. This organizational model was intended to serve multiple purposes simultaneously. First, it aimed **to accelerate execution** by reducing handoffs between functions. Second, it acted **as a mechanism for change management** by embedding AI capabilities directly into business processes rather than treating them as external tools. Finally, it allowed leadership to **retain control over architectural coherence** while still leveraging local domain knowledge.

Governance also incorporated early alignment with emerging AI regulation. Compliance with forthcoming regulatory requirements was framed not as a constraint, but as a design principle shaping model development, documentation, and monitoring practices.

5.3.3 Main Use Cases

The AI use cases identified and developed by the organization reflect a strong focus on operational and process-level transformation. In manufacturing environments, AI-driven optimization tools are deployed to improve line efficiency, detect anomalies in production data, and support predictive maintenance. These systems aim to reduce downtime, stabilize output quality, and improve asset utilization across plants with different levels of technological maturity.

In commercial functions, AI models support dynamic pricing decisions by combining customer behavior data, historical sales performance, and margin objectives. Demand forecasting tools are used to better align production planning with market signals, reducing inventory volatility and improving service levels.

Knowledge-intensive functions also represent a significant area of application. Virtual expert systems support engineers and R&D teams by enabling faster access to technical documentation, historical project data, and best practices. In legal departments, AI assistants are used to analyze contracts, retrieve relevant clauses, and support compliance activities, reducing cycle times and increasing consistency in document handling.

5.3.4 Adoption Drivers

Several drivers explain the organization's decision to invest heavily in AI. At a strategic level, the **leadership** change created a window of opportunity to **relaunch digital transformation** and signal a break with incrementalism. AI provided a visible and credible focal point for this renewed ambition.

Operationally, persistent **inefficiencies in manufacturing and planning** created strong pressure to improve productivity and reliability. Traditional lean and continuous improvement initiatives had

reached diminishing returns, leading managers to search for new levers. AI was perceived as a way to extract additional value from existing processes by leveraging data that had previously been underutilized.

External expectations also played a role. Customers, partners, and investors increasingly expected the organization to demonstrate progress in digitalization and advanced analytics. AI initiatives were therefore seen as a way to reinforce the group's positioning as a modern, forward-looking industrial player.

5.3.5 Challenges

Despite strong top-level support, the AI program encountered significant challenges. **Data emerged as the most critical bottleneck**. Years of decentralized operations had resulted in inconsistent data definitions, variable data quality, and widespread reliance on manual data manipulation. While a centralized data platform was under construction, executives recognized that technical integration alone would not resolve these issues without deeper process redesign.

Cultural resistance also surfaced as a major obstacle. The introduction of fusion teams and agile delivery models challenged established hierarchies and role definitions, particularly in engineering and IT functions accustomed to waterfall planning and clear functional boundaries. In some areas, skepticism toward AI was fueled by concerns about loss of autonomy or increased transparency.

Finally, the organization faced constraints in terms of **specialized skills**. Demand for data scientists, machine learning engineers, and AI product owners exceeded internal supply, increasing reliance on external partners and raising concerns about long-term capability building.

5.3.6 Data and Infrastructure

At the time of the interviews, the group's data and infrastructure landscape was in transition. However, full harmonization had not yet been achieved, and many use cases continued to rely on partial or manually curated datasets.

5.3.7 People and Change Management

Change management was explicitly recognized by the organization as a critical success factor for the adoption of artificial intelligence. From the outset, the introduction of AI was deliberately used as an opportunity to **promote new ways of working** across the organization. These included stronger cross-functional collaboration, the adoption of more iterative development approaches, and closer interaction between business and IT functions, which had previously operated with clearer separations.

The fusion team model played a central role in diffusing new skills and mindsets throughout the organization. Within this model, development activities are carried out by teams that blend business, IT, and functional experts, working under agile principles. At the same time, the organization has adopted a **hybrid waterfall**–agile approach, combining structured planning phases with iterative design and development sprints. By working side by side with data scientists and engineers, business experts progressively developed a more nuanced understanding of AI's possibilities and limitations. At the same time, leadership remained attentive to the risk of change fatigue, particularly in manufacturing plants already under significant pressure from cost, efficiency, and performance targets.

Upskilling programs currently prioritize IT functions, where the most immediate skill gaps were identified. A broader rollout of training initiatives to business functions is planned once pilot projects reach a sufficient level of maturity. The headquarters retains overall coordination responsibility in order to prevent the emergence of uncontrolled "shadow AI" practices.

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Across the organization, AI is explicitly framed as a capability enhancer rather than a job replacement technology. The company's focus is on developing hybrid skills that combine digital, analytical, and process-related competencies, with the aim of augmenting existing roles rather than eliminating them.

5.3.8 Future Outlook

The organization emphasizes that the quality of early co-design experiences determines adoption, and it explicitly highlights the need to **find a balance between central control and local experimentation**. Within this perspective, **AI is framed as a lever that can drive organizational change**, but only if it is paired with governance, good data, and culture. Over the next two years, priorities are clearly articulated around two objectives. The first is scaling successful pilots globally. The second is harmonizing data and processes in order to enable more advanced use cases, particularly in R&D and predictive maintenance. In parallel, the company plans to develop an AI governance model aligned with the EU AI Act, integrating risk, bias, and audit frameworks. The long-term vision is described as **an AI-powered factory**, where intelligence enhances productivity, safety, and competitiveness.

5.4 Case Study 4 – Fastengine

5.4.1 Introduction

This case study examines Fastengine, a high-performance automotive and engineering company operating in the design, development, and production of advanced vehicles and components. The organization is characterized by a strong engineering culture and a long-standing focus on performance, precision, and innovation. Its activities span vehicle design, simulation, testing, prototyping, and close collaboration with external partners and customers, particularly in contexts where development cycles are short and performance requirements are extremely demanding.

Within this environment, **Artificial Intelligence is** not approached as a generic digital technology, but as **part of a broader tradition of advanced numerical modeling, simulation, and data-driven engineering** *(see Figure 8)*. The company's engagement with AI is therefore deeply embedded in its core technical activities and reflects a long-term evolution of engineering practices rather than a sudden technological shift.

