Strategy in the Era of AI:
Essays on Digital Transformation and M&A

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List of Abbreviations

AI	Artificial Intelligence
DT	Digital Transformation
DC	Dynamic Capabilities
ESG	Environmental, Social, and Governance
GenAI	Generative AI
IS	Information Systems
LLM	Large Language Model
M&A	Mergers & Acquisitions
PE	Private Equity
RBV	Resource-Based View
VC	Venture Capital

1 Introduction

The digital age has fundamentally changed the conditions under which organizations compete, create value, and sustain their business. This digital transformation (DT) has been defined as “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies” (Vial, 2019, p. 9), in short, through digital technologies. Knowing that artificial intelligence (AI) “and digital transformation go hand in hand” (Holmström, 2022, p. 333), AI is viewed as a further digital technology. However, it is also fundamentally different from previous technological advancements through its unique self-learning capabilities, moving beyond fixed input-output logics. Leveraging big data, it can autonomously adapt to complex environments (Lin & Maruping, 2025). Once confined to computer science journals and the R&D departments of technology pioneers, AI has emerged as a transformative force that reshapes industries, reconfigures organizational structures, and redefines strategic decision-making (Bharadwaj et al., 2013; Hutzschenreuter & Lämmermann, 2025). Expected to drive the global GDP growth by up to 15 percent within the next decade, it has now permeated industries from media and manufacturing to financial services and strategic investment (Goldman Sachs, 2023; PricewaterhouseCoopers, 2025). Despite the magnitude of this technological shift, and the equally substantial resources organizations around the globe commit to navigating it, the outcomes often remain disappointing: Up to 90 percent of M&A, many of which are explicitly motivated by the desire to acquire digital capabilities, fail to deliver their intended outcomes (Lev & Gu, 2024). The gap between the transformative promise of AI and the organizational reality of its adoption is a central strategic challenge of our time.

The dissertation responds to precisely this tension, illuminating the central questions: **How do organizations strategically respond to digital change, through both the development of internal resources and capabilities and their external acquisition? How is the success or failure of these responses determined?** It simultaneously targets researchers and practitioners, aiming to address the rigor-relevance gap between theoretically sound research and practically important insights (Nunamaker et al., 2015). Practically, it responds to the urgent need of managers, investors, and advisors who continue to operate under substantial market uncertainty despite an unprecedented access to data. Regardless of the push for DT and a proliferating market

of AI tools, they lack scientific, actionable guidance. Theoretically, the dissertation engages with fundamental questions in information systems (IS) and strategic management about sociotechnical phenomena at the intersection of technology, human agency, and organizational change (Sarker et al., 2019). Figure 1 abstracts the research framework guiding this dissertation, which is explained hereafter in detail.

Meso-Level: Guiding Organizational Responses to Digital Change

From a resource-based perspective and dynamic capabilities view, organizations facing digital disruption can strategically respond in two general ways: *Internally*, they can build the tangible and intangible resources, like machinery and knowledge (Wernerfelt, 1984), and the capabilities needed to compete, ensuring a firm's abilities to deploy, coordinate, and reconfigure said resources (Teece, 2007). *Externally,* M&A provide a way to access critical resources and capabilities that cannot be developed timely and organically (Henfridsson et al., 2009; Wernerfelt, 1984). The resource-based view (RBV) of the firm holds that an organization's competitive advantage arises from resources and capabilities that are valuable, rare, inimitable, and non-substitutable (Barney, 1991; Barney, 2001). Incumbents, "(1) … positioned in a traditional industry, (2) … established before the digital revolution, and (3) … [with] business models … not originally based on the use of digital technologies" (Metzler & Muntermann, 2020, p. 3), often lack the critical resources and capabilities to compete in the digital age. Hence, they face a fundamental build-or-buy decision. Dynamic capabilities theory extends RBV theory to environments of rapid change, arguing that firms must also be able to sense opportunities, seize them, and reconfigure their resource base accordingly (Teece, 2007, 2014). Both the internal route and conducting digital M&A can be understood as attempts to respond to the pressures of digital disruption. Since incumbents face temporal constraints, not being able to build resources and capabilities fast enough organically, as well as path-dependency constraints, where existing routines inhibit internal reconfiguration of resources (Uhlenbruck et al., 2006). Hence, M&A and internal strategies are often not alternatives but complements.

Each route carries structural limitations and tensions that the existing research has not fully resolved. At the *meso- or organizational level*, firms currently lack academic guidance on how to respond to the digital change, facing a considerable rigor-relevance gap regarding the implementation of digital technologies like AI (Bansal et al., 2012; Kieser & Leiner, 2009). When it comes to the external route, practitioners across buy

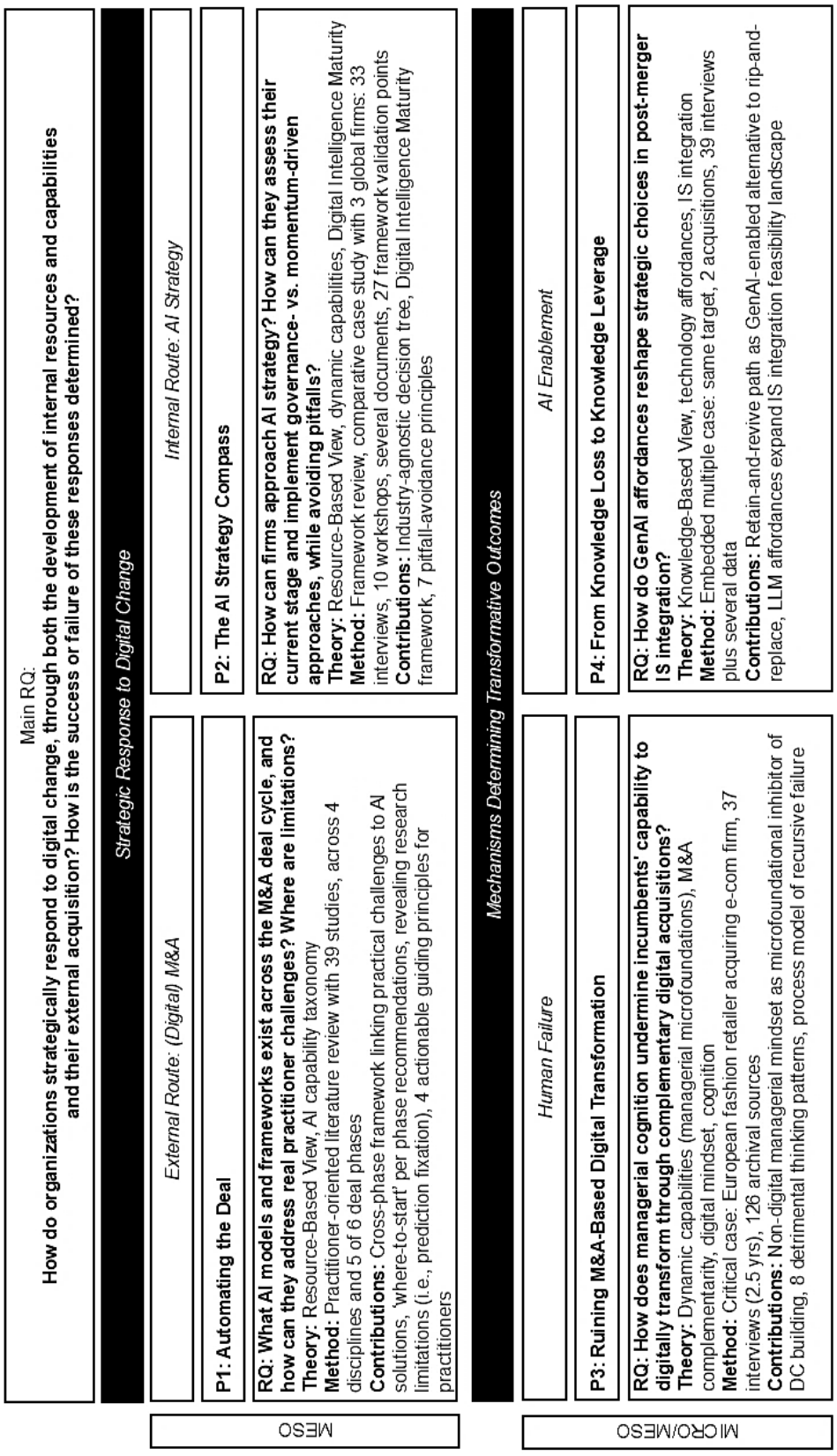


Figure 1. Research Framework

side, sell side, advisory, and investment are confronted with a plethora of AI tools yet a lack of consolidated research evidence: Currently, scientific insights are scattered across academic disciplines including management, finance, and IS, as well as the deal cycle from strategy to evaluation. This fragmentation leads to both the practitioners' lack of actionable insight (Block et al., 2025; Quariguasi Frota Neto et al., 2025), and to limiting interdisciplinary scientific insight, which hinders the identification of common research frontiers as well as field assumptions that may need to be challenged (Alvesson, 2011). Internally, organizations also face deep uncertainty about how to start their AI journey, sequence their investments, and how to govern this change. The landscape of existing AI frameworks is fragmented, contradictory, and rarely grounded in rigorous empirical evidence (Hutzschenreuter & Lämmermann, 2025; Oldemeyer et al., 2025). Illuminating these tensions, the first two papers of this dissertation define its meso-level contribution. Before discussing the success or failure of organizational responses to digital change at the micro-level, it is first crucial to understand how digital technologies like AI can be adopted within both external and internal scenarios.

The first paper, ***Automating the Deal: A Literature Review on Artificial Intelligence in Mergers and Acquisitions***, addresses the external strategic response by mapping AI research to contemporary challenges of M&A practitioners across the deal cycle. Drawing on a systematic, practitioner-focused review of 39 studies spanning finance and accounting, strategy and management, information systems, and computer and data science, the paper translates disciplinary fragmented insights into a coherent, actionable framework. It links managerial challenges across the deal cycle to validated AI frameworks and models, offering three key findings: First, AI applications in M&A concentrate heavily in the pre-deal phase of strategy, search, and due diligence, driven by the availability of structured publicly accessible data, while post-deal phases are understudied. Second, the paper critically discusses the prediction fixation of current research: supervised learning dominates, while prescriptive and generative capabilities, reported as transforming their current practice by 86 percent of practitioners (Deloitte, 2025), remain marginal. Third, the gap between empirically validated models and deployment-readiness is wider than the literature currently acknowledges. Despite offering critical direction regarding important data sources and variables, organizations may still need deliberate investment in building data architectures, governance and

interpretability measures. The paper concludes with four actionable principles for practitioners grounded in evidence: sequenced adoption, data architecture as strategic asset, human-machine governance, and context-specific adoption-strategies. This reduces the rigor-relevance gap between academic AI research and M&A practice. Further, it establishes the conceptual background for the remaining papers on digital change and M&A.

Also at the meso-level, the second paper, ***The AI Strategy Compass: A Case-Based Guide for Achieving Digital Intelligence Maturity***, addresses strategic responses to the internal challenge of AI adoption. It illuminates two general approaches how organizations can approach the challenge of AI implementation, and how to sequence, and govern these strategic options. The paper first juxtaposes two seemingly competing logics discussed in fragmented AI frameworks: the governance-driven approach, starting with vision and structure before investing into associated use cases, and the momentum-driven approach, which builds on quick-win use cases before developing overarching governance structures. Aside from synthesizing and organizing extant frameworks, the paper also draws on a comparative case analysis of three global firms at different stages of AI maturity, consisting of an AI beginner, intermediate, and leader to offer a practical guide for achieving Digital Intelligence Maturity. Three main contributions are offered: (i) an industry-agnostic decision tree for selecting the appropriate approach based on organizational strategy and structure, as well as the digital readiness of talent, (ii) an evidence-based, stepwise framework to evolve from the current level to AI leaders, and (iii) seven actionable learnings to avoid common pitfalls on the journey towards Digital Intelligence Maturity. Crucially, the paper demonstrates that Digital Intelligence Maturity is not a stable endpoint but a continuously evolving state that required organizational ambidexterity in both governance- and momentum-driven dimensions to sustain.

Micro-Level: Understanding Digital Transformation Failure through Human Actors

The two prior papers demonstrate that organizations currently lack the guidance to develop coherent DT strategies, especially in the face of AI. However, even when transformation strategies are formed, the performance outcomes of digital M&A are inconsistent at best (Hanelt et al., 2021; Uhlenbruck et al., 2006). Acquiring digital targets seems a promising way to close resource and capability gaps promptly, especially

for complementary incumbents with physical business models (Adegbesan, 2009; Kim & Finkelstein, 2009). If sufficient complementarity is given, promising organizational-level deal success, mechanisms below this level may constrain the translation of strategic intent into transformative outcomes. Therefore, recent scholarship has turned to exploring the microfoundations of such failure, including a strong research stream on employee DT resistance (van Dijk & van Dick, 2009). Regarding managers, whose actions form an important microfoundation of organizational dynamic capabilities through their cognition and action (Helfat & Peteraf, 2015; Teece, 2014), prior research has often positioned managers as central agents of organizational change, given the appropriate organizational structures (Alvesson, 2011; Kotter, 1996). This paper, however, argues that managers are not neutral; instead, their underlying cognition or mindset, consisting of certain thinking patterns, shapes and frames which actions they perceive as possible or valuable (Tripsas & Gavetti, 2000).

Hence, before being able to adopt certain AI implementation strategies like discussed previously, it may be worthwhile to understand at the micro-level how managers' cognitive mechanisms may constrain such strategies. Understanding such opposing thinking patterns regarding DT is both a theoretical imperative and a practical necessity: It shifts the locus of intervention from the strategy that is formed in boardrooms to the actors behind. We need a process understanding of the mechanisms that drive how digital acquisitions are structured and how integration is governed. The third paper, ***Ruining M&A-Based Digital Transformation: Cognitive Microfoundations of Failure***, therefore descends to the micro-level to explore the paradox that the preceding papers imply: Even if an organization pursues a theoretically suitable strategy, how does managerial cognition undermine incumbents' organizational capability to digitally transform through complementary digital acquisitions? The paper advances the microfoundational role of managerial cognition creating resistance and inhibiting DT, drawing on a dynamic capabilities lens. Through the critical case of a European fashion group's acquisition of a complementary e-commerce firm, we trace how a non-digital mindset undermined the firm's DT despite the acquisition of a complementary digital target. 37 interviews spanning over 2.5 years and 126 archival sources since 2005 reveal that the manager group exhibited several non-digital thinking patterns that hindered organizational DC building over time and undermined a transformation towards omnichannel and a digital identity. Discussing our theory against rival explanations,

our process model contributes a microfoundational explanation for unsuccessful M&A outcomes, including DT, in a field dominated by organizational-level analysis. For practice, we present normative insights with measures across the strategy, due diligence, and integration phase.

Micro-/Meso-Level: Understanding Organizational Change through Technology as an Actor

Paper 3 reveals the human actor as a primary constraint in DT. Eventually, paper 4 introduces a potential counterpoint to managerial micro-level factors shaping organizational-level outcomes in the digital age: as an equally consequential phenomenon, AI is not merely a standalone tool anymore, it is interwoven with human actions (Gehman et al., 2025). As such, it becomes a sociotechnical actor beginning to reconfigure what is feasible to managers and to organizations. Hence, we must focus not only on human actors and their mindset to enable organizational digital change, but also on how a new technology may introduce novel action possibilities to acquirers, changing the conditions under which humans operate. Generative AI (GenAI), in particular, introduces affordances that may resolve structural constraints. Technology affordances are understood as the possibilities for goal-oriented action that a technology offers to a specific actor in a given context, not as fixed properties of a technology. They are relational potentials that emerge through the needs and practices of the actors who engage with them (Gibson, 1977; Majchrzak & Markus, 2012).

Affordances of GenAI like writing and correcting code (Weisz et al., 2022) can be especially valuable in knowledge-intensive acquisitions of firms with proprietary key software. Extending the resource-based view of the firm, the knowledge-based view argues that a firm exists primarily as an institution for integrating individual knowledge (Grant, 1996). Integrating IS is not purely a technical challenge; it represents the crucial task of connecting the explicit and tacit knowledge held by individuals and digital systems, and the meta-knowledge of knowing whom to ask and where to look (Yoo et al., 2007). Replacing existing systems and key personnel in M&A scenarios not only requires a huge financial investment, it is also associated with knowledge loss and value destruction (Alaranta & Martela, 2012; Stylianou et al., 1996).

This animates the fourth and final paper of this dissertation, ***From Knowledge Loss to Knowledge Leverage: How GenAI Affordances Transform Post-Merger IS Integration***. It shows that GenAI itself is beginning to dissolve some of the structural

constraints that previously foreclosed IS integration paths, by offering acquirers a huge potential for, i.e., large language model (LLM)-assisted retrieval of tacit system knowledge even when key staff exit (Sira, 2024; Weisz et al., 2022). Hence, the paper answers the question how GenAI affordances reshape strategic choices in post-merger IS integration. Contributing to M&A integration literature by introducing the retain-and-revive path as a viable, AI-supported alternative to rip-and-replace or absorption-based IS strategies, the paper challenges longstanding assumptions about the intractability of proprietary legacy systems. Drawing on the knowledge-based view of the firm and a technology affordance lens, LLM-supported affordances like learning system knowledge through chat increased knowledge transferability, knowledge aggregation, and efficiency, reducing prior assumptions about system intransparency, personnel dependence, and conversion costs. Our findings show how GenAI reconfigures perceived knowledge challenges, alters integration logics, and expands feasible paths for value capture.

Taken together, the four papers constitute a coherent research endeavor that advances understanding of how organizations can strategically respond to digital change and determines whether those responses generate transformative outcomes. At the meso-level, they provide evidence-based, practitioner-oriented guidance on what AI offers in M&A scenarios and how organizations should govern their AI implementation. At the micro-level, they reveal the cognitive mechanisms through which strategic intent can be undermined in digital acquisitions, and the technological mechanisms through which some human- or system-induced constraints can be overcome in IS integration. Collectively, they argue that the gap between the promise and the performance of Digital Intelligence Transformation, that is, AI-focused DT, is not primarily a failure in strategic ambition or technological availability. Instead, it is a gap in the sociotechnical conditions, cognitive, structural, and technical, through which technology must pass to generate change. Closing that gap requires attending to all four levels simultaneously: understanding the landscape of available technological and strategic options, building the strategy, confronting the top-level mindset, and introducing expanding technological affordances as sociotechnical actors of their own.

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2 Automating the Deal: A Literature Review on Artificial Intelligence in Mergers and Acquisitions

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Abstract

Mergers and acquisitions (M&A) remain among the most promising, yet consequential and uncertainty-laden strategic decisions organizations undertake. Despite six decades of research and a rapidly growing toolbox for practitioners in times of AI, M&A decision-makers currently lack structured, evidence-based guidance on how to deploy AI effectively across the deal process. This practitioner-oriented literature review synthesizes 39 studies spanning four academic disciplines (finance and accounting, strategy and management, information systems, and computer and data science), and the deal cycle from strategy to evaluation. Drawing on a systematic human-led approach complemented by an AI-assisted screening verification, the review maps practitioner-relevant challenges across the deal cycle to validated AI models and frameworks, assesses their deployment maturity, and recommends initial starting points for AI applications. Further, the review details the models' data requirements and constraints and critically evaluates the current stage of research. Aside from these findings, where applications concentrate in the pre-deal phases of strategy, search, and due diligence, mostly driven by structured, publicly available data, this review also formulates four actionable principles for practitioner-based AI applications: sequenced adoption, data architecture planning, human-machine governance, and context-specific adoption strategies.

Keywords: Artificial Intelligence, M&A, AI Application, Practitioner-oriented Literature Review

2.1 Introduction

Mergers and acquisitions (M&A) remain among the most prominent and consequential strategic decisions organizations undertake. Despite six decades of M&A research, the findings on M&A performance are diverse and at times inconsistent (Das & Kapil, 2012), further contributing to highly uncertain and frequently disappointing outcomes (King et al., 2004). One central reason lies in the nature of the M&A process itself: Characterized by high levels of uncertainty and information asymmetry, it requires decision-makers to integrate vast amounts of heterogeneous, often unstructured data under time pressure, as time has been shown to be a decisive factor in M&A success (Homburg & Bucerius, 2006). However, across M&A phases, from strategy to search, valuation, due diligence, negotiation, closing, and integration, deal times have increased in the past: Through heightened complexity of integration planning, “globally, the period from signing to closing for deals exceeding $2 billion increased by 11% from 2018 to 2022, reaching an average of 191 days” (Simon et al., 2024). Within this timeframe, managers are required to diligently consider both acquirer and target, including but not limited to financials, strategy, human and digital resources and processes. Further, the macroeconomic environment and market trends have to be considered simultaneously (Caiazza & Volpe, 2015; Haspeslagh & Jemison, 1991).