Figure 8

Fastengine's AI footprint.
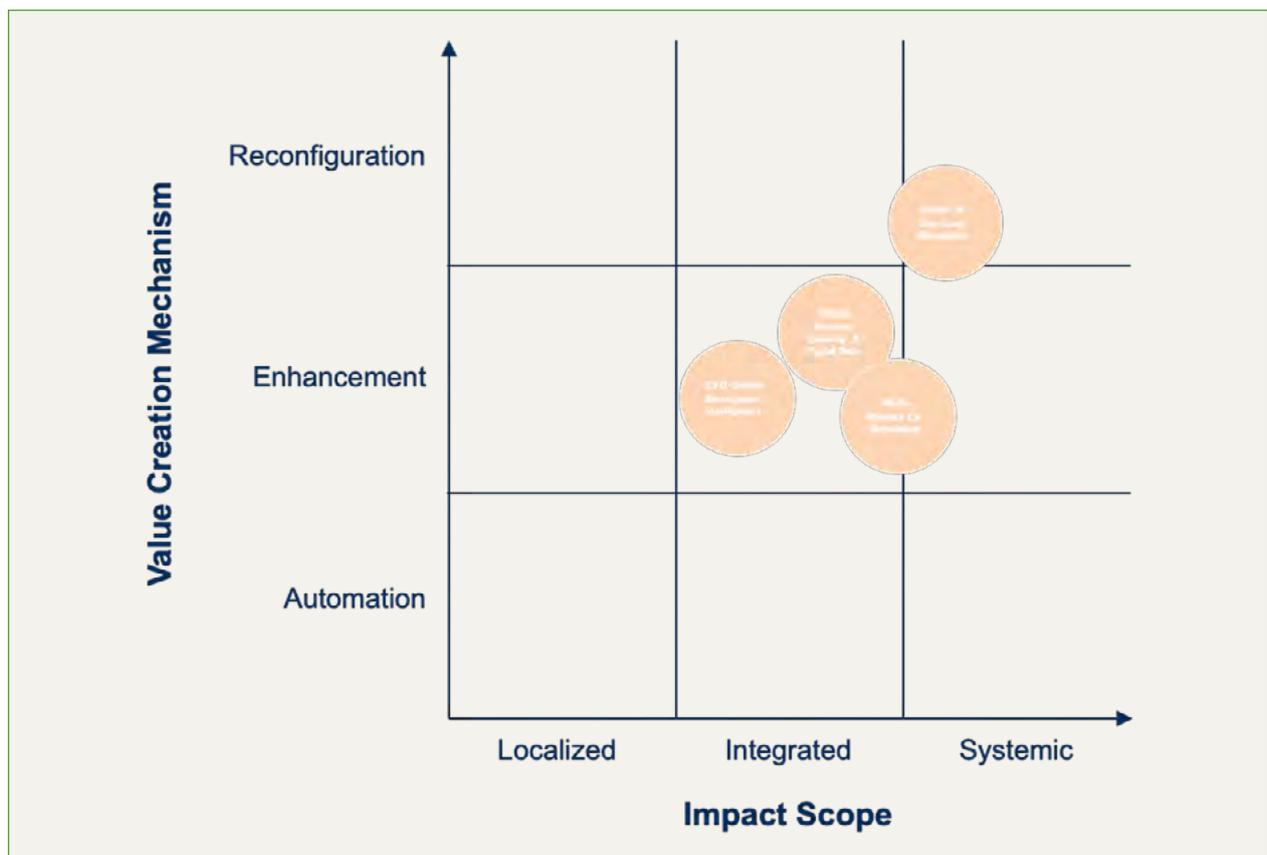
5.4.2 Strategy and Governance

The company's strategy is centered on a "**virtual-first**" approach to product development, in which digital models and simulations guide engineering decisions before physical prototypes are produced. Simulation and modeling capabilities are treated as strategic assets that support speed, accuracy, and repeatability in development processes.

Governance of AI-related activities is centralized within a core technical function responsible for simulation and modeling. This function defines methods, standards, and validation protocols that apply across engineering teams, including aerodynamics, vehicle dynamics, and testing. A clear distinction is maintained between activities aimed at supporting ongoing production programs and those dedicated to research and method development, allowing the organization to balance stability with experimentation.

Collaboration with external partners is governed through standardized interfaces and contractual arrangements that define model boundaries and data exchange rules. This governance structure is designed to protect intellectual property while enabling co-development and integration of external components into internal simulation environments.

5.4.3 Main AI Use Cases

The company applies AI and algorithmic techniques across a range of engineering activities. A central use case is full-vehicle virtual prototyping, where integrated digital models are used to assess performance, behavior, and design trade-offs before physical builds. These models combine aerodynamic, mechanical, and control system components to support early-stage decision-making.

Driver-in-the-loop simulation represents another key application. Real-time simulators are used to test vehicle configurations, evaluate setup choices, and explore scenarios that would be costly or impractical to assess through physical testing alone.

Computational fluid dynamics plays a major role in aerodynamic development. High-performance computing resources support large volumes of simulations, often executed through automated pipelines that enable overnight testing of multiple design variants. Results are systematically compared with wind tunnel data to validate and refine models.

Additional use cases include the integration of multi-physics models from external partners, rapid prototyping through additive manufacturing, and the provision of engineering support services to customers based on simulation and data analysis.

5.4.4 Adoption Drivers

Several factors have driven the company's adoption of AI-enabled engineering practices. First, **competitive pressure** in high-performance automotive contexts creates a strong incentive to reduce development time while maintaining or improving quality. Virtual testing and simulation-based decision-making offer a way to accelerate iteration cycles without increasing physical testing costs.

Second, the **growing complexity of vehicle systems** has increased the need for integrated modeling approaches capable of capturing interactions between components. AI and advanced algorithms are seen as necessary tools to manage this complexity and support system-level optimization.

Finally, **customer expectations** play a significant role. Clients increasingly demand not only physical products but also engineering insight and performance support, reinforcing the strategic importance of digital and analytical capabilities.

5.4.5 Challenges

Despite its advanced technical capabilities, the organization faces several challenges. One persistent issue concerns the **integration of data and models** across different engineering domains. Ensuring consistency and traceability between simulation outputs and physical test results requires significant coordination and methodological rigor.

The availability of **specialized skills** represents another constraint. The company relies on engineers who combine deep domain knowledge with strong capabilities in numerical methods, software, and data analysis. Recruiting and developing such hybrid profiles is demanding and time-consuming.

Finally, maintaining a **balance between experimentation and reliability** is an ongoing challenge. While innovation is critical, errors in simulation or modeling can have significant downstream consequences, making validation and quality assurance essential.

5.4.6 Data & Infrastructure

The company operates an advanced technical infrastructure based on high-performance computing resources and specialized simulation environments. Data generated from simulations, wind tunnel testing, and physical experiments are systematically collected and used to calibrate and improve digital models.

Automation plays an important role in managing this infrastructure. Standardized workflows, scripting, and version control mechanisms support repeatability and reduce manual effort. At the same time, the organization recognizes that data quality and consistency depend not only on tools, but also on disciplined engineering processes and governance practices.