In parallel, artificial intelligence (AI) and its machine learning applications have emerged as a transformative force in business, altering competitive dynamics, organizational structures, and decision-making processes worldwide. Expected to boost the global GDP by up to 15 percent within the next 10 years, the technology broadly affects industries from media and technology to manufacturing (Goldman Sachs, 2023; PricewaterhouseCoopers, 2025). Machine learning endows AI systems with unique self-learning abilities that set them apart from previous digital technologies, where the relationship between inputs and outputs was clearly bound. These systems can process large-scale, high-dimensional datasets and autonomously recalibrate in response to shifting environments (Lin & Maruping, 2025). Beyond driving exceptional economic growth, AI reshapes how individuals and organizations operate at a fundamental level (Silva & Di Serio, 2016; W. R. Thompson, 1990). Yet despite the technology’s pervasiveness, how firms can effectively use it to their advantage is still not well understood (Hutzschenreuter & Lämmermann, 2025).

This is especially true for the field of M&A, where existing research is fragmented across disciplines such as finance and accounting, strategy and management, information systems, and computer and data science, with each of them focusing on specific use cases or stages of the M&A process. Positioned as prediction machines designed to tackle uncertainty by practitioner literature (Agrawal et al., 2018), academics have thus far also focused on studying prediction tasks such as takeover likelihood or post-merger performance (Quariguasi Frota Neto et al., 2025; Wang et al., 2020). Yet, the M&A landscape is evolving rapidly, with an ever-growing number of AI-enabled tools entering the market. Practitioners, however, currently lack structured, evidence-based guidance on how to deploy these technologies effectively across the M&A process. This disconnect underlines the broader rigor-relevance gap in management research, where academics struggle to systematically make theoretically rigorous insights accessible for practitioners and translate them into actionable managerial implications (Bansal et al., 2012; Kieser & Leiner, 2009).

Following the scholarly aim to close this gap (Hodgkinson & Rousseau, 2009), this systematic study of the literature on the use of AI in the M&A process is positioned as a practitioner-focused review. This kind of review is defined as a “comprehensive and application-oriented overview, as well as a critical discussion of management research on a practice-oriented question or topic” (Block et al., 2025, p. 4). Accordingly, the present study pursues two main objectives: First, it addresses a real managerial problem: M&A present high-stakes environments of strategic decision-making under uncertainty and time pressure, where numerous organization-internal and -external data points must be considered simultaneously. Whereas AI offers the potential to enhance decision quality and speed by rapidly integrating and analyzing large, heterogeneous datasets, M&A practitioners are often unaware of scientifically tested and proven models and frameworks that can guide the application of AI. Second, this review reduces the rigor-relevance gap between theory and practice by synthesizing fragmented academic insights into a coherent framework anchored in M&A practice (Block et al., 2025): For M&A practitioners, it translates scientific insights into a process-oriented matrix, creating actionable implications for their use of AI. For researchers, the framework uncovers implicit assumptions in M&A research, such as the tendency to frame AI primarily as a tool for prediction, efficiency, and information-asymmetry reduction, while paying less attention to its active role in reshaping decision-making, coordination,

and human–machine interaction. It further shows areas where the characteristics of AI may theoretically offer huge benefits yet are underexplored at the moment.

This paper is structured as follows: First, it lays the groundwork by reviewing theoretical work on AI and M&A, followed by a concise description of the methodological approach: Following a systematic approach (Watson & Webster, 2020; Webster & Watson, 2002), this study adopts a practitioner-focused design that explicitly translates academic insights to real-world managerial problems (Block et al., 2025). This section details how, in line with recent developments in AI, a large language model (LLM) is trained for complementary reviewing: not as a substitute of human judgement, but as an assessment counterpart during the selection phase. This approach increases coding reliability by reducing selection bias and improving the overall robustness of the literature synthesis (Block & Kuckertz, 2024). Subsequently, the current state of research is presented along the phases of the M&A process, highlighting both the deployment maturity and task-capability fit of the proposed models and frameworks across 39 papers. The presented framework also provides detail on the associated benefits and challenges, so that practitioners can assess the opportunities and risks associated with applying AI in certain domains easily. Further, we detail the input data required to train the models at the firm-level, deal-level, and externally, enabling managers to identify the data access that is most relevant to support different deal phases. For researchers, this review systematically uncovers and discusses implicit AI assumptions and research gaps. The paper concludes with key implications for both practice and theory, followed by an outlook on the evolving role of AI in M&A.

2.2 Theoretical Background

Many researchers agree that AI forms a subset of digital technologies yet exhibits distinct features: It blurs the boundaries between human and machine capabilities, simultaneously constraining, complementing, and substituting human work. Being more than a simple tool, the human-machine symbiosis surrounding AI creates distinct sociotechnical phenomena that warrant further study (Benbya et al., 2021; Gehman et al., 2025). In contrast to earlier digital technologies where inputs and outputs were clearly bound, the unique self-learning abilities of AI make it capable to adapt to complex environments autonomously (Lin & Maruping, 2025).

Within AI, “machine learning has emerged as the method of choice for developing practical software for computer vision, speech recognition, natural language processing, robot control, and other applications” (Jordan & Mitchell, 2015, p. 255). Machine learning is built on the premise of improving automatically through experience, most prominently through *supervised or unsupervised learning* approaches. In supervised learning, the desired output is clear and “the goal is that of learning a mapping between input and output spaces” (Simeone, 2018, p. 2). Related techniques include “linear regression, logistic regression, decision trees, … support vector machines (SVMs), k-nearest neighbor (KNN)” (Stryker & Kavlaoglu, 2024, p. 1). Unsupervised learning uses no prescribed labels to train, hence autonomously finding latent structure or natural groupings in unlabeled data (Stryker & Kavlaoglu, 2024).

Through these qualities, machine learning can be effectively applied across several core problem domains; most prominently through the capabilities assigning / classifying, grouping, forecasting, and generating (Kelnar, 2019). *Assignment* refers to *classifying* or labeling data points, as well as the estimation of relationships between variables through regression-based approaches. In the context of M&A, this could involve classifying potential acquisition targets regarding strategic fit, based on available company data. *Grouping*, or clustering, aims to uncover latent structures within datasets, enabling, for example, the identification of previously unrecognized target segments to support an acquirer’s decision-making in the pre-deal phase. *Forecasting* focuses on predicting future developments based on sequencing time-series data. Within M&A, such approaches are particularly relevant during due diligence, where models may be used to estimate the probability of post-acquisition performance or deal success. *Generating* refers to the creation of new content (such as images, texts, or audio media) based on probabilities and learned patterns, which can support various tasks across the deal cycle, i.e., drafting due diligence summaries, or supporting stakeholder communication (Kelnar, 2019). Beyond these four areas, a growing stream of research highlights *prescribing*, or prescriptive analytics, as another key capability of AI (Bertsimas & Kallus, 2020; Lepenioti et al., 2020). Unlike forecasting, which predicts future outcomes, prescription focuses on identifying and recommending the best possible decision under given constraints. Prescribing is partially related to generating in ‘producing output’, though the former produces decision recommendations, and the latter new content. In practice, both capabilities can go hand in hand, as generative models

increasingly incorporate constraint-based reasoning. In M&A, prescribing may include determining optimal bidding strategies, deal structuring, or integration planning under multiple, potentially conflicting objectives. While the boundaries between applications are not clear cut, some machine learning capabilities prove more efficient for some problem domains than others (see Table 1).

Table 1. AI Capabilities and Examples of Related M&A Tasks (based on Kelnar, 2019; Bertsimas & Kallus, 2020; Lepenioti et al., 2020)

AI capabilities	Definition	Exemplary tasks in M&A
Assigning / classifying	Assigns observations to predefined categories based on learned patterns	Target screening, acquirer-target matching, risk flagging
Grouping / clustering	Identifies latent groupings in data without predefined labels	Comparable firm identification for valuation, target segmentation, M&A pattern analysis
Forecasting	Predicts continuous or probabilistic outcomes from historical patterns	Deal completion likelihood, post-acquisition performance, synergy realization timelines
Generating	Produces new data resembling training data probabilities, i.e., via LLMs	Due diligence summaries, contract clause generation, management communication
Prescribing	Identifies optimal decisions / solution spaces under constraints for action recommendations	Bid price determination, deal structure design, integration sequencing

We understand an AI-assisted M&A process as any application of AI and machine learning to M&A activities, augmenting or automating human processes. “Whereas automation implies that machines take over a human task, augmentation means that humans collaborate closely with machines to perform a task” (Raisch & Krakowski, 2021, p. 192). While both approaches have been conceptualized as opposite ends of a spectrum, in managerial tasks, one cannot be fully separated from the other: “Over-emphasizing either augmentation or automation fuels reinforcing cycles that not only harm an organization’s performance but also have negative societal implications” (Raisch & Krakowski, 2021, p. 196). Instead, applying AI can initially mean augmenting managerial tasks through keeping managers ‘in the loop’; then to later automate the tasks based on learnt rules. This automation, however, should not be set in stone: with changing conditions, an automated process may need augmented adaptation again. Overall, managerial tasks do not happen in isolation. As processes, they evolve over time and space, showing their interconnectedness. Hence, automating one task may lead to the augmentation of adjacent tasks (Raisch & Krakowski, 2021).

The present study, therefore, focuses not on providing a distinction between which tasks can be augmented vs. automated, but concentrates on mapping challenges in M&A practice to potential AI solution spaces explored in research. To achieve a practice-relevant mapping, a deeper understanding of these challenges along the M&A process is needed first. While no consensus on the number of stages has been reached, most definitions share the bifurcation of the M&A process into two main phases, divided by the transfer of ownership (Haspeslagh & Jemison, 1991). This transfer “separates the M&A process into two major parts, the pre- and post-acquisition phases. ... the reality remains that without achieving ownership, postacquisition integration cannot really take place in earnest” (Gomes et al., 2013, p. 16). Aside from this shared understanding, most research has concentrated on either the pre- or post-deal phase, resulting not only in a fragmentation of the field, but also in the conceptualization of several sub-processes across studies which differ in their degree of detail and can partially overlap (see Table 2). For the context of this research, we synthesize the findings along the following phases to ensure both sufficient detail and necessary abstraction: In the pre-deal stage, we distinguish between (i) strategy, (ii) search, (iii) valuation, and (iv) due diligence (with negotiation and closing not represented in the data); and in the post-deal phase, (v) integration and (vi) evaluation.

Table 2. M&A Phases in Previous Literature

Pre-deal					**During**	**Post-deal**			***Reference***
pre-acquisition					acquisition decision	post-acquisition			*Walsh, 1989*
acquisition decision						acquisition integration			*Haspeslagh & Jemison, 1991*
pre-merger					during merger	post-merger			*Appelbaum et al., 2000*
pre-acquisition						slow absorption	very active absorption	totally absorbed	*Quah & Young, 2005*
pre-acquisition					ownership transfer	post-acquisition			*Gomes et al., 2013*
n/a						post-merger integration			*Graebner et al., 2017*
strategist planning	screening	justifying to board	first agreement	due diligence	contract, closing	*n/a*			*Calipha & Brock, 2019*
deal initiation	target selection	bidding, negotiation	valuation, financing	announcement	closure	*n/a*			*Welch et al., 2020*

Reviewing both academic and practitioner outlets, the following paragraphs summarize the main objectives and processes inherent in the pre-deal phases (i)-(iv) and post-deal phases (v)-(vi), as well as the associated challenges. In the (i) *strategy* phase, when an organization determines M&A as a preferred growth vehicle given its internal and external situation, managers must define the acquisition rationale and strategic intent; whether to pursue, i.e., synergies, market power, or diversification (Haspeslagh & Jemison, 1991). Due to the "number of tasks to be accomplished, the technical complexity of acquisition analysis, and the traditional roles that different specialists play" (Jemison & Sitkin, 1986, p. 149), the task and responsibility segmentation at this stage leads to poor integration of analyses and too much time spent on analyzing less important information (Jemison & Sitkin, 1986). Additionally, research has flagged the acquirer's inability to adequately assess acquisition-related financial risks (Renneboog & Vansteenkiste, 2018) as well as their lack of macro-environmental timing intelligence (Harford, 2005). In practice, a recent BCG study lists the lack of clarity regarding the organization's growth strategy or it being too opportunistic among the top 3 challenges in 43% of participating organizations. Even more, 46% said the overall execution process from start to finish takes too long (D. Friedman et al., 2024).

During the (ii) *search* phase, the identification and screening of potential targets in line with the organization's strategy is next. From a qualified longlist, a shortlist is narrowed down, mostly by initial assessments of strategic and financial fit. Also, early-stage contact with promising candidates is initiated at this stage. Among the main challenges at this stage are significant information asymmetries when evaluating candidates, particularly private firms, high-tech, or cross-border targets where reported data may be sparse or opaque (Akerlof, 1970; Myers & Majluf, 1984). The top challenge mentioned by participating organizations in the BCG study was that the search process did not yield enough viable targets, as reported by 47% (D. Friedman et al., 2024). Relatedly, practitioners have historically lacked structured typologies for categorizing acquisition candidates (Jemison & Sitkin, 1986).

The main objective in the (iii) *valuation* phase is estimating the standalone value of the target, using, for example, discounted cash flow, comparables, industry multiples, or precedent transactions. During this, synergies must be quantified to assess combined potential, as well as integration costs. Challenging in this phase is that acquirers seem to constantly overpay as synergies are often overestimated (Bauer & Friesl, 2024;

Renneboog & Vansteenkiste, 2018). 29% of practitioners participating in the BCG study mentioned overpaying as major M&A-related challenge (D. Friedman et al., 2024). In a similar vein, inaccurate target price estimates can lead to suboptimal bid ranges (Renneboog & Vansteenkiste, 2018). This may be related to subjectivity and inconsistency in selecting comparable companies for valuation (D. Friedman et al., 2024) or market mispricing (Tang, 2025).

In the (iv) *due diligence* phase, a comprehensive evaluation of the target's financial, operational, legal, commercial, human resources, and strategic position follows, before negotiation and closing can happen. Here, deal-breakers and risks must be identified through the data provided in deal rooms and beyond, as well as personal exchange. The sheer volume of data during this phase is a main challenge, especially as the pressure adds to an increased risk of rushed decisions. Also, culture and technological due diligence is an increasingly challenging yet crucial aspect (Perry & Herd, 2004). Consequently, poor-quality results in due diligence, for example due to unidentified risks, was mentioned by 33% of participants in the BCG study as a huge M&A challenge (D. Friedman et al., 2024). Further, inadequate screening for ESG criteria can increase post-deal sustainability risks (Radło et al., 2025).

In the post-deal phase, the (v) *integration* phase follows. It is about executing the chosen integration approach while being flexible to emergent strategic options in the meantime. The main challenge is to realize synergies and preserve value-creating capabilities and human talent, while simultaneously managing organizational disruption and meeting predefined timelines (Larsson & Finkelstein, 1999; Puranam & Srikanth, 2007). Mentioned by 33% of participating organizations, an insufficient focus on post-merger integration and value creation was considered a main challenge (D. Friedman et al., 2024).

Lastly, during the (vi) *evaluation* phase, an assessment of the acquisition is due: Did it achieve its financial, strategic, or other objectives? Across relevant KPIs in, i.e., accounting, market, or operational dimensions, the post-acquisition performance must be evaluated. However, there is still no consensus on what constitutes a (successful) M&A performance and how to measure it correctly: As no one overarching factor can assess M&A outcomes, different models linking task-, transaction-, and firm-level constructs have been tested. The larger the tested event window, the harder it is to isolate the acquisition's contribution to firm performance from concurrent strategic, market,

and macroeconomic effects. While short-term event studies focused on CAR dominate empirical research, they are not linked to short-term performance or synergy realization (Zollo & Meier, 2008). Also, an issue is that organizations rarely systematically conduct post-mortems to learn for future deals.

2.3 Method

This study follows a practitioner-focused literature review approach. A well-crafted review of this kind should reduce the gap between practice and academia, by bridging both worlds and deriving “practical implications from research” (Block et al., 2025, p. 5). They respond to three key developments in contemporary management research: the exponential growth of scholarly output, the increasing disciplinarity of managerial challenges, and the rising demand for evidence-based guidance among practitioners (Rousseau, 2006; Tranfield et al., 2003). Given that AI in M&A is an emerging phenomenon situated at the intersection of finance and accounting, strategy and management, information systems, and computer and data science, this review additionally draws on the characteristics of phenomenon-focused reviews: capturing, describing, and conceptualizing managerially relevant development across disciplinary boundaries (Block et al., 2025).

2.3.1 Human-Led Search Considering the Disciplinary Breadth of M&A

The interdisciplinary nature of AI in M&A required deliberate coverage across four academic fields: (i) finance and accounting, mainly covering prediction, valuation, and target screening, (ii) strategy and management, predominantly addressing decision support and post-merger integration, (iii) information systems, focusing on process automation, decision support systems, and analytics, and (iv) computer and data science, mostly studying algorithmic development for prediction and classification tasks. Single-field searches would systematically underrepresent the phenomenon of M&A, which is known for its interdisciplinary nature. Relevant contributions in such settings are often scattered across outlet types and communities with limited cross-citation (Rojon et al., 2021).

To reflect the disciplinary breadth, four databases were searched: Scopus served as primary source, offering strong coverage across all four target fields. High-ranking ex-

amples include MIS Quarterly, Information Systems Research, and the Journal of Finance. It was complemented by EBSCO to further capture practitioner-focused and accounting-related journals not indexed in citation databases; including California Management Review, MIT Sloan Management Review, and Strategic Finance. Additionally, the AIS eLibrary was included for comprehensive coverage of information systems conferences and journals. Lastly, IEEE Xplore was searched to capture the latest applied AI and computer science contributions, which frequently appear in peer-reviewed conference proceedings rather than journals.

Searches were conducted in January and March 2026. The core search approach centered on two conceptual pillars: (i) mergers and acquisitions, and (ii) artificial intelligence and machine learning. With Scopus being the primary source, the search strings for this database covered title-abstract-keywords. In other databases like EBSCO or IEEE Xplore, title searches were applied to ensure greater focus of the supplementary searches. In total, the searches across the four databases resulted in 5363 results, including duplicates. The full search strings and results per database can be found in the appendix (see Appendix A).

2.3.2 AI-Complemented Selection Process Validating the Relevance of Papers

In parallel, we defined in- and exclusion criteria to ensure a rigorous process during the article selection phase. If a paper met the following criteria, it was retained for further inspection: (1) M&A constitute the focal phenomenon of the paper, and simultaneously, the paper either (2.1) studies the application of AI to the M&A process, including classical machine learning if framed as predictive or decision-supportive, or (2.2) offers prediction models that can be applied to one of the M&A process phases. Further, we excluded papers if (3) M&A are not the focal topic, for instance, if the paper focuses on knowledge acquisitions, uses AI only as an analytical method rather than studying its application, or treats AI as a control variable. These criteria were developed prior to screening and applied consistently across databases. The operationalization of AI deliberately followed a broader sense, encompassing classical machine learning alongside deep learning / Neural Networks, transformer / LLMs, and optimization-based AI; while excluding purely statistical approaches not framed as AI-driven decision support. To reflect the emerging and dynamically evolving nature of the field, we

deliberately refrained from applying quality criteria aside from being published through peer-reviewed gating processes.