5.4.7 People & Change Management

AI-enabled engineering has had a significant impact on roles and competencies within the organization. Engineers are increasingly expected to combine traditional mechanical expertise with skills in simulation, scripting, and data interpretation. This shift has led to the emergence of hybrid profiles and closer collaboration across previously distinct engineering domains.

Change management efforts focus on supporting this transition through **on-the-job learning and cross-team collaboration** rather than through large-scale formal training programs. Working side by side with specialists in simulation and data analysis allows engineers to progressively develop new skills and adapt to evolving practices.

Throughout this process, **AI is framed as a tool that augments human expertise** rather than replacing it. The organization emphasizes the continued importance of engineering judgment, particularly in interpreting model outputs and making design decisions.

5.4.8 Future Outlook

Looking ahead, the company expects to further evolve its digital engineering capabilities through a progressive **move toward real-time digital twins** and continuous model updating. Rather than relying on discrete simulation cycles, future development is oriented toward tighter feedback loops in which digital models are continuously refined based on new data and testing results.

In parallel, the organization anticipates an increased use of agent-based simulation approaches and autonomous testing frameworks. These solutions are expected to support more advanced exploration of design alternatives and performance scenarios, reducing the need for manual intervention while maintaining engineering control over validation and decision-making processes.

Another important direction concerns the deeper integration of engineering workflows with customer usage data. By incorporating information generated during product usage into development and simulation environments, the company aims to strengthen the connection between design assumptions and real-world behavior, further improving model accuracy and relevance.

Finally, the company considers the potential creation of an **ecosystem-level simulation environment** shared with partners and suppliers. Such an environment would enable coordinated development and testing across organizational boundaries, while requiring appropriate governance mechanisms to manage data sharing, intellectual property, and responsibility.

5.5 Case Study 5 – Bankaria

5.5.1 Introduction

This case study focuses on Bankaria, a large European commercial bank operating across retail, corporate, and private banking. The organization manages a high volume of transactions and customer interactions through a combination of physical branches and centralized digital channels. Its operating model includes extensive back-office, risk management, compliance, and IT functions, reflecting the regulatory intensity of the banking sector.

Within this context, the adoption of Artificial Intelligence takes place under strict constraints related to reliability, control, and compliance. AI initiatives are therefore evaluated not only in terms of technological feasibility, but also with respect to governance, risk management, and alignment with regulatory expectations. The bank's AI journey has evolved progressively, moving from early experimentation toward a more structured and centralized approach *(see Figure 9)*.

5.5.2 Strategy & Governance

The bank's AI strategy has developed through successive phases. In an initial phase, AI initiatives were largely decentralized, with individual functions and business units launching experiments independently. This resulted in a high number of proof-of-concept projects, characterized by heterogeneous technologies, limited reuse, and uneven quality.

Over time, the limitations of this approach became evident. As a result, the bank moved toward a **centralized governance model**. Budget allocation, prioritization, and delivery responsibilities were consolidated under a central transformation function. A **dedicated AI Factory** was established with the objective of industrializing AI development, defining common architectural standards, and ensuring consistency across initiatives.

Governance mechanisms emphasize strict discipline. Each AI initiative must be supported by a clear business case and measurable impact. Cross-functional committees involving business, IT, risk, and legal functions assess initiatives before approval. Particular attention is devoted to generative AI, which is subject to additional constraints due to its probabilistic nature. Generative systems are not exposed directly to customers and are primarily used for internal support activities.

5.5.3 Main AI Use Cases

The bank has developed a wide range of AI use cases, primarily focused on operational efficiency, compliance, and employee support. In back-office and middle-office functions, AI is used extensively for document-intensive processes. Smart document recognition and information extraction technologies support the processing of heterogeneous inputs such as invoices, contracts, and customer documentation, reducing manual effort and improving consistency.

Figure 9

Bankaria's AI footprint.
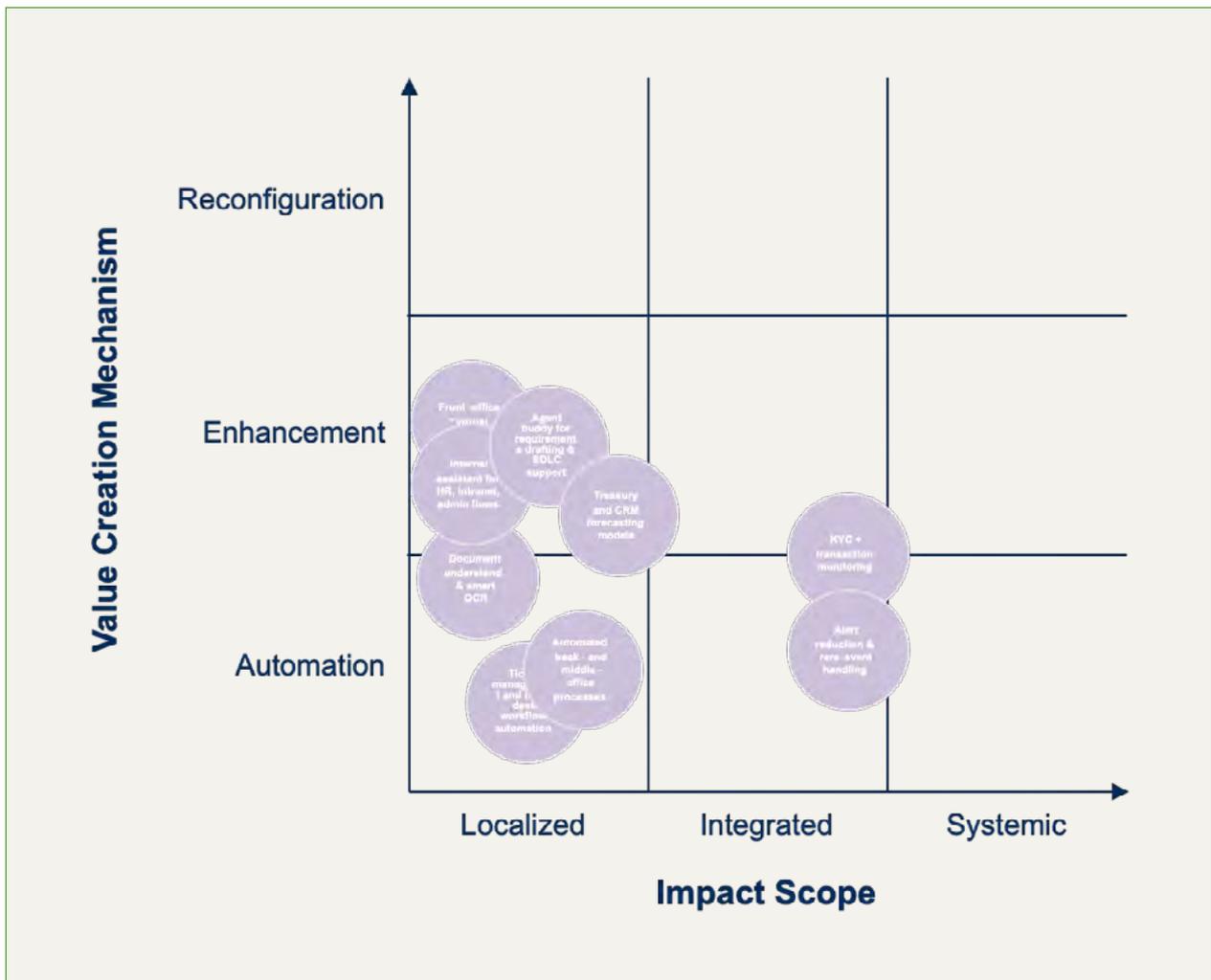
In the area of compliance and risk management, AI supports activities such as customer due diligence, transaction monitoring, and anomaly detection. Predictive models are used to prioritize alerts and support analysts in identifying cases that require further investigation. Generative components assist in summarizing information and supporting case handling, always within controlled environments.

Virtual assistants represent another important category of use cases. These assistants support employees in front-office activities by providing guidance on procedures and internal processes. Similar tools are used internally to support navigation of intranet content and administrative workflows. In IT functions, AI tools are applied across the software development lifecycle, supporting activities such as requirements drafting, testing, and documentation.

Traditional predictive analytics continues to be used in specialist domains such as treasury and customer relationship management, where AI supports expert decision-making rather than automated execution.

5.5.4 Adoption Drivers

Cost efficiency represents a primary driver of AI adoption. Increasing transaction volumes and growing regulatory requirements place sustained pressure on operating costs; AI is viewed as a way to absorb additional workload without proportional increases in headcount.

Regulatory complexity is another important driver. The expansion of compliance obligations has increased the need for scalable monitoring and control mechanisms. AI is adopted to support these activities while maintaining required levels of oversight and traceability.

Internal demand has also played a role. As early AI initiatives demonstrated tangible benefits, interest grew across functions, creating pressure to expand the portfolio of use cases. This bottom-up demand reinforced the need for stronger central coordination.

5.5.5 Challenges

One of the main challenges concerns **measuring AI performance**. AI initiatives are subject to particularly strict evaluation criteria, requiring clear and quantifiable evidence of value creation. This limits the scope for exploratory experimentation and places pressure on delivery teams.

Managing expectations is another challenge. Both executives and employees may hold unrealistic views of AI capabilities, particularly with respect to generative models. At the same time, concerns about reliability and errors require careful communication and governance.

Organizationally, the transition from decentralized experimentation to centralized delivery created **capacity constraints**. Demand for AI projects exceeds the available resources of the centralized AI Factory, making prioritization unavoidable.

5.5.6 Data and Infrastructure

The bank's data landscape reflects the accumulation of legacy systems over time and has historically been fragmented. AI adoption has highlighted the **need for more standardized data pipelines** and stronger governance.

In response, the organization is converging toward a unified machine learning and AI platform that supports development, deployment, monitoring, and maintenance of models. Significant investment has been made in technologies for document digitization, data extraction, and knowledge retrieval, which underpin many AI use cases.

Data security, access control, and traceability remain central design principles, given the sensitivity of financial and customer data and the regulatory environment in which the bank operates.

5.5.7 People & Change Management

The bank has invested heavily in AI literacy programs designed to reach a broad and heterogeneous workforce. Training initiatives are differentiated by level and role. At a basic level, **awareness programs** aim to provide employees with a shared understanding of what AI is, how it is being used within the bank, and what its limitations are. These initiatives are intended to reduce uncertainty and misinformation, particularly in relation to generative AI technologies, which have attracted significant attention both internally and externally. More advanced training programs are targeted at specialists involved directly in AI delivery, governance, and oversight, including data scientists, engineers, architects, and product owners.

Alongside training, the introduction of AI has contributed to the emergence of **new hybrid roles** within the organization. These roles combine technical knowledge with deep understanding of banking processes and regulatory constraints. Examples include AI product owners responsible for translating business needs into AI requirements, and technical profiles tasked with ensuring that models are deployed and monitored in compliance with internal standards. While these roles are still evolving, they reflect a broader shift toward closer integration between business, IT, and risk functions.

Change management efforts also address the emotional and cultural dimensions of AI adoption. Interviewees highlighted the coexistence of **contrasting reactions among employees**, ranging from fear of job displacement to unrealistic expectations regarding the capabilities of AI systems. Leadership has sought to manage these dynamics through continuous communication, emphasizing that AI is intended to augment human work rather than replace it. This framing is consistently reinforced in internal messaging and training activities.

At the same time, the organization acknowledges the operational pressures associated with AI adoption. As AI initiatives scale, demand for specialized skills increasingly exceeds available internal capacity, particularly within the central AI Factory. This imbalance creates workload pressures and reinforces the need for prioritization. Managing these constraints while maintaining employee engagement and avoiding change fatigue represents ongoing challenges.

5.5.8 Future Outlook

The bank's future outlook with respect to artificial intelligence is characterized by a **cautious, pragmatic, and highly disciplined orientation**. Rather than pursuing rapid expansion or radical experimentation, leadership emphasizes the importance of consolidating what has already been built. Priority is given to stabilizing existing AI solutions, ensuring their reliability over time, and embedding them into standard operating procedures across the organization. This consolidation phase is viewed as a necessary step to move from experimentation toward sustainable, industrialized use of AI.

A central element of the future outlook concerns the strengthening of governance and control mechanisms. As AI initiatives scale, the bank intends to further reinforce its centralized governance model, ensuring that prioritization, delivery, and monitoring remain aligned with strategic objectives and regulatory expectations. Particular attention will continue to be devoted to generative AI, which is expected to remain confined to controlled internal use cases unless reliability and risk management conditions allow otherwise.

In parallel, the bank anticipates a gradual evolution from isolated automation initiatives toward more integrated redesign of selected processes. Areas such as compliance workflows, onboarding, and document management are seen as candidates for deeper integration of AI capabilities, provided that solutions can be developed and deployed in a way that maintains transparency, auditability, and human oversight.