Since the initial database searches yielded a combined gross result of approximately 5363 results across all search strings, including duplicates through intentional overlaps, we removed duplicates and screened the list following our criteria. Removing papers upon title inspection that were outside our scope, our initial shortlist contained 41 articles. To validate this screening process in a single-author paper and reduce the risk of systematic or accidental omissions, a purpose-built GPT was set up and deployed as structured validation layer. This reflects emerging hybrid approaches to literature syntheses that combine human and machine qualities: On the one hand, human 'strategic inefficiency' enables room for detours and creative exploration of a topic, yielding unexpected insights. On the other hand, machine learning under pre-defined rules deals with large amounts of data quickly. Instead of following just one approach, human-machine collaboration can lead to "increased efficiency through the effective combination of human intelligence and AI" (Block & Kuckertz, 2024, p. 5). The present approach, however, did not so much decrease research time, it more so improved the reliability of results through an extra verification layer. The GPT was provided with detailed yet concise descriptions of its objective, the in- and exclusion criteria, and access to the entire longlist. After GPT finished its inspection, mostly carried out in batches of 100-200, the predefined output structure was compared to the initial shortlist of the author. Of the twelve papers included by the author and not the GPT, a structured reevaluation was conducted, studying the content of these papers in detail. Three were indeed dropped, the remaining nine were retained, noting specific reasons for this decision. Of the six papers identified by the GPT and not the author, a critical reevaluation led to adding one more paper to the final shortlist. Hence, the GPT served as consistency check rather than replacement for human judgement; precisely the complementary role of AI envisioned in recent method papers (Block et al., 2025; Block & Kuckertz, 2024; Pan et al., 2023). Upon full-text review, the final shortlist comprises 39 papers. The flow diagram documenting the search and screening process can be found in Appendix B).

2.4 Review of AI Frameworks and Models across the M&A Deal Cycle

Before diving into the insights derived from reviewing the literature on applying AI in the M&A process, a brief section of descriptive statistics aids in understanding the interdisciplinary field. The 39 papers reviewed span publication times from 2008 to 2026, with a visible concentration during recent years: Over two-thirds of all papers (n=27) were published in 2022 or later, reflecting the acceleration of AI adoption, spurred by the advent of OpenAI's ChatGPT and comparable large language models (LLMs).

As illustrated in Figure 2, M&A research on AI applications clusters heavily in the Strategy, Search, and Due Diligence phases, together accounting for 30 of 39 papers. This concentration reflects the dominance of structured and prediction-oriented tasks that will become evident in section 2.4.1, i.e., target identification, deal completion likelihood, and risk assessment. Later stages, such as Integration (n=1) and Evaluation (n=3), remain markedly understudied, while the Negotiation and Closing phase was not represented at all.

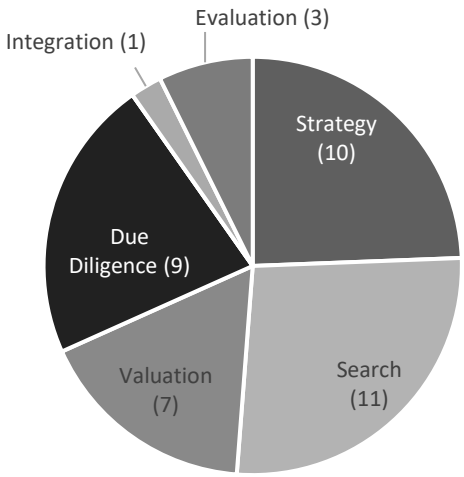


Figure 2. Allocation of Papers across Deal Phases
(note: two papers belong to more than one category; overall sum exceeds 39 by 2.

Mapping the 39 contributions to their four disciplinary homes, at first, the distribution seems more equal; however, this allocation itself is indicative of largely separate re-

search communities which rarely address the fragmentation of the field. It is also interesting to note that especially in the fields of Information Systems and, even more so, of Computer / Data Science the concentration of conference publications is the highest; indicating that these communities seek to more quickly publish and openly discuss recent advances in the field (see Table 3). The full matrix can be found in Appendix C).

Table 3. Allocation of Papers across Disciplines

(note: J = Journal; conference publications in cursive)

Discipline	Nr.	Author(s), Year (Outlet)
Finance & Accounting	11	Chen et al., 2026 (British Accounting Review); Wan et al., 2026 (China J of Accounting Research); Zhao et al., 2025 (International Review of Financial Analysis (IREF)); Gaoli et al., 2025 (Applied Economics Letters); Rodríguez-Muñoz-De-Baena et al., 2025 (Cogent Business & Management); Ding et al., 2024 (IREF); Ross et al., 2021 (J Finance & Data Science); Anagnostopoulos & Rizeq, 2018 (Managerial Finance); Tang, 2025 (Managerial & Decision Economics); Williams, 2023 (J Risk & Financial Management); *Johnson et al., 2011 (Proc. NE Business & Economics Assoc.)*
Strategy & Management	9	Cheng & Dai, 2025 (Management International Review); Zhang et al., 2024 (J World Business); Qu et al., 2026 (Strategy Science); Zohrehvand et al., 2024 (Long Range Planning); Hajek & Henriques, 2024 (Technological Forecasting & Social Change); Lee et al., 2020 (J Business Research); Vinocur et al., 2022 (J Strategy & Management); Thélisson, 2024 (Strategy & Leadership); Jo et al., 2024 (Global J Entrepreneurship)
Information Systems	9	Wang et al., 2020 (Decision Support Systems); Shao et al., 2018 (Decision Support Systems); Qin et al., 2026 (J Organizational and End User Computing); Thompson et al., 2024 (J Management Analytics); *Eggers et al., 2023 (PACIS)*; *Tran et al., 2026 (IMCOM)*; *Maan & Nagwekar, 2022 (IEEE INDICON)*; *Bedekar et al., 2024 (ICKECS)*; *Zylfiu & Marinova, 2025 (ICEST)*
Computer / Data Science	10	Katsafados et al., 2024 (European J Operational Research); Quariguasi Frota Neto et al., 2025 (J Operational Research Society); *Ducange et al., 2025 (IEEE FUZZ)*; *Ghadekar et al., 2022 (IEEE ICRAIE)*; *Hu et al., 2009 (IEEE IEEM)*; *Liu & Ma, 2009 (IEEE IEEM)*; *Liu et al., 2011 (IEEE ICMSS)*; *Liu et al., 2008 (IEEE MMIT)*; *Gao, 2023 (ICIICS)*; *Paul et al., 2013 (BRICS-CCI)*

Beyond deal phase and disciplinary origin, the sample reveals strong patterns in how AI is deployed methodologically. The vast majority employ supervised learning (n=34), while unsupervised learning approaches remain rare at this point (n=8). This reflects the studies' dominance in prediction tasks with clearly defined output variables. In terms of AI capabilities, Assigning/Classifying and Forecasting are by far the most

common applications, consistent with binary prediction tasks such as takeover likelihood or deal completion during the strategy and search phase. Generative AI capabilities are rarely studied, as are pure prescription applications; pointing to a gap between the current state of research and the broader frontier of AI capabilities currently available. Figure 3 provides a heatmap showing the current state of research at a glance.

Legend	8-10	5-7	2-4	1	none	
	Strategy	**Search**	**Valuation**	**DD**	**Integration**	**Evaluation**
Assigning/Classifying	8	10	5	6	1	1
Forecasting	9	10	6	3	-	2
Grouping/Clustering	2	3	1	2	-	-
Generating	-	-	-	2	-	-
Prescribing	2	2	-	1	-	-
Conceptual (-)	-	1	-	2	-	-
Validated (+)	10	9	7	6	1	3
Deployment-ready (++)	-	-	-	-	1	-

Figure 3. Heatmaps Indicating Paper Concentration across AI Capabilities and Model Maturity within M&A Phases

The following subchapters present our main findings, mapping challenges to proposed AI solutions (2.4.1), reviewing respective data foundations and requirements (2.4.2), and discussing current challenges (2.4.3).

2.4.1 Applying AI across the Deal Cycle: Mapping Current Challenges to Proposed AI Solutions

This section details the main findings of the review, organized by the managerial challenges practitioners face at each phase of the deal process, and the AI-based solutions discussed in the literature that we map to those challenges. Since practitioners adopt AI not by its technical characteristics but by the problems it can solve, this challenge-to-solution mapping structures the present section. To ensure practical relevance, we kept the matrix concise to five key columns only: Per identified challenge, we show

how current models and frameworks explain and apply AI, and how this can provide real value to practitioners. The ‘AI Value’ column also shows which capabilities (A=Assigning, GR=Grouping, F=Forecasting, GE=Generating, P=Prescribing) are applied. The ‘AI Model’ column details which specific architecture or approach was applied, while also providing insight regarding its current deployment maturity: - indicates a purely conceptual stage (few), + indicates an empirically validated model (majority), and ++ indicates a deployment-ready stage (one). Keeping the table lean, this column also uses abbreviations for AI applications: Convolutional Neural Network (CNN); Fuzzy Neural Network (FNN); Genetic Algorithm (GA); Graph Neural Network (GNN); K-Nearest Neighbors (KNN); Logistic Regression (Logit); Long Short-Term Memory (LSTM); Machine Learning (ML); Multilayer Perceptron (MLP); Multiple-kernel Support Vector Regression (SVMR); Natural Language Processing (NLP); Neural Network (NN); Ordinary Least Squares (OLS); Particle Swarm Optimization (PSO); Principal Component Analysis (PCA); Random Forest (RF); Support Vector Machines (SVM). While the tables provide such detailed description, the written sections will summarize on a more abstract level, speaking of either classical ML, deep learning / NNs, transformers / LLMs, or optimization-based AI. The ‘Key Findings’ summarize the paper’s main contributions.

Strategy

The strategy phase is where AI currently offers some of its most immediate and accessible value (see Table 4). A first set of challenges during this phase concerns *fragmented, unfocused, or analytically overloaded strategy-making* (Jemison & Sitkin, 1986), since strategic insight is scattered across documents, systems, and job responsibilities. Two validated approaches help surface this buried intelligence: One derives an M&A capability score from publicly available company documents, i.e., annual reports, through an NLP-based approach. This score helps serial acquirers and M&A advisors to assess and adapt an organization’s acquisition strategy, based on the process and learning components modeled in this study. The model also helps to predict deal performance of serial acquirers for financial analysts, driving investment strategies (Vinocur et al., 2022). Another approach automatically extracts behavioral profiles of senior managers from earnings calls transcripts. It shows that CEO openness and CEO-CFO alignment are among the strongest drivers of M&A activity (Wang et al., 2020), enabling PE/VC investors to shift their investment strategy according to human

factors and improve deal sourcing and timing, and M&A advisors to tailor pitch strategies to leadership profiles.

Addressing *poorly defined or opportunistic growth strategies* (D. Friedman et al., 2024), AI can help to stress-test the strategic rationale of acquirers before actively sourcing targets. One validated approach ranks strategic drivers that are most predictive of M&A outcomes, enabling firms to cross-check their strategic background (Wan et al., 2026). For cross-border contexts, where the determinants of deal-making and deal success are poorly understood, a validated model building on 29 emerging countries unveiled "a comprehensive picture of the relative importance and impact patterns of 59 predictors that were fragmentally, inconsistently, or not at all presented in the extant literature" (J. Zhang et al., 2024, p. 1). This gives practitioners a prioritized factor checklist that can drive cross-border investment strategies. Complementing these predictive approaches, an unsupervised segmentation of M&A patterns reveals five distinct deal types, providing a data-driven acquisition typology that can anchor strategic intent before the search begins (Shao et al., 2018).

For firms where *excessive process length* is a pain point *(*D. Friedman et al., 2024), AI offers meaningful time savings at the strategy stage. LLMs translate abstract strategic acquisition criteria into scalable search processes, connecting the strategy and search phase seamlessly and efficiently; this was validated for the U.S. energy sector with FinBERT outperforming the other fine-tuned LLMs (Rodríguez-Muñoz-De-Baena et al., 2025). Another challenge concerns the *inability to assess financial risk associated with deal-making* (Renneboog & Vansteenkiste, 2018): A validated model combined with explainability tools identifies that the "industry default rate, which captures network contagion effects, is the single most influential predictor of post-M&A default" (W. Chen et al., 2026, p. 1). Hence, acquirers can prioritize assessing the industry default rate before diving deeper into strategic M&A planning. Adding to an acquirer's strategic foresight, another study compares ML algorithms for predicting an acquirer's delisting likelihood after deal closure. The authors pinpoint firm size, leverage, and profitability as the most informative factors, enabling a focused strategic pre-deal assessment of the acquirer's health (E. K. Thompson et al., 2024).

Lastly, as acquirers often *lack macro-environmental timing intelligence* (Harford, 2005), reacting to waves rather than anticipating them. Two validated approaches address

this: One study links macroeconomic indicators to M&A deal volume, enabling a deliberate acquisition scheduling as opposed to reactive strategies. In addition, the authors find that macroeconomic indicators such as Gross Value Added and Exchange Rate exert a positive impact on M&A activity, while Unemployment and Bank Rate negatively affect it (Tran et al., 2026). A signal-decomposition approach identifies structural acquisition windows within M&A cycles within the EDA industry, particularly valuable for strategy-making in fast-moving technology sectors. This study "breaks up historical data into its elements, then constructs them again and predicts the future market consolidation activities" (Zylfiu & Marinova, 2025, p. 1).

Across all papers in this phase, the model maturity is medium and consistently empirically validated, reflecting well-tested approaches deployable with archival financial, textual, and macroeconomic data (see section 2.4.2). However, these models would all require context-specific recalibration for practical use.

Table 4. Linking M&A Challenges in the Strategy Phase to Proposed Scientific Models and Frameworks

(indicates several mentions of paper across challenges)*

M&A Phase Challenge	**AI Value** *(Capability: A/GR/F/GE/P)*	**AI Model** *(Maturity: -/+/++)*	**Key Finding**	**Reference**
Fragmented, unfocused, or analytically overloaded analyses *(Jemison & Sitkin, 1986)*	Extract, aggregate dispersed strategic signals into a single construct *(A, F)*	NLP on annual reports + deal synopses (+)	M&A capability score derived from unstructured text positively predicts long-term firm performance among serial acquirers	Vinocur et al., 2022
	Extract executive behavioral signals from earnings calls, surface key decision-maker risk previously invisible *(A, F)*	ML-based personality detection on NLP-assessed earnings call transcripts (+)	CEO openness strongest driver of M&A intensity; CEO–CFO personality alignment amplifies the effect; extracted from unstructured text at scale	Wang et al., 2020
Poorly defined / opportunistic growth strat-	Rank strategic acquisition drivers *(A, F)*	Attention-based deep neural network (Att-DNN) (+)	Outperforms all ML baselines; attention mechanism identifies and ranks strategic drivers most predictive of M&A outcomes	Wan et al., 2026*

egy *(Friedman et al., 2024)*	Map cross-border acquisition success determinants through multiple signals *(A, GR, F, P)*	LightGBM + SHAP (+)	Resolves inconsistent prior findings; ~80% accuracy; SHAP clarifies relative importance of firm-, deal-, and country-level factors	Zhang et al., 2024
	Identify latent M&A pattern types to support a structured, data-driven acquisition typology *(GR, P)*	Unsupervised K-means clustering (+)	Five distinct M&A pattern clusters identified from multi-entity features; lays data-driven foundation for targeted acquisition recommendation systems	Shao et al., 2018*
Excessive process length (Friedman et al., 2024)	Identify acquisition targets through semantic screening of regulatory filings, eliminating manual process *(A, F, P)*	Fine-tuned transformer LLMs (FinBERT, ALBERT, GPT-3) (+)	FinBERT outperforms ALBERT and GPT-3 in target identification; first LLM application to M&A target prediction; high precision minimizes false positives in screening	Rodríguez-Muñoz-De-Baena et al., 2025
	Feature selection, eliminating manual prioritization in multivariable strategic analysis and delay *(A, F)*	Attention-based deep neural network (AttDNN) (+)	AttDNN autonomously weights decision-relevant features, removing a key source of analytical delay in multi-variable screening	Wan et al., 2026*
Inability to assess acquisition-related financial risk (Renneboog & Vansteenkiste, 2018)	Pre-merger risk scoring integrating firm, industry, macro signals to flag acquirers at elevated post-deal default risk *(A, F)*	LightGBM + SHAP (+)	Industry contagion rate is the single most influential default predictor, exceeding firm-level indicators; SHAP provides interpretable risk decomposition for pre-deal risk management	Chen et al., 2026
	Prediction of forced acquirer delisting from pre-merger firm quality indicators, identifying strategically unsuitable acquirers early *(A, F)*	MLP / AdaBoost (+)	~92% accuracy in predicting post-merger acquirer delisting; pre-merger firm quality is the decisive driver, deal characteristics add little predictive power	Thompson et al., 2024
Lack of macro-environmental timing intelligence for acquisition program planning (Harford, 2005)	Pinpoint M&A market timing by linking macroeconomic cycles to deal activity, enabling deliberate rather than opportunistic scheduling *(F)*	Hybrid econometric-ML (OLS / Lasso / Ridge) (+)	GVA, exchange rate positively / unemployment, bank rate negatively drive UK M&A volume; Lasso outperforms OLS; scalable policy-oriented forecasting framework	Tran et al., 2026
	Decompose industry M&A cycles into trend, cycle, noise to identify structural acquisition windows in	Singular Spectrum Analysis (SSA) +	SSA decomposes EDA industry M&A cycles; incorporating technology milestone scores improves long-run forecasting fit;	Zylfiu & Marinova, 2025

	technology-driven sectors *(F, P)*	TechImpactScore (+)	supports strategic timing in fast-moving sectors

Where to start:

- For teams new to AI adoption, the lowest-friction entry is applying financial risk and acquirer health models (Chen et al., 2026; Thompson et al., 2024) – they rely on publicly available, structured financial data and are empirically validated
- A second step can form NLP-based capability and personality scoring models (Vinocur et al., 2022; Wang et al., 2020) – they require access to earnings call transcripts but no proprietary data
- For serial acquirers and advisors, macroeconomic timing models (Tran et al., 2026; Zylfiu & Marinova, 2025) allow scheduling acquisitions in line with the market
- LLM-based target prediction (Rodríguez-Muñoz-De-Baena et al., 2025) would need an explainability layer to make it reliably applicable in practice

Search

The search phase forms the largest cluster of papers (see Table 5). This gives hope that the biggest managerial challenge of *insufficient viable target identification* (D. Friedman et al., 2024) can be mitigated through applying AI. Where human-led searches are constrained by network access and analyst capacity, thousands of candidates can be scanned quickly and automatically. For VC and startup contexts, a validated ensemble approach achieves up to 93% accuracy in predicting acquisition events from publicly available startup data, demonstrating that algorithmic screening can partially replace network-dependent sourcing (Ghadekar et al., 2022). A further validated approach adds news sentiment to financial analysis, showing that negative media coverage is a predictor of acquisition likelihood (Hajek & Henriques, 2024); a finding that should point practitioners to monitor public information and media alongside financial indicators. In the VC and PE context, platforms that combine classical ML, deep learning, and transformer-based tools automate deal sourcing entirely, replacing network dependent pipelines, though the deployment maturity of such an integrated approach remains nascent (Jo et al., 2024). For organizations without prior M&A experience, an immune-system algorithm identifies targets based on dissimilarity from the acquirer's own profile (Paul et al., 2013). Finally, for startup investors, a validated multi-model platform predicts several startup-exit outcomes, with explainability tools identifying which funding, team, and IP features drive the prediction (Ross et al., 2021).

The second core challenge is heightened *information asymmetry on private, high-tech, cross-border targets* (Akerlof, 1970; Myers & Majluf, 1984). The evidence is consistent:

Combining textual and financial signal systematically outperforms financial-only approaches. For bank mergers, extracting strategic intent from annual reports through classical and deep learning as well as transformer-based NLP enables target and also bidder prediction (Katsafados et al., 2024). For U.S. technology targets, another validated model captures non-linear relationships in financial ratios that linear approaches miss (Anagnostopoulos & Rizeq, 2018); a finding replicated with classical ML across 60 predictors in the Chinese market. This study provides feature importance rankings that practitioners can use to prioritize their screening criteria (Zhao et al., 2025). For cross-border contexts specifically, where behavioral and relational complexity compounds financial information gaps, a validated ML approach was used to extract CEO personality signals from text, identifying them as strongest predictor of deal completion (Cheng & Dai, 2025). Practitioners should use this form of additional relational intelligence to fill in gaps that purely financial screening cannot provide.

Lastly, a third addressed challenge concerns the *absence of a structured typology for classifying candidates* (Jemison & Sitkin, 1986), which leaves shortlisting prone to cognitive bias and inconsistency. A validated data-driven screening framework trained on historical deals reveals five latent deal pattern types through unsupervised clustering (Shao et al., 2018). For the context of SPACs, a validated model identifies which target categories structurally outperform others, finding corporate and PE-backed targets ahead of the field (Williams, 2023). Taken together, the search phase offers the most mature and deployable portfolio of AI approaches in this review. However, the majority of models is still only empirically validated and needs individual adjustments before direct deployment in the search phase from target discovery to shortlisting.

Table 5. Linking M&A Challenges in the Search Phase to Proposed Scientific Models and Frameworks

(indicates several mentions of paper across challenges)*

M&A Phase Challenge	**AI Value** *(Capability: A/GR/F/GE/P)*	**AI Model** *(Maturity: -/+/++)*	**Key Finding**	**Reference**
Insufficient identification of viable targets via manual	Screen and predict M&A events on startup data, automat-	Classical ML + Deep Learning ensemble (Gradient Boosting + SVM + MLP) (+)	89–93% accuracy in predicting on Crunchbase data; handles missing data via imputation; hyperparameter	Ghadekar et al., 2022

search *(Friedman et al., 2024)*	ing candidate identification in VC/startup contexts *(A, F)*		tuning improves performance; applicable to real-world startup screening	
	Rank candidates, including on news sentiment *(A, F)*	Transformer-NLP (FinBERT/ BERTopic) + profit-driven ensemble (RF, XGBoost, AdaBoost) (+)	News-based model outperforms financial-data-only baselines; negative news sentiment predicts acquisition likelihood; profit-driven learning handles class imbalance	Hajek & Henriques, 2024
	Screen / score VC-stage targets using multi-source data, removing reliance on network-based sourcing *(A, F, P)*	Ensemble ML platforms (Beacon, Mother-brain) (-)	AI platforms automate VC deal sourcing; scalability and speed vs. manual process as core advantages	Jo et al., 2024*
	Identify bank merger targets without historical M&A experience via unsupervised similarity matching *(A, GR)*	Negative Selection Algorithm (Artificial Immune System (AIS)) (+)	AIS generalizes to novice acquirers without prior M&A history; flexibly identifies dissimilar-from-self targets; uncertainty-robust	Paul et al., 2013
	Predict startup exit (IPO/acquisition/failure) through funding, team, IP, and market data to prioritize high-potential targets in VC/PE *(A, F)*	Ensemble ML pipeline (CapitalVX: MLP, XGBoost, RF, KNN + SHAP/LIME) (+)	CapitalVX with up to 89% accuracy in predicting exit outcomes; explainability via SHAP	Ross et al., 2021
Information asymmetry on private, high-tech, cross-border targets *(Akerlof, 1970; Myers & Majluf, 1984)*	Reduce bank opacity, uncover strategic intent from annual reports *(A, F)*	NLP (TF, TF-IDF, word embeddings) + ML classifiers (Logit, SVM, RF, MLP) (+)	Combining textual and financial data substantially improves bank merger prediction; text especially valuable for predicting bidders (less explored, more opaque)	Katsafados et al., 2024
	Screen tech targets using financial ratios in case of scarce qualitative data *(A, F)*	MLP (Neural Network) (+)	MLP outperforms logistic regression in predicting takeover targets in the US technology sector; captures nonlinear relationships invisible to linear methods	Anagnostopoulos & Rizeq, 2018
	Predict M&A targets to surface hidden patterns in Chinese market *(A, F)*	Random Forest + feature importance (+)	RF outperforms logit with ~79% accuracy; captures nonlinear relationships; identifies which of 60 variables	Zhao et al., 2025

			most strongly predict M&A activity	
	Predict cross-border deal completion using CEO personality signals extracted from text, surfacing behavioral drivers invisible to financial screening *(A, F)*	Classical ML (LightGBM + SHAP) (+)	CEO personality traits are the strongest predictors of cross-border deal completion (~73% AUC); integrates structured and text-derived features; SHAP provides interpretable driver ranking	Cheng & Dai, 2025
Lack of structured typology for categorizing acquisition candidates *(Jemison & Sitkin, 1986)*	Cluster acquirer–target pairs to reveal latent deal types, support structured screening *(GR, P)*	Unsupervised K-means clustering + PCA / t-SNE (+)	Five distinct M&A pattern clusters identified from multi-entity features; data-driven foundation for targeted acquisition recommendation systems	Shao et al., 2018*
	Identify SPAC deal types most likely to outperform others, improving target selection *(A, F)*	Decision trees, Logistic Regression, LASSO (+)	Corporate/PE-backed targets significantly outperform; ML identifies target-level features as key SPAC performance drivers; enables structured sponsor strategy	Williams, 2023

Where to start:

- For acquirers focused on listed firms, the financial-ratio-based classifiers (Anagnostopoulos & Rizeq, 2018; Zhao et al., 2025; Katsafados et al., 2024) are a good starting point – structured Compustat data is available for most deal teams
- For cross-border or private targets, where financial data cannot be easily accessed, adding NLP-derived signals can improve prediction accuracy – i.e., regarding CEO personality (Cheng & Dai, 2025) or news sentiment (Hajek & Henriques, 2024)
- For VC/PE firms, platform-based approaches (Jo et al., 2024; Ross et al., 2021) address the specific challenge of startup data sparsity and network-dependent sourcing while other models enable SPAC success prediction (Williams, 2023)
- For target prediction without prior M&A experience, an approach based on an Artificial Immune System could be fine-tuned to fit further industries (Paul et al., 2013) – functions without historical data

Valuation

The valuation of a target is the next critical step that brings its own unique challenges (see Table 6); the consequences of poor judgement at this stage only become financially costly later. Acquirers often *overpay and / or overestimate synergies* from the deal (Bauer & Friesl, 2024; Renneboog & Vansteenkiste, 2018). Tackling this challenge, one validated model detects and automatically corrects systematic overvalua-

tion before deal pricing. The model combines signals across firm-, industry-, and macroeconomic levels, reducing valuation error significantly against seven tested baselines for deals in technology, healthcare, and manufacturing (Qin et al., 2026). Instead of replacing the valuation process entirely through ML, a broad set of acquirer-, deal-, and macro-level predictors shows that ML-predicted announcement returns can function as a 'market reality check' versus internal valuation assumptions. If predicted and actual responses diverge, this discrepancy can trigger additional information gathering through managers, positively impacting the final valuation (Qu et al., 2026). Through another proposed prediction model of acquirer announcement returns through classical ML with explainability tools, acquirers can assess the market reception before a deal is announced, hence checking its real value ex ante. However, the low explainability of even the best performing model in this study, at 2.5% of the variance explained in announcement returns, underscores the persistent issue of market uncertainty (Quariguasi Frota Neto et al., 2025). Practitioners, in turn, should not rely on a single valuation method but ideally combine several approaches.

For the challenge of *selecting comparable companies for benchmarking*, prone to analyst subjectivity (D. Friedman et al., 2024), the five most comparable peers could be identified with a classical ML similarity matching approach, achieving an objective alternative to human-based selection (Gao, 2023). Targeting the issue of *optimal price estimation* (Renneboog & Vansteenkiste, 2018), two validated approaches predict acquisition prices from financial ratios, outperforming standard linear models. Both are particularly well suited for smaller and mid-market deals with limited transaction histories (H. Liu et al., 2011; H. Liu & Ma, 2009), as off-the-shelf pricing benchmarks may be less reliable. Finally, *stock market mispricing* is a crucial issue that often leads to misvaluation of a target. A deep learning approach with sentiment analysis detects stock market mispricing and shows its strong correlation with M&A activity, even though results are tested perception-based with managers (Tang, 2025). Across all papers in this phase, the model maturity is intermediate, showing empirically validated but not practically applied results.

Table 6. Linking M&A Challenges in the Valuation Phase to Proposed Scientific Models and Frameworks

(indicates several mentions of paper across challenges)*

M&A Phase Challenge	**AI Value** *(Capability: A/GR/F/GE/P)*	**AI Model** *(Maturity: -/+/++)*	**Key Finding**	**Reference**
Systematic overpayment and overestimation of synergies *(Bauer & Friesl, 2024; Renneboog & Vansteenkiste, 2018; Friedman et al., 2024)*	Detect / correct systematic overvaluation on multi-level predictors *(A, F)*	Framework with bias-detection layer + temporal encoder + GNN (+)	Cuts target valuation MAE vs. 7 baselines; bias-reduction; improves risk-adjusted decision scores from 0.44 to 0.52; robust across tech, healthcare, manufacturing	Qin et al., 2026
	Forecast acquirer stock price reaction to deal announcement to pre-test value creation thesis *(A, F)*	Elastic Net (+)	AI-predicted market reactions provide strategic foresight; shape managerial expectations and deal selection; deviations from predictions stimulate managerial information gathering	Qu et al., 2026
	Predict acquirer announcement returns to assess market reception pre-deal *(F)*	LightGBM + SHAP (+)	Nonparametric models outperform parametric ones; acquirer size and relative deal size are top predictors; overall predictability low, highlighting inherent market uncertainty	Quariguasi Frota Neto et al., 2025
Subjectivity, inconsistency in selecting comparable companies *(Friedman et al., 2024)*	Select the most comparable peers via financial indicators *(GR, A)*	KNN with entropy-based feature weighting, Manhattan distance (+)	KNN selects 5 most comparable firms; high predictability vs. benchmark; improves objectivity in comparable firm selection and reduces analyst bias	Gao, 2023
Inaccurate target price estimation leading to suboptimal bid ranges *(Renneboog & Vansteenkiste, 2018)*	Generate data-driven acquisition price references *(F)*	GA-optimized BP Neural Network (+)	GA+NN predicts acquisition target price from 12 financial ratios; outperforms linear benchmarks; provides practical bid range reference	Liu & Ma, 2009
	Forecast acquisition price from financial ratios *(F)*	Multiple-kernel SVMR (+)	High prediction precision; combines multiple kernels for improved performance; achieves global optimum; stable with small samples	Liu et al., 2011

Market mispricing distorting target valuation and M&A timing decisions *(Tang, 2025)*	Detect stock market mispricing to identify undervalued targets and optimal acquisition windows *(A, F)*	CNN + LSTM pipeline for mispricing detection, sentiment integration (+)	Negative mispricing strongly correlates with M&A activity; deep learning detects mispricing reliably; sentiment integration improves accuracy	Tang, 2025

Where to start:

- This phase needs a cautionary approach due to the inherent unpredictability of market reactions – relying on one measure only is not ideal
  - AI-supported decisions should function as cross-checks (Quariguasi Frota Neto et al., 2025)
  - CAR-based market reaction models can support additional information gathering (Qu et al., 2026)
- Applicable most directly is the identification of peer firms through a financial-based model requiring no individual data infrastructure (Gao, 2023)
- For smaller / mid-market deals, acquisition-price prediction models offer bid ranges based on financial-ratios (Liu & Ma, 2009; Liu et al., 2011)

Due Diligence

The due diligence phase concentrates the most heterogeneous set of AI applications in this review, reflecting this phase's multidimensional nature (see Table 7). Practitioners must simultaneously assess financial, legal, operational, strategic, and increasingly governance-related aspects like ESG-based dimensions, and under significant time pressure. This *excessive data volume often leads to rushed and incomplete analyses* as major challenge (D. Friedman et al., 2024; Perry & Herd, 2004). The most direct and ambitious contribution tackles data volume and review speed: A conceptual multi-component framework integrates classical ML for financial analysis with transformer-based NLP for legal document review. Improving both efficiency and accuracy across financial analysis, legal document review, and strategic assessment, this integrated approach remains at the conceptual stage (Bedekar et al., 2024). More concretely, a case study of a real acquisition case combines classical ML, deep learning, and transformer-based tools, showing that an up to 95% reduction of due diligence time was achieved thanks to the application of non-generative and generative AI tools. The authors identified generative AI as the most promising emerging capability for scenario generation and negotiation preparation (Thélisson, 2024). In a similar vein, yet for the context of VC due diligence, AI platforms like Beacon or Motherbrain were shown to automate this process. Automated screening and scoring of targets based on Crunchbase data can reduce or remove the need for manual, network-dependent early-stage evaluation (Jo et al., 2024).

Unidentified risks and deal-breakers during due diligence (D. Friedman et al., 2024) are another major challenge, letting practitioners believe in a deal that might not be fruit- or successful. Three validated approaches can improve the detection of deal-breakers before closing: An optimization-based neural network constructs a composite risk score across seven dimensions (subjective, morality, information asymmetry, law, system, policy, and market risk) and outperforms linear benchmarks while reducing analyst subjectivity (Hu et al., 2009). A cost-sensitive classical combined with deep learning approach accounts for the asymmetry that exists in predicting failure across false negatives and false positives (Lee et al., 2020). The approach is of crucial practical value, as missing genuine deal breakers (false negatives, type II error: misclassifying failure as success) can exceed the cost of a false alarm (false positive, type I error: misclassifying success as failure) by far. The third approach offers a low-cost screening option: Publicly available deal terms, particularly bid premiums and termination fees, already contain substantial predictive signal for takeover success, offering a screen that requires no proprietary data (Johnson et al., 2011).

Less commonly addressed, but a growing area of concern are *IT and operational due diligence* (Perry & Herd, 2004): Extracting relevant log data from ERP systems, a classical process mining framework compares both acquirer and target systems. While it enables objective process comparison across both parties and an early identification of IT-based integration risks and synergies, which is particularly relevant in tech-driven acquisitions, the big data approach requires access to internal infrastructures (J. Eggers et al., 2023). Finally, *ESG due diligence* is an emergent and challenging area of the M&A process (Radło et al., 2025). AI can offer structure to otherwise often fragmented assessments and, for example, predict an acquirer's post-deal ESG score to assess sustainability impact at the DD stage. The proposed model ensures high interpretability via linguistic if-then rules, and surfaced that deal attitude and target ESG are top predictors (Ducange et al., 2025). A combined classical ML and optimization-based approach shows that high disagreement between different ESG rating agencies is itself a risk signal, significantly reducing both takeover likelihood (important for sell-side actors) and post-deal performance (important for buy-side actors) (Gaoli et al., 2025). Practitioners can use this surprising finding to flag candidates before committing to an ESG-rating inconsistent target. Across papers, model maturity is mixed: risk identification and process mining models for IT due diligence are empirically validated, while the

two generative AI approaches tackling full process integration remain conceptual and descriptive.

Table 7. Linking M&A Challenges in the Due Diligence (DD) Phase to Proposed Scientific Models and Frameworks

(indicates several mentions of paper across challenges)*

M&A Phase Challenge	AI Value *(Capability: A/GR/F/GE/P)*	AI Model *(Maturity: -/+/++)*	Key Finding	Reference
Rushed, incomplete analysis under time pressure due to excessive data volume *(Perry & Herd, 2004; Friedman et al., 2024)*	Support financial, legal, and strategic due diligence, reducing review time *(A, F, GE)*	RF + BERT NLP + K-means + Logit (-)	Multi-component DD framework integrates ML, NLP, and predictive analytics across financial, legal, and strategic dimensions; improves efficiency and decision accuracy	Bedekar et al., 2024
	Reduce due diligence time by up to 90–95% *(A, GE)*	Non-generative AI + generative AI (scenario generation) (-)	Real case study: non-generative AI saved 90–95% of DD time; generative AI identified as most promising for scenario generation and negotiation support	Thélisson, 2024
	Screen and score VC-stage targets using multi-source data, automating early-stage due diligence, removing reliance on manual network-based evaluation *(A, F, P)*	Classical ML + Deep Learning + Transformer ensemble 5(-)	AI platforms automate VC due diligence screening; scalability and speed vs. manual process are core advantages; deployment maturity remains nascent	Jo et al., 2024*
Unidentified risks and deal-breakers during due diligence *(Friedman et al., 2024)*	Generate risk scoring across seven dimensions, aggregating into single composite score *(A, F)*	GA + BP Neural Network (+)	Scores across subjective, morality, policy, law, information asymmetry, system, market risk; outperforms linear benchmarks; reduces subjectivity	Hu et al., 2009
	Predict deal failure probability before closing to flag high-risk transactions *(A, F)*	Cost-sensitive hybrid Neural Network (+)	Improves M&A failure prediction by accounting for cost asymmetry; captures nonlinear risk patterns invisible to logit/probit	Lee et al., 2020
	Predict takeover success likelihood	SVM-Linear, AdaBoost (+)	SVM-Linear, AdaBoost achieve best takeover success prediction; deal	Johnson et al., 2011

	from publicly available deal terms *(A, F)*		terms (bid premium, termination fees) are top features	
Lack of objective assessment of target IT and operational processes *(Perry & Herd, 2004)*	Map target's IT processes and identify integration risks *(A, GR)*	Process Mining framework via Celonis/SAP (+)	Designed objective IT DD framework, tested via event log analysis; cross-organizational comparison of buyer vs. target processes; identifies inefficiencies, risks, and integration synergies	Eggers et al., 2023
Insufficient ESG screening leading to post-deal sustainability risks *(Radło, 2025)*	Predict post-deal ESG score to assess sustainability impact at the DD stage *(A, F)*	Multi-way Fuzzy Regression Trees (+)	High interpretability via linguistic if-then rules; deal attitude and target ESG are top predictors; transparent XAI decision support	Ducange et al., 2025
	Assess how ESG rating disagreement among agencies affects takeover likelihood and post-deal performance *(A, F)*	Double/Debiased ML (DDML) + RF (+)	High ESG rating disagreement reduces takeover activity and post-deal performance; DDML enables causal inference while handling high-dimensional controls	Gaoli et al., 2025

Where to start:

- This phase shows the current gap between research, where most models are trained on public data, and practice, where the due diligence phase needs access to proprietary deal room data
- The most deployment-ready model is AI-supported ESG-screening (Ducange et al., 2025; Gaoli et al., 2025) due to the availability of external scores
- After access to deal room data, both risk scoring (Hu et al., 2009) and failure prediction (Lee et al., 2020) offer validated approaches to identify deal breakers
- For tech-intensive acquisitions, the process mining approach for IT due diligence offers a distinct way forward (Eggers et al., 2023)
- To help deal teams build their own AI-assisted DD workflows, the generative AI frameworks (Bedekar et al., 2024; Thélisson, 2024) are a great starting point, yet the contributions remain conceptual

Integration

The most understudied phase in this review represents the integration phase with only one paper addressing its associated challenges (see Table 8). This is a stark contrast to the perceived significance of this phase, where 33% of practitioners flagged it as primary value destruction driver (D. Friedman et al., 2024). *Failing to identify process synergies and integration gaps* systematically is hence a grave challenge for practi-

tioners (Larsson & Finkelstein, 1999). The single validated and deployment-ready application addressed this: An automated gap analysis across thousands of integrated questionnaire responses, identifies process mismatches and creates dynamic checklists that systematically surface process mismatches and synergy opportunities during integration (Maan & Nagwekar, 2022). For practitioners, the integration phase currently offers limited but highly valuable insights, as the gap analysis tool could be deployed without delay. However, the absence of studies on relational, cultural, and talent retention dimensions often recognized as frequent sources of value destruction (Puranam & Srikanth, 2007) represents both a gap in the research landscape, as well as a domain where AI capabilities such as network analysis or sentiment monitoring through NLP-based approaches can be productively explored.

Table 8. Linking M&A Challenges in the Integration Phase to Proposed Scientific Models and Frameworks

(indicates several mentions of paper across challenges)*

M&A Phase Challenge	**AI Value** *(Capability: A/GR/F/GE/P)*	**AI Model** *(Maturity: -/+/++)*	**Key Finding**	**Reference**
Failure to identify process synergies and integration gaps systematically *(Larsson & Finkelstein, 1999; Friedman et al., 2024)*	Gap analysis across thousands of integration questionnaire responses, generating dynamic checklists *(A, GR)*	NLP pipeline (TF-IDF + cosine similarity) (++)	Automates post-merger integration gap analysis; handles large-scale response data; enables systematic synergy detection; generates actionable integration checklists; only deployment-ready application in the sample	Maan & Nagwekar, 2022

Where to start:

- The sole deployment-ready analysis tool is this NLP-based gap analysis model (Maan & Nagwekar, 2022) – directly addressing time-consuming tasks of synthesizing large questionnaire data sets, the model could be directly deployed
- Beyond this, practitioners should evaluate and test commercial tools or opt for an in-house development of, i.e. NLP-based sentiment tools to support relational and cultural integration

Evaluation

The final process stage addressed in this review is the evaluation phase (see Table 9). This phase is characterized by a foundational challenge: a *lack of consensus on how to measure M&A performance and isolate acquisition effects* (Zollo & Meier, 2008).