The future development of AI within the bank is therefore framed in explicitly incremental terms. Leadership does not articulate a vision of rapid or transformative change driven by AI. Instead, emphasis is placed on execution discipline, learning from experience, and maintaining trust with regulators, employees, and customers. **AI is positioned as a long-term capability that must mature within the constraints of a regulated financial environment**, rather than as a technology to be deployed aggressively or opportunistically.

6.

CROSS-CASES ANALYSIS

The analysis of the five cases suggests that **AI adoption is best understood** not as a linear maturity journey, but **as a configuration problem**. Organizations do not "progress" uniformly toward a single end state; instead, they assemble distinct combinations of AI technologies, data architectures, governance mechanisms, and organizational capabilities. These combinations define how and where AI creates value.

The **AI Transformation Matrix** we propose in this research *(see Figure 10)* provides a structured way to interpret these configurations along two dimensions: ecosystem impact and value creation mechanism. Rather than describing a sequence of stages, the matrix captures alternative strategic postures that organizations can occupy simultaneously or selectively, depending on context and constraints.

Figure 10

The AI Transformation Logics matrix with the footprints of the five case studies.
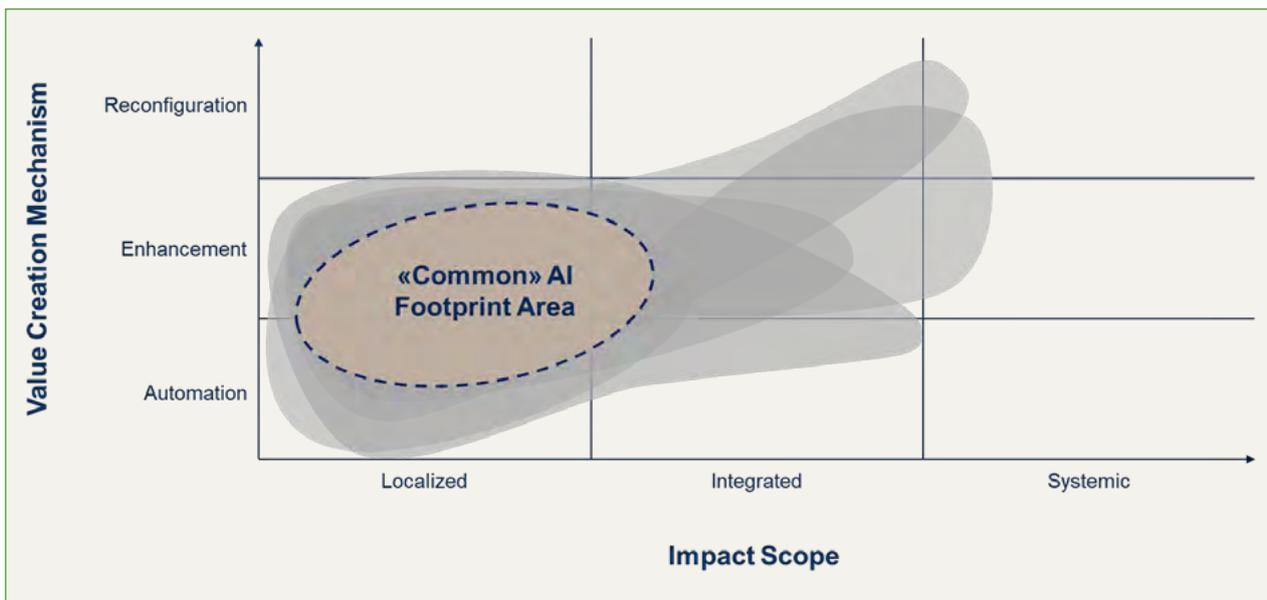
Across the cases, **performance differences are not explained by the absolute level of technological sophistication, but by the coherence of the configuration adopted**. Organizations that align AI use cases, data governance, coordination structures, and people capabilities around a clear logic are able to generate sustained value, even when operating in relatively conservative or localized positions within the matrix.

6.1 Interpreting the Ecosystem Impact Dimension

The ecosystem impact dimension captures the scope of coordination enabled by AI, ranging from localized applications to integrated and ecosystem-level configurations. The cases show that **advancing along this axis is primarily a governance and coordination challenge** rather than a technological one.

Localized AI initiatives emerge naturally as entry points, driven by functional needs and relatively self-contained data. At this level, AI adoption is shaped by local optimization goals and limited interdependence. These initiatives can be effective in generating efficiency gains, but they remain structurally constrained in their ability to scale impact.

Movement toward integrated AI reflects a qualitative shift. Here, AI becomes embedded in processes that span multiple functions, requiring shared data, aligned incentives, and formal coordination mechanisms. The analysis shows that organizations succeed in this transition only when they invest explicitly in data standardization, enterprise platforms, and centralized or federated governance structures. Without these elements, attempts at integration lead to fragmentation rather than synergy.

Ecosystem-level AI configurations represent a further shift in scope and exposure. In these cases, AI systems depend on inter-organizational data flows and coordinated decision-making across firm boundaries. The analysis highlights that such configurations are feasible only under restrictive conditions: modular architectures, clearly defined interfaces, contractual and regulatory frameworks, and the capability to manage third-party and compliance risk. Importantly, the cases demonstrate that ecosystem-level impact is not a natural or necessary objective for all organizations, but a selective strategic choice.

6.2 Interpreting the Value Creation Mechanism Dimension

The value creation mechanism dimension distinguishes how AI contributes to organizational performance, moving from automation to enhancement and reconfiguration. The analysis shows that **transitions along this axis are closely tied to both the type of AI deployed and the maturity of data governance**.

Automation-oriented configurations are predominantly enabled by traditional machine learning and rule-based systems. These applications rely on structured data and stable processes, allowing organizations to generate efficiency gains even in fragmented data environments. At this level, AI remains largely invisible to decision-makers and does not challenge existing organizational structures.

Enhancement-oriented configurations emerge when AI begins to support human judgment rather than replace tasks. Generative AI plays a central role in this transition, particularly in knowledge-intensive and interaction-heavy contexts. However, the analysis shows that generative AI alone is insufficient to drive enhancement. Success depends on curated knowledge bases, semantic consistency, access controls, and clear accountability for AI outputs. Where these governance conditions are absent, enhancement initiatives remain experimental or superficial.

Reconfiguration-oriented configurations represent the most demanding form of AI-enabled value creation. Here, AI enables the redesign of processes or value creation logics, often through the integration of multiple AI technologies, including machine learning, optimization, simulation, and generative components. The cases indicate that reconfiguration is possible only when AI is embedded within coherent architectures supported by end-to-end data governance. In the absence of such foundations, organizations revert to enhancement or automation, regardless of technological ambition.

7.
KEY INSIGHTS

While the case studies provide detailed insights into how organizations deploy artificial intelligence in practice, and the subsequent findings distill recurring empirical patterns, a deeper analytical step is required to explain **how organizations move across different AI configurations and why some trajectories generate more value than others**. This section addresses this aspect by interpreting the cases through the lens of transition dynamics and strategic coherence.

Building on the empirical evidence, the section examines the conditions under which organizations advance along each axis, the organizational and governance requirements associated with different forms of movement, and the constraints that shape feasible trajectories. Particular attention is given to the role of data interdependence, coordination mechanisms, and regulatory exposure, as well as to the interaction between different types of AI technologies and data governance maturity.

The section concludes by synthesizing these analytical insights into a set of strategic implications for executives. These insights do not prescribe a single optimal path; they instead clarify the trade-offs and design choices involved in AI-enabled transformation.

7.1 Transitioning Across the Two Axes of AI Transformation

7.1.1 Advancing along the Ecosystem Impact Axis

Advancing along the ecosystem impact axis – from localized to integrated and eventually ecosystem-level AI – reflects an increasing degree of data interdependence, organizational coordination, and exposure to external actors. Across the cases, this dimension emerges as primarily driven by governance and coordination requirements rather than by algorithmic sophistication.

At the localized level, AI initiatives are typically embedded within individual functions, teams, or business units. Data used by these systems is largely self-contained, often drawn from local databases or function-specific repositories. Interdependencies with other units are limited, and coordination requirements remain relatively low. Governance at this stage focuses on local data quality, model performance, and operational reliability. Regulatory exposure and third-party risks are also limited, as AI systems operate within well-defined organizational boundaries and rarely affect external stakeholders directly.

Movement toward integrated AI significantly increases data interdependence. Use cases begin to span multiple functions or processes, requiring shared access to data across organizational silos. In the cases analyzed, this transition consistently coincides with the need to consolidate data platforms, harmonize data definitions, and establish enterprise-wide data governance mechanisms. Local ownership of data and models becomes insufficient, as decisions in one part of the organization increasingly depend on data generated elsewhere.

As data interdependence grows, coordination structures must evolve accordingly. Integrated AI requires formal process governance to align objectives, manage dependencies, and resolve trade-offs across functions. This often leads to the creation of centralized or federated governance bodies, such as AI steering committees, data offices, or AI factories, responsible for prioritization, architectural coherence, and risk management. Without such coordination mechanisms, organizations may struggle to scale AI beyond isolated applications, leading to fragmentation and duplication.

Advancing further toward ecosystem-level AI introduces an additional layer of complexity. In these configurations, AI systems rely on data that crosses organizational boundaries, involving partners,

suppliers, customers, or, in some cases, public institutions. Data interdependence becomes inter-organizational, raising issues of data ownership, access rights, interoperability, and trust. The cases show that only organizations with modular architectures and clearly defined interfaces are able to explore this level of impact.

At this stage, governance extends beyond internal coordination to include contractual, legal, and regulatory considerations. Exposure to third-party risk increases, as failures or biases in AI systems can propagate across the ecosystem. Regulatory scrutiny also intensifies, particularly in safety-critical or highly regulated contexts. As a result, ecosystem-level AI requires not only technical integration, but also robust frameworks for compliance, accountability, and liability management.

Importantly, the cases indicate that advancing along the ecosystem impact axis is not inherently desirable for all organizations. While ecosystem-level configurations can unlock new forms of value, they also entail higher coordination costs, greater regulatory exposure, and increased dependence on external actors. For many organizations, strengthening integration within existing boundaries represents a more balanced and sustainable objective than pursuing full ecosystem-level AI.

7.1.2 Advancing along the Value Creation Mechanism Axis

Advancing along the value creation mechanism axis – from automation to enhancement and reconfiguration – entails a progressive shift in how AI is embedded into organizational work. Automation-oriented initiatives focus on efficiency gains through task replacement or acceleration, typically within stable and well-defined processes. But advancing also reflects a change in the type of artificial intelligence deployed and in the way data are governed and used. Automation-oriented use cases across the cases are predominantly based on traditional machine learning and rule-based systems. These applications are typically trained on structured, historical data and are embedded in relatively stable processes, such as document processing, demand forecasting, anomaly detection, or predictive maintenance. At this stage, data governance requirements, while important, remain relatively contained. Data is often managed at the functional level, and model performance can be monitored through well-defined metrics. As a result, automation can often be pursued even in organizations with fragmented data landscapes, provided that local data quality is sufficient.

The transition from automation to enhancement is marked by a shift in both AI technology and organizational use. In this phase, AI systems are no longer limited to executing predefined tasks but begin to support human judgment and decision-making. Generative AI plays a central role in this transition, particularly in knowledge-intensive and interaction-heavy processes. Across the cases, generative models are used to summarize information, generate content, support reasoning, and provide contextual assistance to professionals.

This transition significantly raises data governance requirements. Enhancement-oriented use cases depend on broader, more heterogeneous data sources, including unstructured content such as documents, technical reports, and procedural knowledge. Data consistency, semantic clarity, and access controls become critical, as AI outputs are directly used by humans in decision-making contexts. The cases show that without stronger governance – such as curated knowledge bases, controlled training data, and clear accountability for outputs – organizations struggle to move beyond isolated experimentation with generative AI.

Advancing toward reconfiguration represents a further qualitative shift. In this stage, AI enables the redesign of processes, workflows, or value creation logics rather than incremental improvements.

The cases suggest that reconfiguration is rarely driven by generative AI alone. Instead, it emerges from the combination of traditional machine learning, optimization algorithms, simulation-based models, and generative components integrated within coherent architectures. Examples include closed-loop engineering environments, integrated compliance workflows, or agent-based systems that orchestrate multiple AI components.

At this stage, data governance becomes a central architectural concern rather than a supporting function. Reconfiguration requires end-to-end visibility of data flows, shared data standards, and governance mechanisms capable of spanning functions and, in some cases, organizational boundaries. The ability to ensure traceability, accountability, and auditability of AI-driven decisions is essential, particularly in regulated or safety-critical contexts. The cases indicate that without mature data governance, attempts at reconfiguration either stall or revert to more limited enhancement-oriented applications.

Overall, the evidence suggests that movement along the value creation mechanism axis is constrained not only by technological maturity, but also by the organization's ability to govern data and integrate different types of AI into coherent systems. Traditional machine learning enables efficiency and predictability, generative AI expands the scope of human–AI interaction, and reconfiguration emerges only when these technologies are combined within robust governance and architectural frameworks.