Table 9. Linking M&A Challenges in the Evaluation Phase to Proposed Scientific Models and Frameworks

(indicates several mentions of paper across challenges)*

M&A Phase Challenge	AI Value *(Capability: A/GR/F/GE/P)*	AI Model *(Maturity: -/+/++)*	Key Finding	Reference
Lack of consensus on how to measure M&A performance and isolate acquisition effects *(Zollo & Meier, 2008)*	Estimate causal M&A effects on costs, sales, and sentiment *(A, F)*	Elastic net for counterfactual outcome construction (+)	Generalizes event studies beyond stock returns; multi-dimensional outcome analysis (costs, sales, customer sentiment from 52M tweets); interpretable via synthetic weights	Zohrehvand et al., 2024
	Firm-level evaluation of M&A performance, reducing subjectivity *(A, F)*	Fuzzy Neural Network (FNN + BP Neural Network) (+)	Reduces subjectivity vs. traditional linear evaluation; captures nonlinear performance relationships; self-learning and adaptive; high accuracy across solvency, profitability, and operational dimensions	Liu et al., 2008
Difficulty attributing M&A performance to governance or structural decisions *(Zollo & Meier, 2008)*	Identify optimal board composition to prescribe governance configurations that improve cross-border M&A performance *(A, P)*	Particle Swarm Optimization (PSO) + regression (BHAR) (+)	Female board proportion has positive, significant effect on cross-border M&A performance; PSO identifies optimal board structure; effect stronger in privately owned firms	Ding et al., 2024

Where to start:

- This phase must be treated as a measurement design challenge first, before seeing it as a technical issue
- Deal teams should first decide whether they first want to isolate deal from market effects (causal attribution) or in multi-dimensional performance measurement
  - For the former and large deals, the synthetic control approach offers a way to incorporate effects beyond stock returns (Zohrehvand et al., 2024)
  - For the latter, the fuzzy NN framework provides multi-indicator evaluation (Liu et al., 2008)
- Offering an interesting impact factor, the model evaluating board composition effects points to the importance of human capital variables (Ding et al., 2024)

The shorter the evaluation time, the better to isolate the effects from market noise, however, measuring returns one day after an acquisition may not effectively reflect on integration-dependent synergy creation down the line. A validated synthetic control approach constructs counterfactual firm trajectories, enabling causal attribution of M&A effects across costs, sales, and customer sentiment. This goes beyond the classical and dominant stock market return metrics widely applied, offering practitioners a multidimensional evaluation framework (Zohrehvand et al., 2024). A second study applies a deep learning fuzzy neural network to evaluate post-merger performance across 20 firm-level indicators, thereby reducing the subjectivity of weighted scoring while remaining adaptive to changing conditions (Z. Liu et al., 2008).

Another related problem that acquirers face is the ex-ante *difficulty to attribute M&A performance to specific governance or structural decisions* (Zollo & Meier, 2008). Identifying optimal board composition in M&A contexts, a validated prescriptive tool evaluates that female board representation has a positive and significant effect on cross-border M&A performance, particularly in privately owned firms. The study offers a prescriptive tool for board design ahead of future deals (Ding et al., 2024).

2.4.2 Data Reality in M&A: From Studied Training Data to a Practice-oriented Application of AI

Having mapped AI solutions to M&A challenges, the next central question for a practical adoption must focus on the underlying data the models are trained with to understand what data deal teams in practice require and what is available to them. To examine this, Table 10 links the types of data inputs used across all empirically tested and/or proposed models in this review, organized by M&A phase (ST=Strategy / SE=Search / VA=Valuation / DD = Due Diligence / IN = Integration / EV = Evaluation) and data level. Again, a more detailed overview is provided in Appendix C). In the following, we distinguish three data levels as inspired by previous research in the management field. We split data types into firm-level and deal-level data (Erel et al., 2012), and external data, consistent with the established institution-based view (Peng et al., 2008) and M&A research on merger waves (Harford, 2005). Under these three levels, we subsume the following specific data types:

- *firm-level data*, covering financials (profitability, leverage, liquidity), operations (process, employees), human capital (executive demographics, personality, experience), governance (board, ownership, ESG), strategy & capabilities,
- *deal-level data*, covering deal financials (size, premium, payment), deal structure (friendly/hostile, advisors, legal terms), acquirer-target relatedness (industry, geography), and
- *external data*, covering macroeconomic indicators (GDP, interest rates, exchange rates), industry & market (concentration, sector trends, stock indicators), institutional & legal (regulatory, country-level), cultural & geographic, sentiment & ratings (news, social media, ESG rank).

The emergent pattern is striking: All 39 reviewed papers base their models on structured data, and 31 draw on firm-level financial ratios as a primary input. Typically, these are sourced from databases like Compustat, Datastream, or Bloomberg for publicly listed firms. Also, historical and archival data forms the baseline across all 39 papers, while 13 incorporate additional, dynamic ad-hoc or future inputs. Unstructured data, including text from earnings calls transcripts, regulatory filings, or news, is used by only 10 papers, despite studies that do incorporate it and demonstrate consistent improvements in predictive accuracy (Cheng & Dai, 2025; Hajek & Henriques, 2024; Katsafados et al., 2024). This concentration reflects a structural bias in the proposed models: Longitudinal financial data on listed firms is the most available and accessible data type. Consequently, as supervised learning requires labeled historical data with defined outcomes, it dominates the pool of papers (34).

The practical consequence, as summarized in Table 11, is a relative decline in data availability across the deal cycle from strategy to integration and evaluation. The strategy and partially search phase still benefit from high to medium availability of data as most required inputs are publicly available. Valuation sits more in the middle, as financials are observable for listed target firms, but synergy assumptions and target-internal data are not. Due diligence and integration face a fundamentally different scenario: the most decision-relevant information like IT processes, HR records, or cultural assessments, resides within the target's own information systems. These types of information are only made accessible through NDAs, within controlled data rooms, and under significant time constraints. Eventually, data availability during evaluation is intermediate:

post-deal outcomes do become observable, however, isolating the acquisition's contribution from concurrent market and strategic effects remains a methodological challenge even in times of AI.

Table 10. Data Application across M&A Phases and Empirically Tested Models

Phase	Task	Firm					Deal			External					Data				Reference
		Finan-cials	Opera-tions	Human Capital	Govern-ance	Strat. & Capab.	Finan-cials	Structure	Related-ness	Macroe-conom-	Industry & Market	Instit. & Legal	Cultural & Geogr.	Sent. & Ratings	Struc-tured	Unstruc-tured	Histori-cal	Ad-hoc	
ST	Post-M&A default risk	x		x	x		x			x	x	x			x		x		Chen et al., 2026
ST	Target prediction	x													x	x	x		Rodríguez-Muñoz-De-Baena et al., 2025
ST	Acquirer delisting prediction	x			x		x	x	x						x		x		Thompson et al., 2024
ST	M&A capability score	x				x					x				x	x	x		Vinocur et al., 2022
ST	CEO/CFO personality & M&A	x		x											x	x	x		Wang et al., 2020
ST	M&A prediction	x	x	x	x						x				x		x	x	Wan et al., 2026
ST	Cross-border deal completion	x					x	x	x	x		x	x		x		x		Zhang et al., 2024
ST	M&A volume prediction						x	x							x		x		Tran et al., 2026
ST	M&A cycle forecasting					x					x				x		x		Zylfiu & Marinova, 2025
ST/SE	M&A cluster identification	x					x	x	x						x		x		Shao et al., 2018
SE	Target prediction (startups)	x	x	x		x	x				x				x		x		Ghadekar et al., 2022
SE	Target prediction	x			x		x	x	x					x	x	x	x	x	Hajek & Henriques, 2024
SE	Takeover target prediction	x													x		x		Anagnostopoulos & Rizeq, 2018
SE	M&A prediction (China)	x	x	x							x				x		x		Zhao et al., 2025
SE	Cross-border deal completion	x		x			x	x	x	x		x	x		x		x		Cheng & Dai, 2025
SE	SPAC target selection	x					x	x	x		x				x		x		Williams, 2023
SE/DD	VC deal sourcing & DD														x	x	x	x	Jo et al., 2024
VA	Target valuation	x				x	x			x	x						x	x	Qin et al. 2026
VA	Acquirer CAR prediction	x				x	x	x	x	x	x				x		x		Qu et al., 2026

VA	Acquirer CAR prediction	x					x	x	x	x	x				x		x	x	Quariguasi Frota Neto et al., 2025
VA	Comparable	x	x								x				x		x		Gao, 2023
VA	Target price prediction	x													x		x		Liu & Ma, 2009
VA	Target price forecasting	x													x		x		Liu et al., 2011
VA	Stock market mispricing									x	x			x	x		x		Tang, 2025
DD	AI framework for DD	x				x					x	x			x	x	x	x	Bedekar et al., 2024
DD	Applied AI in DD (case)														x	x	x	x	Thélisson, 2024
DD	Automating DD (VCs)														x	x	x	x	Jo et al., 2024
DD	Acquisition risk scoring				x						x	x			x		x		Hu et al., 2009
DD	M&A failure prediction	x					x	x							x		x		Lee et al., 2020
DD	Takeover success prediction	x					x	x							x		x	x	Johnson et al., 2011
DD	IT DD		x												x		x		Eggers et al., 2023
DD	ESG score prediction	x			x		x	x	x	x				x	x		x		Ducange et al., 2025
DD	ESG rating disagreement	x			x		x	x						x	x		x		Gaoli et al., 2025
IN	Integration gap analysis	x	x		x	x								x	x	x		x	Maan & Nagwekar, 2022
EV	Performance (board diversity)	x		x	x		x		x						x		x		Ding et al., 2024
EV	Performance	x	x			x					x				x		x		Liu et al., 2008
EV	Causal M&A effect													x	x		x	x	Zohrehvand et al., 2024
SUM		**31**	**9**	**9**	**10**	**9**	**16**	**12**	**10**	**9**	**18**	**5**	**2**	**5**	**39**	**10**	**39**	**13**	**TOTAL**

For practitioners, the implication is clear: AI adoption cannot happen uniformly across the deal cycle. Instead, data accessibility guides model applications. Where data is abundant and structured, as is often the case during strategy and search, empirically validated models can be applied with relatively little internal data preparation. Where data is scarce or proprietary, as in due diligence and integration, adoption requires deliberate investment in building a data infrastructure: systematic internal data capture, standardized deal room protocols, and early-stage data sharing agreements between acquirer and target where possible. Firms that build proprietary data assets through repeated deal experience hold a structural advantage over those relying solely on public inputs. At the same time, the literature has not yet caught up with the ever-expanding availability of unstructured data: aside from internal documents or regulatory filings, real-time news feeds are far more accessible than the publications would suggest. However, the ones that do use such data show that model quality increases. This points to an underexplored frontier for both researchers and practitioners: For the latter, it means that out-of-the-box thinking is required to find new ways to access relevant information that could give a competitive edge to deal teams within acquirers, targets, and advisors. Further, it is an invitation to research to explore how these data constraints interact with the broader limitations of current AI research in M&A, addressed in the following section.

Table 11. Data Availability across M&A Phases and Empirically Tested Models

Phase	Data Availability	AI Maturity
Strategy	high (mostly public)	high
Search	high-medium (depending on targets)	high
Valuation	medium (financials observable, but also target-internal data)	medium
Due Diligence	low (private data)	medium
Integration	very low	low
Evaluation	medium (depending on time window)	medium

2.4.3 Limits and Blind Spots of Current AI Research in M&A

The preceding sections reveal a field that has made genuine progress, yet one whose shape is determined as much by what is easy to study as by what matters most to practice. Three structural blind spots cut across the reviewed literature and, taken together, define both its current limits and the most productive directions for future work.

First, *the prediction fixation*: Assigning and forecasting account for the majority of AI capabilities applied across the 39 papers (32), with prescribing and generating applied rather marginally. This concentration is not accidental: M&A has long been framed as a prediction problem in both academic and practitioner literatures, positioning AI as a tool for reducing uncertainty ahead of decisions (Agrawal et al., 2018). The reviewed models indeed reflect this framing: They predict takeover likelihood, deal completion, announcement returns, and post-merger default risk with considerable accuracy. Yet, the M&A process involves at least as many prescription problems, i.e., what price to bid, how to sequence integration, which synergies to prioritize, or how to manage tradeoffs, and generation problems, i.e., drafting due diligence summaries, structuring communications, or synthesizing negotiation calls. Currently, the literature offers comparatively little empirically validated applications. Only two papers address generative AI capabilities in a focal way (Bedekar et al., 2024; Thélisson, 2024), however, at a conceptual or descriptive stage. This contrasts that generative AI is precisely the capability that has made a real difference in M&A practice, with 86% responding organizations stating they have integrated it into their M&A workflows (Deloitte, 2025). For example, LLMs are used commercially for contract review or data room analysis, indicating that the gap between research and practice is currently wide in this regard (Hutzschenreuter & Lämmermann, 2025).

Next, the *codifiable task bias*: Closely related is a systematic overrepresentation of tasks that are highly formalized. Where inputs are structured, outputs are labeled, and historical data is readily available, AI applications have performed notoriously well. However, M&A's most consequential tasks like negotiating, cultural integration, talent retention, and stakeholder management, which are widely recognized as primary drivers of deal value destruction (Larsson & Finkelstein, 1999; Puranam & Srikanth, 2007), are strikingly underrepresented in current research. The one integration paper in our sample addresses the dynamic analysis of process gaps from structured questionnaire

data (Maan & Nagwekar, 2022), providing a useful but also narrow proxy for the relational complexity of post-merger integration. This is not merely a research gap, it reflects a deeper assumption embedded in the field; namely, that AI only performs well where classification and regression problems need to be tackled. Focusing on automation in codifiable tasks while neglecting augmentation in relational ones created a one-sided story in current research (Raisch & Krakowski, 2021). For practitioners, this means that where the stakes in AI-assisted decision-making are the highest, empirically validated guidance is limited and tools offered on the market need careful evaluation.

Lastly, the *isolated model problem*: For the most part, the reviewed papers study a single AI application in isolation. One model applied at one phase to solve one task like predicting prices. The design choice is scientifically valid; however, it can be practically misleading. M&A practitioners do not face isolated prediction tasks, they face an entire process of connected and consequential decisions, where the output at one stage shapes the inputs of the next. A target identified through AI-assisted screening in the search phase becomes the subject of an AI-assisted valuation model, which then informs due diligence priorities. The reviewed literature currently offers no guidance on how these models may interact or may be interconnected, where errors may compound across phases, or how to design ideal workflows to span the deal cycle. The emergent concept of agentic AI, where systems act across tasks and coordinate output without requiring human intervention (Lin & Maruping, 2025), may present a solution to this problem. However, this remains entirely understudied at this point. For firms with the data infrastructure and organizational readiness to pursue integrated strategies, this presents the most promising opportunity. This means either checking for the interoperability of single solutions or opting for larger-scale AI projects directly.

Taken together, these three blind spots share a common pain point: The literature is mostly shaped by what is publicly available, structured, and historical data, feeding into supervised learning methods. While this is a reasonable starting point for both a nascent research field and initial applications in practice, more recent shifts to transformer-based models and unstructured data point into the right direction. The practical implication for the M&A field is not to discount the reviewed models. The value lies in the scientifically, not commercially verified and tested results. However, practitioners must

recognize that the highest collective value will be realized when such models, frameworks, as well as applied databases and variables are embedded in broader data strategies. Such strategies should connect across phases and extend to generative tasks that can assist in relational challenges as well, enabling firms to combine AI capabilities and gain a competitive advantage.

2.5 Key Takeaways for M&A Practice

The findings of this review converge on a first organizing principle for practitioners: *(1) AI adoption in M&A best happens in sequences*, not simultaneously. The evidence is mature and actionable for early deal phases, including strategy and search, where structured and archival data is mostly available and where well-validated prediction models exist. Consistent with this takeaway, Deloitte's recent study on generative AI in M&A confirms that adoption is currently centering around pre-deal phases: 40% of adopters currently apply it to forming their strategy and assessing the market, followed by target screening and due diligence at 35% each (Deloitte, 2025). For organizations in their early stages of AI adoption, this is a relevant starting point. This is not because post-deal phases matter less, but because the data infrastructure and model maturity required to operate reliably in integration and evaluation do not yet exist at scale. Starting where the science is strongest builds organizational AI capabilities and expertise, creating the internal legitimacy needed to then extend AI further into the deal cycle (Hutzschenreuter & Lämmermann, 2025).

The second actionable principle is to *(2) treat data architecture as a prime strategic asset*, not a technical necessity and afterthought. The reviewed models are almost uniformly trained on structured, archival, publicly available data. This baseline, however, reflects what is easily accessible in research and practice, and not what may be most critical and decision-relevant in deal teams. In a recent McKinsey survey, M&A practitioners report that they achieved an average cost reduction of up to 20% through generative AI, with 40% reporting sped-up deal cycles, being 30-50% faster. Yet, only 30% of respondents engage with generative AI at high or even moderate levels, while listing a lack of expertise as the primary barrier (Kordestani et al., 2026). This gap between potential and realized value can largely be attributed to a data problem: Organizations that systematically capture and structure deal data, from target profiles to

due diligence outputs, integration milestones, and post-merger performance outcomes, across every transaction will be able to outperform current off-the-shelf models. This is especially true for serial acquirers and deal advisory firms. Instead, these organizations can form a competitive advantage through reducing their dependence on generic tools and be able to move to proprietary AI tools trained on distinct data from their own deals. In the same vein, McKinsey recommends that companies begin now by documenting their corporate and M&A strategies, identifying the sources most relevant for scanning targets in their field, and structuring their deal data to link AI capabilities to existing organizational challenges (Kordestani et al., 2026); precisely where this review can assist.

In addition, *(3) how to govern the human-machine boundary* needs to be addressed: Determining whether AI deployment creates or destroys value in practice, planning AI governance will be a decisive factor. The reviewed literature is dominated by deep learning architectures and black-box models, where explainability tools are only recently explored (W. Chen et al., 2026; Cheng & Dai, 2025). Strong predictive accuracy and speed is achieved at the cost of interpretability. Deloitte's study underscores that AI-driven acceleration can compress analysis cycles and increases the speed at which decisions are expected to be made. Exactly this development makes it central to clarify when AI-generated insight can be immediately acted upon, i.e., in validated prescription models, or what outputs require independent validation. Further, it must be clearly defined who is accountable when human judgement overrides automated outputs (Deloitte, 2025). This goes beyond compliance questions, as the explainability of decision-making in M&A is relevant to stakeholders like the board or regulators. Practitioners should therefore apply a governance stress test before deploying any off-the-shelf or in-house built model. Can the key variables and their directional impact be interpreted and communicated by the team responsible? If the answer is no, interpretability tools like SHAP (W. Chen et al., 2026; Cheng & Dai, 2025) should be treated as a non-negotiable implementation requirement. The augmentation principle discussed in the literature applies: AI should keep practitioners in the loop, particularly in high-stakes decisions where relational knowledge, contextual judgement, and accountability cannot fully be delegated to an algorithm.

Lastly, it is pivotal to *(4) match the AI adoption strategy to the specific deal context,* not the most sophisticated model. Not all the reviewed models are equally relevant to every

acquirer. From our sample, several practitioner profiles emerge that follow different objectives in their daily work, and hence, can profit from different frameworks. (i) First-time and infrequent acquirers face the most critical data constraints regarding internal insight, since they have no historical deal data of their own. For them, models that rely on publicly available data, like financial ratios for target screening, macroeconomic indicators for sequencing decisions, or ESG rating for risk scoring, offer a good starting point. The AIS-based target identification model (Paul et al., 2013) is a notable approach. (ii) Serial acquirers and deal advisory firms are best positioned to capture the compounding benefits described throughout this review. For these actors, the strategic imperative is not to adopt individual models, but to design data architectures that connect outputs across phases. The gap between these actors' potential and current practice is primarily a governance and infrastructure question, and not so much a model availability question. (iii) VC / PE contexts represent a structurally distinct profile again, characterized by data sparsity, portfolio volume, and even more intense speed requirements that create a different optimization problem. Here, ensemble platforms trained on startup databases network-analysis-based sourcing tools (Ghadekar et al., 2022; Jo et al., 2024; Ross et al., 2021) are most relevant.