7.2 Cross-case Findings

7.2.1 Finding 1 – There is no "optimal" AI footprint, but incoherent footprints generate sub-optimal results

Across the cases analyzed, the research does not identify a single optimal or universally superior position within the AI Transformation Matrix. Effective AI configurations differ significantly across organizations and industries, reflecting variations in competitive dynamics, regulatory environments, organizational legacies, and strategic priorities. What emerges consistently, however, is that **weak outcomes are associated with incoherence between strategic intent and the operational logic through which AI is deployed.**

Several cases indicate that the critical issue is not an organization's position in the matrix per se, but the rationale underlying that position. Organizations that articulate ambitious, innovation-oriented narratives while relying primarily on fragmented, localized automation initiatives tend to experience limited returns. **In these situations, AI investments typically yield incremental efficiency gains but remain disconnected from broader strategic objectives**. By contrast, organizations whose AI initiatives are aligned with their strategic posture – whether oriented toward operational excellence, engineering performance, or service augmentation – display more consistent and intelligible patterns of value creation.

The evidence further suggests that **misalignment between ambition and execution leads to fragmentation, organizational ambiguity, and diluted returns**, even when technical capabilities are available. Ecosystem-level AI configurations and process reconfiguration, in particular, emerge as powerful but demanding forms of AI-enabled transformation. They require high degrees of data interdependence, robust governance across organizational boundaries, modular architectures, and the capability to manage regulatory and third-party exposure.

Only a subset of organizations in the cases possess the structural and institutional conditions necessary to pursue these strategies effectively. For others, especially in highly regulated or

asset-intensive contexts, the costs and risks associated with ecosystem-level coordination may outweigh the benefits. In such cases, reinforcing integration and enhancement within organizational boundaries represents a more viable and sustainable trajectory.

This finding challenges the implicit assumption that all organizations should converge toward the same AI end state. Instead, the matrix should be interpreted as a **strategic design space**, in which different positions can be equally valid depending on context, constraints, and priorities. Across the cases, organizations that generate sustained value from AI are not those that pursue the most advanced technologies, but those that maintain coherence between strategic intent, organizational capabilities, and AI deployment logic. For executives, this implies that the primary strategic question is not how rapidly to move along the matrix, but how to ensure internal consistency across data, governance, people, and use cases.

7.2.2 Finding 2 – Platform-oriented AI architectures outperform project-based approaches over time

While localized automation initiatives often generate short-term benefits, the cases highlight a significant risk associated with the uncontrolled accumulation of isolated AI use cases. **As the number of local projects increases, organizational complexity and maintenance costs rise, frequently without corresponding gains in strategic impact**.

The evidence indicates that **transformation is driven not by the volume of AI projects, but by architectural coherence**. Organizations that prioritize the number of pilots over the integration and scalability of solutions tend to accumulate technical debt and organizational confusion. By contrast, those that manage AI as a coherent portfolio – guided by shared platforms, standards, and governance –are better positioned to scale value creation.

Across the cases, AI initiatives prove more durable and scalable when embedded within shared platforms rather than developed as standalone projects. **Platform-oriented approaches, characterized by common data layers, reusable components, standardized interfaces, and centralized governance, enable organizations to accumulate learning, reduce duplication, and support multiple use cases with lower marginal costs**. Although investments in platforms may slow early progress, they significantly enhance the organization's ability to scale value across both axes of the matrix over time.

7.2.3 Finding 3 – Data infrastructure and governance are the strongest predictors of AI scalability

One of the most robust findings across the cases concerns the **foundational role of data infrastructure and governance in enabling AI scalability**. Organizations with strong, shared data foundations are consistently better positioned to move from localized AI applications toward integrated or systemic use cases.

Where data governance is weak or fragmented, AI initiatives tend to proliferate in an uncoordinated manner, resulting in a growing portfolio of tools that are difficult to integrate, maintain, or scale. In contrast, cases characterized by consolidated data layers, shared data catalogs, and clear governance mechanisms show a smoother progression toward integrated AI solutions.

More advanced, systemic AI applications – such as simulation-based engineering environments or tightly coupled digital platforms – appear viable only when supported by consistent, high-quality data infrastructures. In these contexts, data functions not merely as an input to AI models, but as a shared organizational asset that enables coordination across functions and, in some cases, across organizational boundaries.

7.2.4 Finding 4 – Organizational design and people capabilities are first-order determinants of AI impact

The cases consistently demonstrate that AI adoption affects the nature of work and decision-making, not only operational processes. While automation-oriented initiatives primarily target task efficiency, more advanced forms of AI adoption – such as enhancement and reconfiguration – require explicit reconsideration of roles, responsibilities, and decision rights.

As organizations move beyond automation, new hybrid roles emerge. These include positions such as AI product owners, simulation engineers, and knowledge-management specialists, tasked with supervising, validating, and integrating AI outputs into organizational workflows. In these contexts, **AI becomes a structural component of how organizations reason, learn, and make decisions, rather than a peripheral support technology**.

This shift is observable across sectors, from engineering-intensive environments to regulated service organizations. Crucially, the cases show that such changes do not arise automatically from technology deployment. They depend on **deliberate organizational design choices** and sustained investment in people and capabilities.

7.2.5 Finding 5 – Reconfiguration requires openness and co-innovation

The evidence indicates that achieving systemic AI impact is rarely possible within organizational boundaries alone. Reconfiguration – understood as the redesign of processes, value chains, or business models – often requires collaboration with partners, suppliers, customers, and, in some cases, regulators.

Cases that advance in this direction exhibit **openness in system design, interoperability, and modular architectures**. These characteristics enable external integration and co-innovation, allowing AI-enabled systems to operate across organizational interfaces. Conversely, closed architectures and proprietary silos constrain organizations to incremental improvements and limit the potential for systemic impact.

This pattern is particularly evident in engineering- and platform-based contexts, where ecosystem-level coordination is a prerequisite for realizing the full value of AI-enabled systems.

7.3 Managerial Implications

For executives, these findings suggest a shift in how AI transformation should be governed:

- **Clarify strategic ambition** and identify which transformation logics are appropriate.
- **Assess the AI footprint**, not individual success stories.
- **Consider the interdependencies of AI use cases**, rather than just the impact/feasibility of each.
- **Invest in foundations** – data governance, architecture, and hybrid capabilities – before scaling.
- **Manage transitions deliberately**, recognizing that movement across logics requires different enablers.
- **Avoid the local use-case trap**, where activity substitutes for strategy.

8.
CONCLUSION

This research set out to move beyond abstract discussions of artificial intelligence by examining how organizations actually deploy AI, how value is created in practice, and why outcomes differ so markedly across seemingly comparable initiatives.