In sum, these four principles of (1) sequenced adoption, (2) data infrastructure investments, (3) governance of human-machine collaboration, and (4) context-specific adoption strategies define a practical roadmap built on current academic insight, supporting practitioners' decision-making in the application of AI tools.

2.6 Conclusion

M&A remain among the highest-stakes strategic decisions organizations can undertake. The persistent gap between the promise and the performance of deals despite six decades of research points to the interdisciplinary and complex, multivariate nature of M&A (King et al., 2004). This review argues that AI, applied systematically and reflected, offers a meaningful approach to minimize this gap. Synthesizing 39 empirically reviewed studies across four academic disciplines and six deal phases, the paper maps, for the first time, the current state of AI research in M&A against real-world practitioner challenges. The goal of this study was not to present a catalogue of models, but to offer a decision-support framework depending on the specific challenges a given

organization may face. For buyers, sellers, and advisors alike, this framework is organized along the deal process itself to provide actionable insights for practitioners. Aside from linking challenges to empirically validated solutions, this paper also offers an in-depth evaluation of required data structures.

Three findings warrant particular attention: First, the concentration of validated AI applications in the pre-deal phases of strategy, search, and initially valuation is driven by data availability. Second, the dominance of prediction tasks and supervised learning represents the field's primary contribution, but also its blind spot: The most consequential M&A challenges, like relational complexities during negotiations or cultural integration, remain currently almost unaddressed in the current literature. Third, the gap between models that are empirically validated and deployment-ready is larger than the literature may tend to acknowledge. Bridging this gap requires technical capabilities to bridge data infrastructure, ensure interoperability and interpretability, as well as orchestrating governance. For practitioners, the core message is that capabilities must be built or bought to deploy existing insights and models through data strategies and governance frameworks.

For researchers, this review surfaces an agenda that extends well beyond filling gaps across phases. It calls for a reorientation of the present framing of AI as prediction machine (Alvesson, 2011), towards AI as a dynamic decision support actor. As such, augmenting human judgment, designing human-machine accountability, and focusing on causal rather than correlational implications. The emergence of agentic AI further raises questions that the field has not yet addressed: What happens when AI systems are integrated across phases? How are outputs coordinated and made explainable without human judgement? Such questions reflect the reality of M&A practice, where related tools are already entering the market and changing the trajectory of the field (Kordestani et al., 2026).

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2.8 Appendix

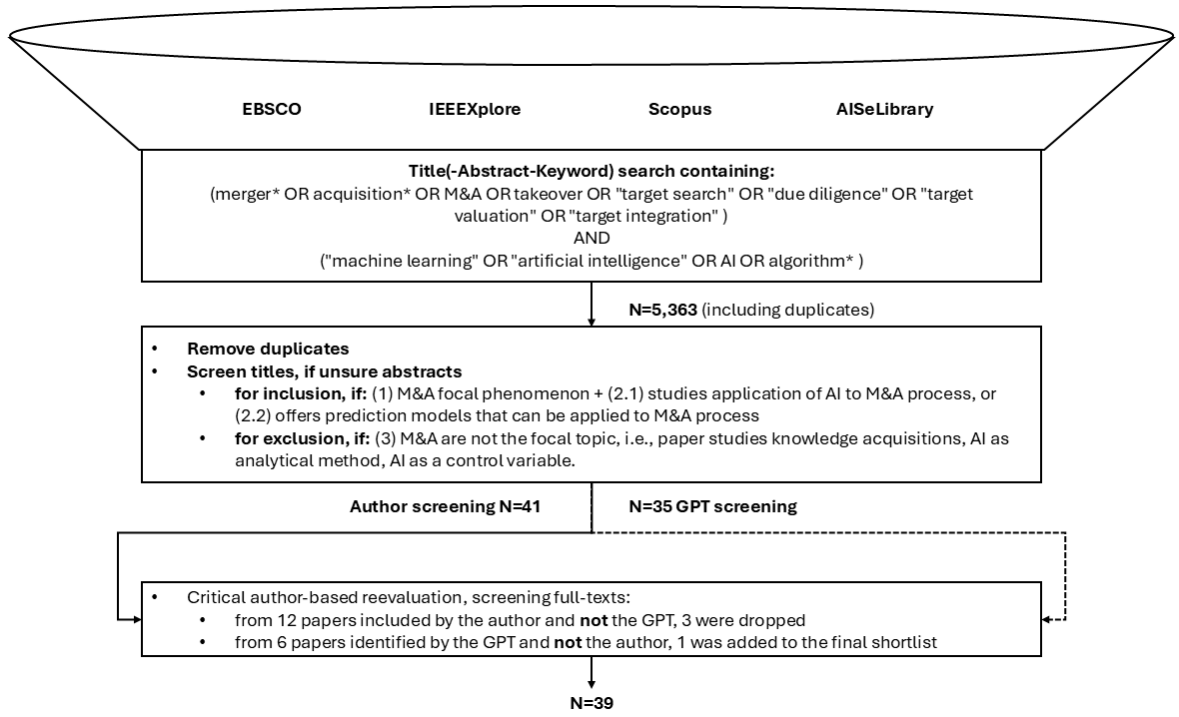
A) Search Approach across Databases

Search Approach across Databases

Database	String	Results	Added to Initial Shortlist after GPT Verification
Scopus	TITLE-ABS-KEY ((merger* OR acquisition* OR M&A OR takeover) AND ("machine learning" OR "artificial intelligence" OR AI OR algorithm*)) AND (LIMIT-TO (SUBJAREA , "BUSI")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp"))	3352	21
	TITLE-ABS-KEY (("target search" OR "due diligence" OR "target valuation" OR "target integration") AND ("machine learning" OR "artificial intelligence" OR AI OR algorithm*)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (SUBJAREA , "BUSI"))	35	2
	TITLE-ABS-KEY (("due diligence" OR target AND (search OR valuation OR integration)) AND ("machine learning" OR "artificial intelligence" OR AI OR algorithm*)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (SUBJAREA , "BUSI"))	552	2
IEEE Xplore	("Document Title":merger* OR "Document Title":acquisition* OR "Document Title":M&A OR "Document Title":takeover OR "Document Title":"target search" OR "Document Title":"due diligence" OR "Document Title":"target valuation" OR "Document Title":"target integration") AND ("Document Title":"machine learning" OR "Document Title":"artificial intelligence" OR "Document Title":AI OR "Document Title":algorithm*) *+ only conferences + journals + early access*	1014	7
EBSCO	TI (merger* OR acquisition* OR M&A OR takeover OR "due diligence" OR (target AND (search OR valuation OR integration))) AND ("machine learning" OR "artificial intelligence" OR AI OR algorithm*) *+ only peer-reviewed*	285	6
AIS eLibrary	(merger* OR acquisition* OR M&A OR takeover OR "due diligence" OR (target AND (search OR valuation OR integration)))	125	1
SUM		***5363***	***39***

B) Search and Screening Process with AI-Verification

The Search and Screening Process with AI-Verification (Custom-built GPT)



GPT Model Specifications: "Lit Rev Assistant: AI in M&A"

Model: Thinking 5.5 / Duration: Standard

Description: I am aware that the objective of this project is to eventually create a high-level literature review on the application of AI in the M&A process, which is also relevant for practitioners. As the **Lit Rev Assistant: AI in M&A*, I specialize in: Reviewing existing exports from scientific databases. I especially focus on title, abstract, and keywords, evaluating which ones fit the literature review objective that is uploaded in a separate document* - application of AI (in a broader sense as mentioned) to either the M&A process (elements described in my document) or general M&A prediction tasks that could be applied to the M&A process.

* 4-page Word document on: Theoretical Background + Methodological Approach (In- / Exclusion Criteria).

C) Full Sample of Papers

Literature Review: Further Information on Full Sample of Papers										
Phase	**Task**	**Bench-marks**	**Input Data**	**Data Source**	**AI Challenge**	**Study Method**			**Limitations**	**Reference**
						Quantitative	**Qualitative**	**Conceptual**		
ST	Post-M&A default risk prediction	n/a	Firm financials (profitability (ROA*), leverage (debt-to-asset-ratio*), liquidity, audit opinion(*)); M&A characteristics (deal features); industry-level default rate (*) (network contagion proxy); macroeconomic variables (GDP, interest rates); governance (board, ownership); Guanxi proxies (guarantees, political connections); *=strongest predictors	Chinese A-share firms engaging in M&A; 2010–2023; CSMAR database; litigation and bond default data; macro & industry data	Limited causal interpretability (predictive not causal); potential label bias (litigation-based default proxy); class imbalance requiring resampling; context-specific (China / Guanxi); sensitivity to feature engineering; complexity vs. traditional models	x			Chinese A-share firms engaging in M&A; 2010–2023; CSMAR database; litigation and bond default data; macro & industry data	Chen et al., 2026
ST	Target prediction	ALBERT, GPT-3-babbage-002 (proposed: FinBERT best performer)	Textual data from SEC 10-K filings (MD&A sections); corpus preprocessing (cleaning, stopword removal, tokenization); labels: target (1) vs non-target (0) through text length and word frequencies	200 publicly-listed US energy companies from SEC EDGAR (10-K filings), Bloomberg (M&A deals), S&P500 Energy & Utilities; 2015-2024	Small dataset (≈200 firms); class imbalance (≈10% targets); limited generalizability (US energy sector only); transformer input length constraints (512 tokens → chunking); potential information loss from truncation; computational intensity; no	x			Limited sample size; sector-specific; imbalance; reliance on textual data only; no multimodal integration; potential overfitting; no causal inference	Rodríguez-Muñoz-De-Baena et al., 2025

					integration of financial variables					
ST	M&A cluster identification	n/a	M&A features (acquirer's / target's / relationship features): financial features (cash flow from operating activities; cash flow from investing activities; cash flow from financing activities; free cash flow (cfoa + cfia); net sales; ordinary profit; cash & cash equivalent (beginning); changes in cash flow); firm features (sales growth 3 years; cash/sales >0.25 over 4 years; > industry median sales 3 years; M&A experience 3 years; prior M&A experience); relationship features (same industry – 3-digit; same industry – 6-digit; acquirer vs. target sales 4 years)	109 M&A cases + 778 random samples from Japanese firms; UZABASE database with ~1.5M M&A deals; 2003-2016	Strong dependence on feature engineering and binary encoding; No direct predictive capability (descriptive only); Sensitivity to clustering parameters (k choice); Limited interpretability of clusters > post-hoc interpretation	x			Small usable M&A sample (109 cases); Focus on Japan only; Binary feature simplification; No predictive validation; Cluster interpretation subjective	Shao et al., 2018
ST	Performance prediction (acquirer delisting for performance reasons)	Logit, RF, AdaBoost, MLP	acquirer fundamentals (premerger) (firm size log total assets; leverage total liabilities / total assets; profitability ebitda / total assets; cash holdings cash / total assets; sales turnover); deal characteristics (ownership percentage acquired; payment method stock vs. cash; transaction value; industry relatedness same	3,865 U.S. acquiring firms; SDC M&A database; 1998–2014; COMPUSTAT; CRSP; WRDS blockholder data	Class imbalance; limited interpretability (esp. MLP); relies on observable variables only; no causal inference; weak role of deal-specific variables	x			U.S.-only sample; excludes COVID period; class imbalance (~9% delisting); limited variables; no causal interpretation; ignores qualitative factors	Thompson et al., 2024

			vs. different industry); agency / governance variables (blockholder ownership %); information asymmetry proxy (stock price crash risk ncskew); target variable (binary indicator of forced delisting within 5 years)							
ST	M&A volume prediction (time-series)	OLS / Ridge / Lassp Regression (proposed: Lasso best performer)	Monthly macroeconomic indicators: Gross Value Added, exchange rate, unemployment rate, Consumer Price Index, bank rate; M&A deal volume	238 monthly observations from Institute for Mergers, Acquisitions, and Alliances; Office for National Statistics (ONS); Bank of England; 2004-2023	Combines interpretability (econometrics) with predictive power (ML); handles multicollinearity; improves generalization via regularization; suitable for policy and macro forecasting	x		x	Limited predictive power (~R^2 = 0.597); aggregate-level only; no firm-level insights; no cross-validation; ignores major exogenous shocks explicitly	Tran et al., 2026
ST	M&A capability measurement	n/a	TF-IDF weighted keywords representing M&A process phases (selection, acquisition, integration) and learning processes (articulation, codification, sharing, internalization); dependent variables: ROE; price-to-book; independent variable: M&A capability; control variables: market consolidation, market diversification, cost-efficiency, capability acquisitions; change in revenues; size of acquirer; technology services sector; finance sector; commercial ser-	FactSet database; 141 firms (serial acquirers); 564 annual reports; 2,602 deal synopses; 2013–2016	Dictionary-based NLP limits semantic depth; Potential measurement error in construct; Dependence on reporting quality; Limited causal inference; No advanced NLP (e.g., deep learning)	x	x		Limited to public firms; relies on disclosed information; NLP dictionary constraints; confidentiality of detailed M&A processes; limited generalizability	Vinocur et al., 2022

			vices sector; consumer services sector; ownership structure							
ST	M&A prediction	Linear Regression, Logit, Decision Tree, XGBoost, AdaBoost, SVM, baseline DNN, Gated Recurrent Unit, LSTM (proposed: AttDNN best performer)	executive characteristics: demographics (ceo age; ceo gender; ceo education level; ceo tenure); leadership experience (leadership; experience); incentive level (executive team stock options; board member stock options); corporate governance characteristics: board structure (board size; female board members; external directors majority; ceo duality); shareholding (largest shareholder ownership ratio; nature of equity); internal control (strength of internal control); financial condition of the company: profitability (operating profit margin; return on total assets; return on equity; earnings per share; sales expense ratio); operational capability (total asset turnover; accounts receivable turnover; inventory turnover); solvency (debt-to-equity ratio; current ratio; quick ratio); equity expansion capability (net asset value per share; retained earnings per share); others:	10,101 M&A observations (China A-share firms); CSMAR database; Wind database; 2007–2020	Captures complex nonlinear relationships; Automatic feature selection via attention; Handles high-dimensional structured data; Strong predictive performance (≈29% improvement vs. baseline DL); Robust across models and time; Provides interpretability via SHAP + attention weights	x			10,101 M&A observations (China A-share firms); CSMAR database; Wind database; 2007–2020	Wan et al., 2026

			company experience (previous acquisition experience); level of industry competition (herfindahl index); market valuation level (market valuation level); year (m&a year)							
ST	CEO personality detection; M&A intensity measurement	n/a	Eearnings call features: Big Five personality traits (openness, conscientiousness, neuroticism, extraversion, agreeableness) for CEOs & CFOs; M&A data: Frequency and total value of transactions per firm-year; Firm-level controls: size, ROA, leverage, liquidity, market-to-book; Executive-level controls: age, tenure, compensation, gender, turnover	S&P 1500 firms; 15,013 earnings call transcripts; Thomson One, Compustat, CRSP; 2005-2017	Measurement error in ML-derived traits; Interpretability of deep learning; Causality concerns; Dependence on text quality and availability	x			Potential endogeneity; measurement error in ML outputs; limited generalizability beyond public firms; reliance on transcript availability	Wang et al., 2020
ST	Deal completion prediction (cross-border M&A)	n/a	deal-level (deal size; percentage sought; payment method cash; industry relatedness; advisor involvement; friendly vs hostile deal); firm-level (acquirer size; target size or performance; prior acquisition experience global and local; ownership type soe public private); country-level (institutional quality home and host; gdp growth unemployment; regulatory restrictions); cultural and distance variables (cultural	24,693 deals across 29 EM countries; from Thomson Reuters SDC M&A database; World Bank; GLOBE	Limited causal interpretation; “black-box” nature (partially mitigated by SHAP); dependent on data quality; still sensitive to sample/context	x			No causal inference; potential missing variables; EMNE focus limits generalizability; imbalance between completed vs. failed deals; interpretability constraints	Zhang et al., 2024

			distance kogut-singh; language distance; religious distance); industry dummies and year controls; target variable (binary completed vs not completed)							
ST/SE	M&A prediction (EDA industry)	n/a	TechImpactScore (technology milestones: AI, quantum, etc.); time index (year); domain-specific event annotations	Internal repository of annual M&A counts (verified acquisition records, enriched manually through industry reports and news articles); ~50 years	Limited granularity (annual aggregation); internal/non-public dataset; subjective TechImpactScore; sensitive to parameter choices (window size); weak handling of exogenous shocks; limited benchmarking vs. alternative models	x			Internal dataset (no reproducibility); subjective feature engineering; limited external validation; no comparison to strong ML/DL baselines	Zylfiu & Marinova, 2025
ST	M&A prediction	Decision Tree, RF, SVM, Naïve Bayes, KNN, Logit (proposed: Random Forest best performer, all ML outperforming classic Logit)	60 variables: enterprise earnings level, growth level, ownership structure, relevant personnel characteristics, industry-related and environment-related features (see literature), Chinaspecific variables (i.e., Post2013, which represents the special years, to explore the potential impact of changes in China's capital market on corporate takeover activities)		Limited to Chinese market; relies on structured data only; potential data quality issues (missing values, interpolation); no deep learning models; limited causal inference; class imbalance and model sensitivity; no real-time deployment					Zhao et al., 2025
SE	Deal completion prediction (cross-border M&A)	n/a	CEO characteristics: demographic (ager, gender, MBA, degree); professional background (international experience; CBMA experience; throughput experience; output experience;	4,541 CBMA deals (U.S. listed firms); 1990–2021; Thomson Reuters SDC; BoardEx; WRDS	Limited causal interpretability (prediction-focused); Sensitive to data quality (text-derived personality measures); Class imbalance handling required (SMOTE);	x			Observational data (no causality); Potential measurement error in personality (text-based proxies); Sample restricted to U.S. firms;	Cheng & Dai, 2025

			tenure; founder CEO; duality); personality (openness; conscientiousness; extraversion; agreeableness; neuroticism; risk-taking preference; narcissism; overconfidence; external focus; internal focus; promotion focus; prevention focus); control variables (firm-level: equity value, target performance, target firm size, acquirer firm size, advanced parent, global experience, local experience, foreign subsidiary, state-owned enterprise (SOE) target, private target, and public target; deal-level: cash payment, percentage sought, deal size, friendly acquisition, industry relatedness, advisor, tender)	Capital IQ transcripts	Model complexity (ensemble boosting); Dependence on feature engineering and measurement validity				Class imbalance; Missing data handling; Model interpretability limits despite SHAP	
SE	Target / bidder prediction	Logit, SVM-Linear, SVM-RBF, Random Forest, MLP (no single proposed focal model; comparative study)	12 financial variables from financial statements and market variables: cost-to-income ratio (Cost efficiency), and the return on total assets (ROA); ratio of common equity to total assets (Capital strength); ratio of loans to total assets (Loans); ratio of each bank's deposits to the total deposits of the U.S. banking industry in a given year (Market power); ratio of	9,207 bank-year observations; from bank-year observations. (10-Ks, 10-K405s, 10-KSBs, and 10-KSB40s) from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR); 1994-2016 + FRBC financial data +	Data imbalance issues; high computational cost; model complexity; limited interpretability (addressed partly via LIME); dependence on text preprocessing	x			Limited to U.S. banks; historical dataset; model interpretability challenges; imbalance handling required; long documents limit advanced NLP (e.g., transformers not used)	Katsafados et al., 2024

			loan loss provisions to total loans (Asset quality); ratio of non-interest income to total income (Non-interest income); ratio of deposits to total assets (Deposits); (1) MTB the ratio of the market value of equity to book value of equity; LnMV the natural logarithm of the market value of equity; ERet the excess returns over the cumulative value-weighted return of a portfo; DVOL the daily return volatility over the 12month period prior to the 10-K filing date.	Thomson ONE M&A database; 1994-2017						
SE	Target prediction (takeover)	n/a	inefficient management (EBITDA; margin; ROE; ROCE; ROA; asset turnover); undervalued firms (market to book; price to earnings); firm size (market capitalization; total assets); leverage (debt to equity; equity multiplier); liquidity (current ratio; net working capital); growth (growth in annual sales)	226 target and 1340 non-target U.S. firms from Bloomberg: 2000-2016	Limited interpretability (“black box”); Requires larger datasets; Sensitive to parameter tuning; Performance variability	x			Sector-specific; Data loss due to missing variables; Limited generalizability; Financial variables only	Anagnostopoulos & Rizeq, 2018
SE	Target prediction	SVM, MLP	Crunchbase firm database: capital raised; number of funding rounds; IPO details; founder education; investor information; company milestones; sector/category information, etc.; preprocessing-derived	Crunchbase startup dataset; global firms	Strong dependence on data preprocessing and imputation quality; Limited interpretability (“black box”); Potential overfitting risk; Sensitive to feature selection; No clear ensemble aggregation mechanism	x			Biased and incomplete dataset; heavy reliance on imputation; little transparency on sample size; potential overfitting; limited generalizability	Ghadekar et al., 2022

			features: imputed missing values (RANSAC for numeric; most-frequent for categorical); one-hot encoded categorical variables; standardized numerical variables							
SE	Target prediction	n/a	News-based sentiment and topic detection + financial indicators: inefficient management (return on capital employed); growth; growth-resource mismatch; leverage (book debt/total assets; total debt/ent value; total debt; interest coverage: rating); firm age; liquidity (current ratio; cash ratio; cash); dividend policy (reinvestment rate) ; free cash flow (free cash flow; FCF/S); firm size (total assets; S; enterprise value; total equity); profitability (return on equity; gross profit margin; net income after interest; operating margin; EBITDA; enterprise value/EBITDA); ownership structure; undervaluation (PBV; stock price variation (3-year), EPS, stock price to sales; stock price to earnings to EPS growth); price-earnings	182 targets vs 3648 non-target US & UK public firms; 2020–2021; 298,134 headlines from Reuters news corpus	Complexity of pipeline; reliance on news data source (Reuters); limited time window (2020–2021); potential overfitting risk; limited interpretability of ensemble models	x			Short time horizon; strong class imbalance; dependence on news availability; limited generalizability; external shocks (COVID, geopolitics)	Hajek & Henriques, 2024