Drawing on five in-depth case studies across diverse industries, the analysis shows that there is no single optimal AI configuration to which all organizations should aspire. Instead, organizations create value through different AI footprints, shaped by their competitive context, regulatory environment, legacy systems, and strategic priorities. **What consistently distinguishes successful cases from less effective ones is not the sophistication of the technology adopted, but the coherence between strategic intent, data and governance foundations, organizational design, and AI use cases.**

Empirically, the analysis also shows that most organizations' AI portfolios today are concentrated in localized initiatives focused on automation and enhancement. These initiatives often deliver tangible, short-term benefits—such as efficiency gains or improved decision support – but rarely reshape coordination mechanisms, decision-making structures, or systemic value creation. This concentration reflects not failure, but the relative ease and lower risk associated with localized AI adoption compared to more integrated configurations.

The AI Transformation Matrix introduced in this study provides a useful lens to interpret these dynamics. By distinguishing between ecosystem impact and value creation mechanisms, the matrix highlights that AI adoption involves a set of design choices rather than a linear maturity path. Organizations must decide how far to extend coordination across functions and partners, and how deeply AI should reshape work, decision-making, and processes. These choices entail trade-offs in terms of complexity, governance requirements, and exposure to risk.

The analysis further shows that **transitions along both axes are constrained by structural conditions**. Advancing toward integrated or ecosystem-level AI increases data interdependence, coordination costs, and regulatory exposure, requiring robust governance and clear accountability mechanisms. Similarly, moving from automation to enhancement and reconfiguration depends not only on the availability of advanced AI technologies, such as generative models, but also on mature data governance, redesigned workflows, and new hybrid roles capable of mediating between AI outputs and organizational decisions.

Importantly, **the findings challenge the assumption that more advanced or more expansive AI configurations are always preferable**. For many organizations, particularly in regulated or asset-intensive contexts, reinforcing integration and enhancement within organizational boundaries may represent a more sustainable and value-generating strategy than pursuing ecosystem-level or reconfiguration-oriented ambitions. In this sense, the matrix should be understood as **a strategic design space rather than a prescriptive roadmap.**

For executives, the central implication is clear. **The key strategic question is not how quickly to adopt AI or how advanced the technology should be, but how to ensure internal consistency across strategy, data, governance, people, and use cases.** AI creates lasting value when it is embedded within coherent organizational systems, aligned with business priorities, and supported by appropriate coordination and governance structures. **Where such coherence is lacking, AI risks becoming a source of fragmentation rather than transformation.**

In conclusion, AI should be approached not as a standalone innovation initiative, but as a catalyst that exposes and amplifies underlying organizational choices. **Organizations that** recognize this and **treat AI adoption as a strategic design challenge are better positioned to translate technological potential into sustained business value.**

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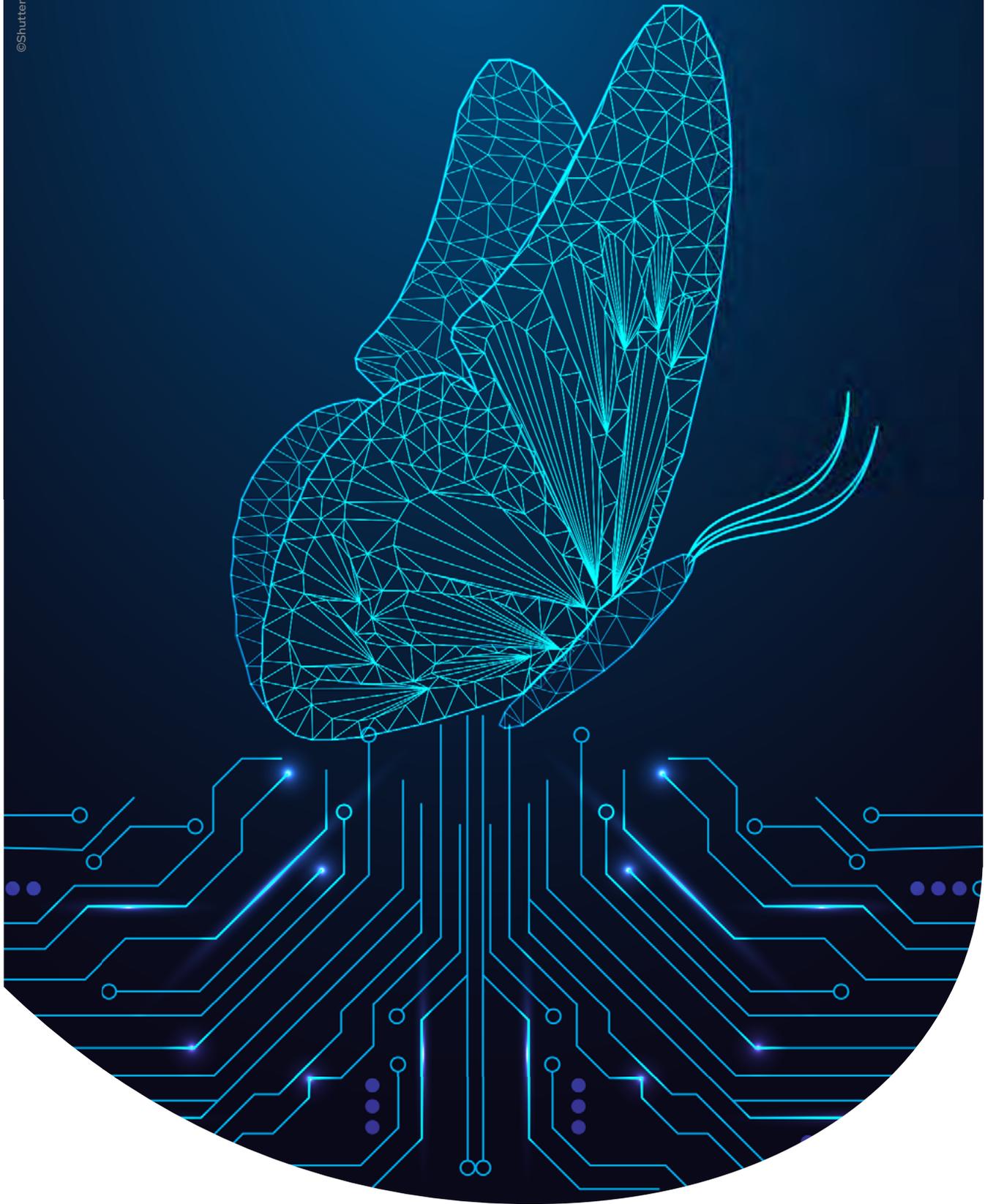
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