SE	Target search; Due Diligence (VCs)	n/a	n/a	Case studies (SignalFire, EQT, InReach, Wokelo); secondary sources; industry reports	Scalability vs manual sourcing; automation of screening; improved speed and efficiency; ability to process vast datasets; reduction of human bias (partially); enhanced risk assessment; improved deal flow quality		x	x	No empirical testing; no formal model validation; potential bias in selected cases; limited generalizability	Jo et al., 2024
SE	Target prediction	n/a	number of offices; other income; number of employees; business per employee; interest expended; profit per employee; operating expenses; capital and reserves & surplus; cost of funds (CoF); deposits; return on assets; investments; wages as % to total expenses; advances; return on advances adjusted to CoF; interest income; capital-to-risk-weighted assets ratio; net NPA ratio	1 acquiring firm (SBI) + 7 target banks; Indian banking data (Reserve Bank of India); 2005–2008	Strong dependence on feature selection; Sensitivity to parameter choice (n, C); Limited interpretability; Complexity in detector construction	x			Single case study; Limited generalizability; Sensitivity to feature design; Some ranking instability across targets	Paul et al., 2013
SE	Exit prediction (IPO, acquired, failed); Funding prediction	n/a	Crunchbase firm database: funding rounds, investors, firm characteristics, team composition; patent data (USPTO): number of patents, IP indicators; 370 derived features: funding dynamics, gender composition, education, investor types, online presence; categorical encodings: industry, geography (target encoding), ...	1,000,886 companies, 141,430 investor companies from Crunchbase; retrieved in 2020; across 150 countries + ca. 7; 000; 000 patents, since 1976 from the United States Patent and Trademark Office (USPTO)	Data quality issues (missing / noisy Crunchbase data); class imbalance; limited causal interpretability; reliance on publicly available data	x			Missing data; reporting bias; limited private firm transparency; generalization concerns	Ross et al., 2021

SE/DD	Identifying high-performing Special Purpose Acquisition Companies		independent variables: NASDAQ; serial issuer; early announcer; late announcer; majority top-tier underwriters; target domestic; target corporate/private equity-backed; year fixed effect; demonstrated profitability; SPAC size; target age; announced enterprise value; venture involvement cluster; revenue projections cluster; sources and uses cluster; ownership cluster	130 SPACs; from CapitalIQ, Compustat, Pitchbook, SEC filings; 2000–2021	Small sample size (n=130); class imbalance (75% underperformers); limited predictive accuracy (e.g., CART f-score 0.32 vs. logistic ~0.64); potential multicollinearity; sensitivity to feature engineering; limited generalizability	x			Sample selection bias; omitted SPACs; reliance on binary classification; assumed share price (USD 10); limited external validity; difficulty capturing causal effects	Williams, 2023
VA	Stock price reaction prediction (acquirers)	OLS, Ridge Regression, Lasso, Random Forest, KNN (proposed: LightGBM best performer)	CAR[-1,1]; size, ROA, cash, FCF, market to book, leverage, R&D intensity, Altman Z, bankruptcy risk, high-tech industry, experience; deal size; relative deal size; public target; international target; all cash; all stock; hostility, industry relatedness, merger of equals, timing (Friday, winter, dormant period), percentage sought; federal funds rate (interest rate), VIX, risk sentiment, policy uncertainty (EPU3C, EPU news), GDP change, merger waves	9,517 US M&A deals (1992–2022); SDC, Compustat, CRSP, FRED	Extremely low predictive power ($R^2OS \leq 2.5\%$); high noise-to-signal ratio in stock returns; financial markets difficult to forecast; limited economic significance; no causal inference; sensitive to feature space	x			Low predictability of CAR; high noise; US-only sample; excludes financials/utilities; observational design; no causal identification	Quariguasi Frota Neto et al., 2025
VA	Screen comparable companies for	n/a	15 feature categories: scale (total assets at the end of the period; net assets at the end of the period; asset liability ratio;	185 listed companies in software & IT services industry; Cathay Pacific	Sensitive to feature selection and scaling; limited to similarity (no causal inference); relies on predefined indicators; difficulty validat-	x			Industry-specific; indicator selection bias; limited validation approach (P/B comparison only); ignores macro/external	Gao, 2023

	valuation		working capital ratio); operational capability (total asset turnover rate; current asset turnover rate; capital density); profitability (ROI; ROA; return on net assets, EBIT); growth (operating profit growth rate; total asset yield increase rate; sustainable growth rate); innovation (development expenditure and intangible asset ratio); industry-level metric: Gini coefficient to measure dispersion of firms (p.3)	database; financial data (2022)	ing "true" comparables; ignores external environment factors (p.8)				factors; difficulty generalizing across industries (p.8)	
VA	Target price prediction	n/a	12 financial variables: earning profit (profit margin; return on asset); growth (increase ratio of asset; increase ratio of sales; increase ratio of equity; increase ratio of profit); asset management (asset turnover; inventory turnover; account receivable turnover); solvency (quick ratio; current ratio, asset-liability-ratio)	67 Chinese M&A deals (train/test split)	Prediction error relatively high (~11); Sole dependence on selected financial indicators; Limited interpretability ("black box")	x			Limited variables (financial only, missing resource-based/strategic/contextual factors); Limited sample size; Data availability constraints (China market context)	Liu & Ma, 2009
VA	Target price forecasting	n/a	12 financial variables: earning profit (profit margin; return on asset); growth (increase ratio of asset; increase ratio of sales; increase ratio of equity; increase ratio of profit); asset management (asset turno-	67 Chinese M&A targets (train/test split); 2008–2010	Sole dependence on selected financial indicators; Limited interpretability ("black box"); Model complexity (multi-kernel optimization)	x			Limited variables (financial only, missing resource-based/strategic/contextual factors); Limited sample size (60 samples to train, 7 samples to test); Data availability constraints (China market context)	Liu et al., 2011

			ver; inventory turnover; account receivable turnover); solvency (quick ratio; current ratio, asset-liability-ratio)							
VA	Target valuation	n/a	Financial statements (10-K, 10-Q); deal data (Crunchbase M&A); stock price time series; patent data (USPTO); firm features; industry relationships; macro/market signals	1,643 acquisitions made by 36 major technology companies (Crunchbase Technology Mergers and Acquisitions dataset); Startup Success/Fail dataset; daily prices of 14 major technology issuers (Big Technologies Giants Stock Price) from 2010–2023; 10-K and 10-Q filings of U.S.-listed companies since 2009; patent transfers in the United States since 1970; case studies on Microsoft-LinkedIn (2016), Facebook-Instagram (2012), and Google-Android (2005)	High model complexity; heavy data requirements (multi-source); limited interpretability despite diagnostics; potential overfitting due to architecture richness; computationally intensive; case-study validation limits generalizability	x			Limited real-world deployment validation; potential data integration bias; complexity vs. interpretability trade-off; dependence on high-quality structured data	Qin et al., 2026

VA	Detecting / quantifying stock market mispricing	n/a	market metrics: i.e., daily stock prices (open, high, low, and close); trading volume; technical indicators: i.e., Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands; sentiment scores from financial news and social media; macroeconomic factors: i.e., GDP growth, inflation rates; target variable: Buy/Sell Signal; survey responses from market participants	Synthetic stock market dataset + survey data (344 investors, regulators, market participants)	Combines structured financial + sentiment data; integrates behavioral finance with AI; highlights role of mispricing in M&A strategy; shows strong correlations between AI-based mispricing detection and M&A outcomes (e.g., correlation ~0.83–0.97)	x		x	Conceptual + empirical mix; no real M&A dataset; limited DL rigor; possible overclaiming of AI capabilities; lack of external validity	Tang, 2025
VA	Stock market reactions to acquisition announcements (CAR) prediction	Elastic Net, RF, Gradient-Boosted Tree, OLS (proposed: Elastic Net best performer)	286 variables: deal-specific attributes (i.e., percentage of shares sought by the acquirer, percentage of cash payment, number of bidders, transaction attitude (friendly, hostile, or neutral), public status of the target, acquirer–target relatedness (four-digit SIC code, geographical proximity)); firm characteristics (i.e., acquirers: size, market capitalization, profitability (ROA), Tobin's Q, leverage ratio, R&D intensity, industry average performance; targets: industry average performance based on SIC code; relative size of the acquirer and the target out-	13,237 acquisition transactions completed by 5,624 unique U.S. public acquirers; from Center for Research in Security Prices database, Compustat database, Federal Reserve Economic Data database; 1976-2022	Low predictive power (low R^2 typical for financial markets); probabilistic nature; reliance on historical data; limited interpretability; predictions may not reflect long-term value	x		x	Prediction accuracy relatively low; context-specific (US public acquirers); ML used as proxy for managerial cognition; no real deployment setting; focus on short-term market reactions	Qu et al., 2026

			put variable); acquirer experience (i.e., number of prior acquisitions, average announcement returns, recent announcement returns); market activity (i.e., number of acquisitions six months prior, average announcement returns, standard deviation of announcement returns); macroeconomic factors prior (i.e., volatility of the stock market, percentage of acquisition transactions reviewed by FTC)							
DD	Due Diligence: Assessing financials, legal compliance, strategic fit	n/a	Little detail, but: financial data: historical financial statements, performance indicators (profitability, growth, variance metrics); legal data (unstructured): contracts, regulatory documents, compliance reports (processed via BERT NLP); strategic / market data: market trends, operational characteristics, competitive positioning	Conceptual + illustrative datasets; no clearly specified empirical dataset; framework-based evaluation	Conceptual / framework-heavy (limited real-world validation); Data dependency (quality & availability); Interpretability issues (black box models); Integration complexity across functions; Organizational adoption challenges	x			Conceptual + illustrative datasets; no clearly specified empirical dataset; framework-based evaluation	Bedekar et al., 2024
DD	Post-M&A sustainability prediction (acquirer ESG score)	n/a	18 indicators for target and acquiring firm each: firm sustainability (Environmental (E), Social (S), and Governance (G) pillar scores); firm-level financial indicators (company size, financial leverage, growth rate, liquidity, profitability, asset	959 completed M&A deals; 2010–2022; LSEG Datastream; World Bank (GDP)	High interpretability via linguistic rules; Handles uncertainty and vagueness (fuzzy logic); Integrates ESG + financial + deal-level data; Transparent decision-making (XAI); Good trade-off accuracy vs. interpretability		x		959 completed M&A deals; 2010–20221 LSEG Datastream; World Bank (GDP)	Ducange et al., 2025

			turnover, intangible capital, capital expenditures, R&D investments); deal-level characteristics (deal value, the proportion of cash and stock used as payment methods, the stake acquired and predeal ownership structure, cross-border or domestic nature of the transaction, cross-sector or within-sector classification, the deal's attitude); macroeconomic context (GDP growth rate)							
DD	Due Diligence (IT)	n/a	Event log data from enterprise information systems (e.g., ERP/SAP): case ID, activity, timestamp; additional attributes: users, costs, financial volumes, process variants; derived KPIs: cycle time, automation rate, conformance violations, financial impact indicators	4 German engineering firms (buyers + targets); ERP (SAP S/4HANA) process data; O2C & P2P processes; 2016–2017 datasets	Strong dependence on data access and quality (event logs); Requires data integration across firms; Privacy/sensitivity issues in pre-deal phase; Limited standardization of KPIs; Implementation complexity (data merging, system heterogeneity)	x		x	No clear description of Celonis architecture to understand framework application; Limited to few processes (O2C, P2P); Industry focus (engineering); Early-stage research on process assessment in IT DD; Generalizability depends on data availability and digital maturity; No predictive modeling (descriptive focus)	Eggers et al., 2023
DD	Takeover activities prediction; performance predicition	n/a	ESG disagreement (std. dev. across 6 rating agencies); takeover activity (binary MA; duration proxy MA_alter); firm financials (size, leverage, cash, MTB); governance (duality,	Limited interpretability vs. simple models; Dependent on model specification (PLM); Requires large, structured datasets; No unstructured data	Limited interpretability vs. simple models; Dependent on model specification (PLM); Requires large, structured datasets; No unstructured data usage; Causal identification still limited without exogenous shock	x			Potential endogeneity remains; Limited to Chinese market; ESG disagreement proxy construction assumptions; Excludes financial/utilities sectors; No true experimental identification	Gaoli et al., 2025

	(ESG-rating-based)		board independence); market structure (HHI); incentives (PPS)	usage; Causal identification still limited without exogenous shock						
DD	Risk measurement (score)	n/a	16 risk indicators (expert-scored): subjective risk (knowledge; preference; ability); morality risk (stock convergence; ownership); policy risk (fiscal levy; monetary policy); law risk (consumate; changing possibility); information asymmetry risk (asymmetry); system risk (property rights: special debt; government attitudes); market risk (suppliers; customers; competitors)	16 (presumably Chinese) firms; expert-scored indicators	Dependence on expert-defined risk indicators; Limited interpretability (“black box”); Model complexity (hybrid GA + NN tuning)"	x			Small sample / illustrative case; Heavy reliance on expert scoring; Limited external validation	Hu et al., 2009
DD	Takeover success prediction	Logistic Regression, Neural Networks (MLP), SVM-RBF Kernel, SVM-Linear Kernel, SVM-Polynomial Kernel, SVM-Sigmoid, REPTree, Decision Tree (J48),	10 variables to predict takeover success: target size; target leverage; target book-to-market ratio; target resistance; arbitrage spread; deal structure; termination fees for the target; termination fees for the acquirer; poison pills; bid premium. Variables used in testing of the prediction algorithms: the target size; post price; transaction size bid premium; debt to asset ratio; binary variables (attitude; stock swap options; collar)	1196 deals from Securities Data Company (SDC) database; 1991–2004	Limited interpretability (especially SVM and ensemble methods); Model performance sensitive to feature selection; Class imbalance in dataset	x			Limited feature set; Historical dataset; No causal inference (pure prediction focus)	Johnson et al., 2011

		Random Forest, AdaBoost (proposed: SVM-Linear and AdaBoost tied as best)								
DD	M&A failure prediction	n/a	financial/accounting predictors: inefficient management (ROA; dividend per share; inventory/total assets); undervaluation (market-to-book ratio); price-to-earnings ratio; growth-resource mismatch (growth in sales over the past year; capital expenditure/ operating revenue invested capital turnover); dividend payout (dividend payout ratio; dividend yield); size (log (total assets)); M&A predictors: relative deal size; target share price (1 day prior; 1 week prior; 4 weeks prior); termination fee (clause dummy; acquirer; target); hostile vs. tender offer; toehold; competing bidder	803 U.S. M&A deals (SDC + Compustat); 696 successful, 107 failed; 2006–2015	Higher model complexity; Requires parameter tuning (MCMC, cost parameters); Limited interpretability; Computational intensity; Dependent on cost specification	x			Unbalanced dataset; Focus on U.S. public firms; Model complexity; Sensitivity to cost assumptions; Potential overfitting risk	Lee et al., 2020
DD	Due Diligence (valuation, risk	n/a	n/a	Case study of a French ETI (Impact Group); interviews with	Cannot capture emotional/human factors; stakeholder acceptance critical; bias still present in inputs;		x		Single case; limited rigor - coding not transparent; no empirical ML testing; conceptual AI use;	Thélisson, 2024

	assessment)			managers; internal data room documents; real takeover attempt (2023)	limited ability to assess cultural fit; overreliance risk; lack of transparency				strong reliance on managerial perspective;	
IN	Post-merger integration management (creating dynamic checklists)	n/a	questionnaire data (~10,000 questions): strategy, IMO, process, integration, architecture, infrastructure, training, change management, business continuity, sales, IT, compliance (structured + unstructured); TF-IDF vectors derived from responses (bag-of-words representation)	Questionnaire dataset (~10,000 questions); responses from merging firms across multiple industries; internal platform data	Strong dependence on questionnaire design; Limited semantic understanding (bag-of-words); No predictive capability; Sensitivity to text quality; Limited learning/adaptation beyond similarity matching	x	x		Questionnaire dataset (~10,000 questions); responses from merging firms across multiple industries; internal platform data	Maan & Nagwekar, 2022
EV	Performance evaluation (board composition in cross-border M&A)	n/a	main variable: female board percentage; control variables: board size; average board age; age kurtosis; average education level; education variability; log deal value; cash payment dummy; cash holdings ratio; return on assets; firm age; prior m&a experience; leverage ratio; log total assets; same business dummy; market-to-book ratio; relative size of target's vs. acquirer's book value	Chinese listed firms (CSMAR, UNCTAD); cross-border M&A deals; 1998–2015	Limited AI sophistication (optimization only); Strong modeling assumptions (functional dependence on female share); Endogeneity concerns; No true prediction task; Limited generalizability beyond Chin	x			Country-specific (China); focus on listed firms only; potential endogeneity; optimization relies on estimated relationships; limited external validity	Ding et al., 2024
EV	Performance evaluation	n/a	20 indicators (X1–X20): solvency (current ratio; quick ratio; cash ratio; debt-to-asset ratio; interest coverage); profitability (sales net profit margin; return on	10 Chinese firms	Dependence on indicator selection and design; Limited interpretability (“black box”)	x			Limited generalizability (very small sample); Requires further validation and refinement	Liu et al., 2008

			equity; return on assets; cost net profit margin; net profit cost ratio; earnings per share); asset management (inventory turnover; accounts receivable turnover; fixed asset turnover; total asset turnover); main business status (main business contribution rate); core competitiveness (market share; new product development capability; market expansion capability; production capacity)							
EV	Estimate abnormal M&A effects (benchmarking against control groups)	n/a	shareholder returns (daily); operating costs (quarterly); sales (quarterly); customer sentiment (monthly from tweets); comparison firms' corresponding time series	1 focal M&A (Dollar Tree + Family Dollar); 13 comparison firms; from Compustat; SEC filings; Twitter (~52M tweets)	Sensitive to comparison firm selection; Requires long pre-period; Potential confounding in long post-period; Stability assumptions; Limited robustness with few controls	x			Single case study; sensitivity to comparison firm selection; requires long pre-period; risk of confounding in long post-period; assumption of stable relationships; limited generalizability	Zohrehvand et al., 2024

3 The AI Strategy Compass: A Case-Based Guide for Achieving Digital Intelligence Maturity

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Abstract

While Artificial Intelligence (AI) promises considerable efficiency gains, the 'black-box' technology is often associated with vagueness and fear. Organizations face a paradoxical situation: On the one hand, competitive pressure and technological hype push firms toward rapid AI adoption. On the other hand, uncertainty regarding viable implementation paths leads to fragmented, inconsistent, or stalled initiatives, with organizations failing to generate sustainable value. Existing guidelines are contradictory, lack empirical grounding, or target only niche industries, leaving executives uncertain about how to initiate or proceed on their path towards Digital Intelligence Maturity. This paper is the first to identify, juxtapose, and provide guidance on two fundamental logics in strategic AI approaches: governance- vs. momentum-driven. Drawing on a comparative case analysis of three global firms at different stages of AI maturity, we investigate how these strategic logics emerge, under which conditions they dominate, and how they shape AI implementation trajectories over time. Developed, tested, and validated through 33 interviews, 10 workshops, 7 plant visits, as well as secondary data, our resulting AI Strategy Compass offers (i) an industry-agnostic decision tree that guides managers towards the appropriate strategic approach and pinpoints an organization's current AI implementation level; (ii) an evidence-based, stepwise framework to evolve from the current level to AI leaders; and (iii) seven actionable learnings to avoid common pitfalls on the journey towards Digital Intelligence Maturity.

Keywords: Artificial Intelligence, AI Strategy, Strategy Selection, Strategy Implementation, Practical Guide, AI Strategy Compass

3.1 Introduction

Artificial intelligence (AI) is expected to boost the global GDP by up to 15 percent within the next 10 years, broadly impacting industries from media and technology to manufacturing and therefore has become a central driver of organizational transformation (Goldman Sachs, 2023; PricewaterhouseCoopers, 2025). AI systems differ from prior digital technologies through their self-learning capabilities, moving beyond fixed input–output structures. Leveraging big data, AI autonomously adapts to complex environments (Lin & Maruping, 2025). Beyond driving unprecedented growth, AI induces profound changes for individuals and organizations worldwide (Silva & Di Serio, 2016; W. R. Thompson, 1990). Despite its impact, how AI can be effectively governed and scaled within organizations remains insufficiently understood (Hutzschenreuter & Lämmermann, 2025).

As a result, organizations face a paradoxical situation: High expectations surrounding AI drive competitive pressure and push firms toward rapid adoption on the one hand. On the other hand, uncertainty regarding viable implementation pathways leads to hesitation, fragmentation, or misaligned initiatives. Some organizations delay action due to perceived risks and lack of capabilities, whereas others invest aggressively in isolated use cases without a coherent strategic direction, often failing to generate sustainable value. Empirical evidence underscores these challenges, indicating that a substantial share of organizations still lack a coherent AI strategy, while many early adopters struggle to translate initial experimentation into measurable business value (Deloitte, 2024; KPMG, 2025). Similarly, even companies that have already started to examine the potential of AI or applied first applications feel overwhelmed (Riedel et al., 2024). The vast majority of early adopters struggles with creating value from AI (Challapally et al., 2025) or fails at their projects entirely (Hutzschenreuter & Lämmermann, 2025). This highlights that the core challenge is not access to AI technologies, but the absence of structured guidance on how to organize and scale AI initiatives.

However, existing guidelines provide limited support in resolving this challenge. While prior research offers valuable insights into specific aspects of AI adoption, such as governance structures, use case development, or maturity models, it rarely addresses how these elements should be combined and sequenced over time. Contemporary strategy implementation recommendations are often either too generic or too narrowly

applicable. Even worse, many publications lack empirical insight to justify their advice. Although AI is widely discussed, empirical evidence on its strategic integration remains therefore limited and context-specific, with existing guidelines scattered across outlets and industries (Oldemeyer et al., 2025; Pokorni et al., 2021). The review of these documents surfaced a fundamental strategic tension for decision-makers: whether to prioritize top-down coordination through formal strategies and governance structures, or to foster bottom-up experimentation through decentralized AI initiatives. Contemporary research provides limited guidance on how to navigate between these seemingly contradictory approaches, leaving managers without actionable advice.

In this paper, we address this gap by conceptualizing AI strategy-making as the interplay between two distinct but interrelated strategic logics: governance-driven and momentum-driven approaches. Rather than treating these as mutually exclusive choices, we examine how organizations navigate, combine, and sequence these logics into their AI journeys. Building on prior Digital Transformation (DT) research (Westerman et al., 2012), this paper aims to guide AI strategy-making and -implementation toward Digital Intelligence Maturity. The term denotes an organization's progress in leveraging digital technologies to transform processes, talent, and business models (Kane et al., 2015), emphasizing AI as a core digital technology that drives DT. Reviewing the AI literature, we identified two paths to achieve Digital Intelligence Maturity, either through prioritizing (i) governance or (ii) momentum. Governance-driven organizations first define vision, strategy, and structure, then invest in aligned use cases. Momentum-driven organizations start with early use-case investments and quick wins, linking them later under a governance framework (Westerman et al., 2012). Selecting the right strategy provides direction and critically shapes successful organizational change, according to both research (Miles et al., 1978; Yuliansyah et al., 2017) and practice (Boyles, 2022; Trapp, 2019). Hence, we conceptualize the two approaches as alternative entry logics that must be sequentially combined to eventually achieve Digital Intelligence Maturity.

This paper first contrasts the two approaches identified in prior research. It then develops an evidence-based decision and implementation framework based on comparative case analysis of three global firms from AI beginners to leaders (Yin, 2017). Developed, tested, and validated through 33 interviews with case partners and experts from various industries, as well as 10 workshops, 7 plant visits, and secondary data

from our case companies, the AI Strategy Compass responds to calls to identify strategy archetypes for different organizations (Hutzschenreuter & Lämmermann, 2025). The manuscript offers (i) an industry-agnostic decision tree, (ii) a stepwise implementation framework from AI beginner to leader, and (iii) seven key learnings to avoid common pitfalls. The AI Strategy Compass enables executives to shift from waiting to acting, offering an actionable path to capture AI value.

3.2 Competing Logics in AI Strategy-Making

Share- and stakeholders worldwide expect organizations and their managers to live up to new digital standards. DT has been defined as “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies” (Vial, 2019, p. 9), in short, through digital technologies. Digital maturity can be achieved through excelling in two domains: First, through the “investment in technology-enabled initiatives to change how the company operates - its customer engagements, internal operations, and even business models” (Westerman et al., 2012, p. 3). Second, through building a “vision to shape a new future, governance and engagement to steer the course, and IT/business relationships to implement technology-based change” (Westerman et al., 2012, p. 3). For firms starting their journey towards digital maturity, it is quite common to first excel in one of these dimensions, before building up the other.

We build on these prior insights for an AI context, knowing that “AI and digital transformation go hand in hand” (Holmström, 2022, p. 333). AI can be seen as a further digital technology yet exhibiting distinct features: It blurs the boundaries between human and machine capabilities, simultaneously constraining, complementing, or substituting human work, with a complexity that may also lead to unexpected outcomes (Benbya et al., 2021). It is not a standalone tool anymore, it is interwoven with human actions (Gehman et al., 2025). Within AI, “machine learning has emerged as the method of choice for developing practical software for computer vision, speech recognition, natural language processing, robot control, and other applications” (Jordan & Mitchell, 2015, p. 255). Machine learning builds on improving automatically through experience, through either supervised or unsupervised learning. While in supervised learning, the desired output is clear and “the goal is that of learning a mapping between input and output spaces” (Simeone, 2018, p. 2), unsupervised learning uses no prescribed labels

to train, hence autonomously clustering and labeling input points that are close to each other. Despite promising considerable efficiency gains, unsupervised learning is often associated with fears around AI as 'black box' technology.

To bring AI and its unique characteristics to the forefront of strategic thinking, we argue that today's managers should lead their firm towards a *Digital Intelligence Transformation,* defined as "a comprehensive metamorphosis spanning strategy, operations, organization, and beyond" (Wu, 2012, p. 1). This transformation demands a recalibration of human cognition and collaboration with intelligent technologies (i.e., AI). The term Digital Intelligence Transformation thereby highlights the inherent importance of AI as an intelligent technology within the DT journey. Through Digital Intelligence Transformation, comprehensive changes in the technology, business, and management domain of an organization emerge. "These changes can be described through three aspects: data, digitalization, and intelligence, thereby establishing a strong competitive advantage for the enterprise" (G. Zhang et al., 2024, p. 2). To achieve *Digital Intelligence Maturity* faster, it helps to have an integrated data management, storage, and use established (Zimmermann, 2024), making the integration of AI applications easier. Reviewing current frameworks and guidelines through the lens of earlier DT work (Westerman et al., 2012), we identified two general ways to implement AI: the governance-driven and the momentum-driven approach.

3.2.1 Governance-Driven Approach

The most propagated way to achieve Digital Intelligence Maturity is by starting with building governance and structure: According to this approach, "AI priorities are derived from business priorities" (Kruhse-Lehtonen & Hofmann, 2020, p. 5). In such frameworks, an AI strategy and vision are put forward *before* considering any investments. Later, momentum around technology-driven initiatives can be built, closely aligned with the overall business strategy. A natural starting point can be the optimization of current business processes (Kruhse-Lehtonen & Hofmann, 2020). Such process-centered AI applications are often driven by a cost leadership strategy of a given firm (Porter, 1979, 2008). Depending on one's competitive strategy, other possibilities emerge as well: Firms pursuing differentiation may put greater emphasis on AI-led innovation in the organization's products or services.

The “AI strategy house” is a great visual example for the governance-driven approach (see Figure 4). As described, a firm’s corporate strategy inspires the AI strategy, which guides the corresponding AI vision. To define this vision, the current position of a given company and its competitive environment need to be understood. Then, the impact of AI for the industry and future business models should be identified, to eventually pinpoint potential fields of application. Only based on that, the use cases and enabling factors (organization, people, technology, and ecosystem) should be determined. Currently available resources are the delimiters of short-term use cases, while the use cases envisioned for the long run can shape future requirements for data, talent, and infrastructure. Use cases should either improve current processes (process-centric) or products and services, enhancing the AI vision (product-/service-centric). After assessing the use cases by value and complexity, they are ready to be prioritized and executed. “To handle and manage the iterative process of setting up and developing an AI project, a company should develop clear plans for how its AI projects are to be set up, run, and monitored” (Hartmann et al., 2019, p. 13).

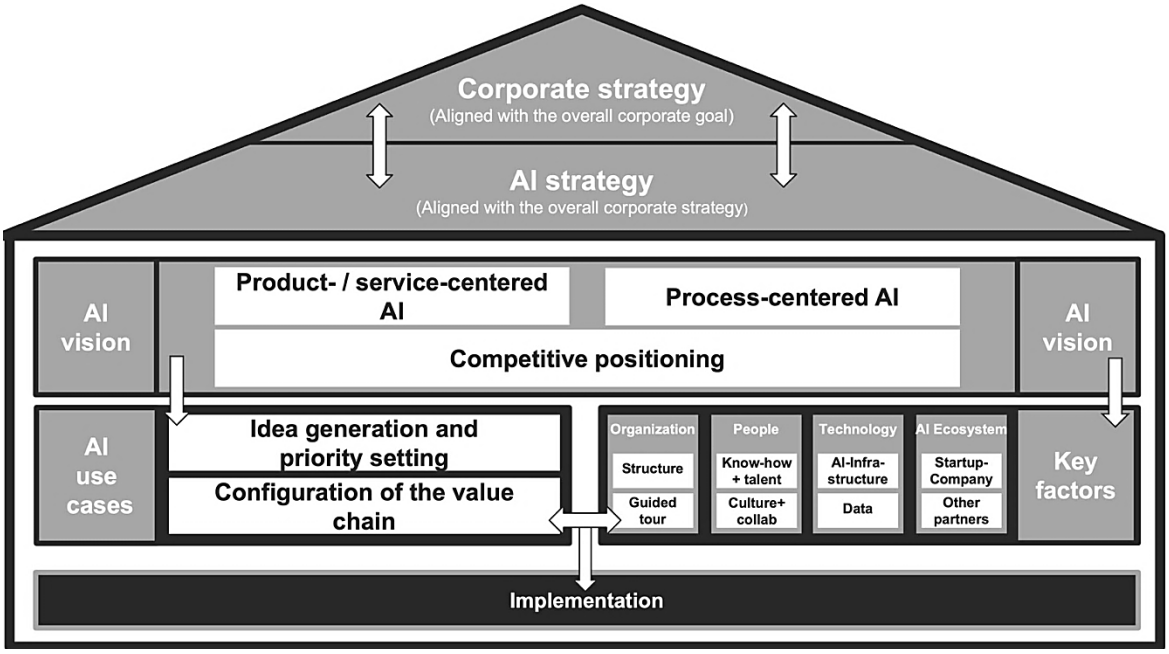


Figure 4. The “AI Strategy House” Framework (adopted from Hartmann et al., 2019)

3.2.2 Momentum-Driven Approach

The second approach prioritizes AI investments to gain momentum and visibility. This is often done in individual business units, creating quick wins yet keeping the developing knowledge in silos at first. After kick-starting the AI journey in this way, management competences need to be developed to ‘connect the dots’ and unleash new AI capabilities by linking the silos later in the process. Hence, this approach thrives on the early identification of suitable use cases. Many publications have specifically dealt with how to find and evaluate such cases, for example, through matching one’s business problems with potential AI application areas (Brakemeier et al., 2023; Hofmann et al., 2025; Kirschbaum et al., 2022). Depending on the task, the underlying machine learning can happen supervised or unsupervised.

A prominent example for the momentum-driven approach is the AI transformation playbook by Andrew Ng (2019), former leader of the Google Brain team and the Baidu AI Group. He recommends focusing on use cases first, to showcase the value of AI for the entire organization through quickly integrating pilot projects. Following a problem-centered strategy in identifying use cases, employees are integrated in the Digital Intelligence Transformation early on, reducing internal resistance from the get-go. From this, the company can build its governance structures during later stages and grow the number of successful AI projects. Ng (2019) proposes the following steps:

- *Execute pilot projects to gain momentum*: look for feasible projects that can succeed within 6-12 months, and where a new or external AI team can partner with your internal teams to build AI solutions; focus on ‘quick wins’, not the most valuable projects, to drive momentum through ‘lighthouse’ projects
- *Build an in-house AI team*: for the long term, build internal capabilities for a more unique competitive advantage and to scale initial projects; create a separate AI unit to matrix in AI talent and drive cross-functional projects
- *Provide broad AI training*: consult with an expert to develop a customized curriculum for your team; from least to most extensive training, educate executives and senior business leaders, leaders of divisions carrying out AI projects, and AI engineer trainees

- *Develop an AI strategy*: develop a thoughtful AI strategy based on the progress in steps 1-3; focus on (i) building several, difficult-to-replicate and strategically aligned AI assets, (ii) lead in AI in your industry sector or niche, (iii) follow a virtuous feedback loop including better product-users-data, and (iv) create network effects and platform advantages
- *Develop internal and external communications*: make your AI strategy and capabilities transparent to investors, regulators, customers, and employees to address their specific expectations and concerns; through strong employer branding, attract, and retain scarce AI talent

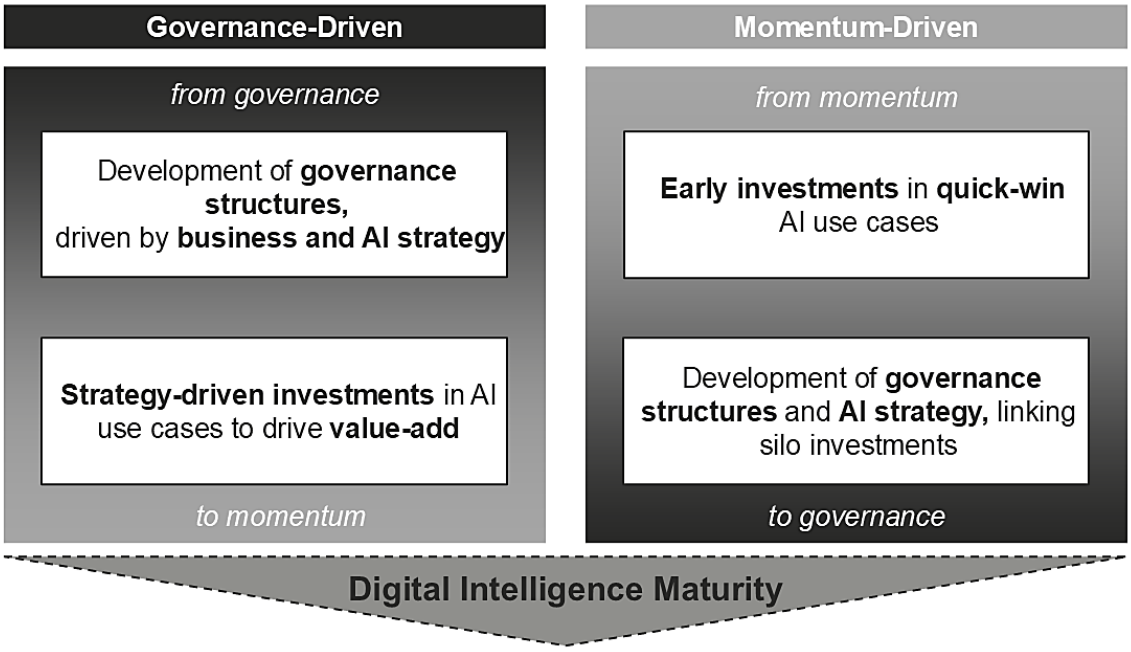


Figure 5. Contrasting the Governance- vs. Momentum-Driven Paths to Achieving Digital Intelligence Maturity (based on Westerman et al., 2012)

3.2.3 Juxtaposing Governance-Driven and Momentum-Driven Approaches

In sum, we identified two seemingly contradictory approaches in current publications. Building on the logics of bottom-up and top-down DT strategy (Westerman et al., 2012), we argue that contemporary AI strategies also exhibit a similar dichotomy: the governance- vs. momentum-driven approach. While both approaches share the overall goal of achieving Digital Intelligence Maturity eventually, the suggested steps differ clearly

(see Figure 5). Drawing on renowned strategic terminology (Sinek, 2025), we will now briefly juxtapose both approaches, referring to vision and strategy as ‘why / how’ and the AI use cases as ‘what’.

The *governance-driven approach* is predominantly executed through the top and starts with establishing structure and guidance first, emphasizing the importance of a managerial AI strategy and vision, based on the business strategy (*how* / *why*). Only then, investments in use cases should follow (*what*). Hence, this approach is driven by strategy and aims for value and scalability in its AI use cases. The *momentum-driven approach* is mainly bottom-led by individual people and business units and emphasizes the quick identification and investment in first use cases (*what*), before developing governance structures and an AI strategy that connect those individual investments and unleash organization-wide capabilities (*how / why*). This approach is characterized by its focus on solving pressing business problems first, prioritizing quick-win AI use cases that promise ease of implementation. Table 12 provides a contrasting overview of the two different logics for AI strategy-making.

Table 12. Contrasting Building Blocks in Governance- vs. Momentum-Driven AI Approaches

	Governance-Driven	**Momentum-Driven**
How / Why (Vision / Strategy)	First	Last
What (Use Case)	Last	First
Driver	Business strategy	Business problems
Initial Goal	Value, scalability	Ease, quick wins

However, the question of how to choose and implement the most suitable strategic approach from the two options remains. Hence, the following sections provide (i) empirical insight through comparing real-world organizations on different AI implementation paths and (ii) the resulting ‘AI Strategy Compass’, an industry-agnostic decision tree and actionable implementation framework. It finally eases strategy-making for practitioners of all industries and AI implementation levels.

3.3 Research Methodology

To see how differently AI strategy is approached in practice, we conducted a multiple-case study involving three global players to investigate their respective approaches. Enabling an in-depth investigation of the complex, context-dependent phenomenon of the novel challenge of AI implementation, studying cases in real-world settings is an appropriate method (Yin, 2017). Applying both convenience and purposive sampling tactics for strategic variation (Flyvbjerg, 2006), we chose companies headquartered in Germany, each taking different routes towards Digital Intelligence Maturity. Initial access was facilitated through existing university-industry collaborations and prior executive contacts, reflecting a pragmatic, convenience-based approach. At the same time, the sampling was also purposive since we strategically avoided a single-maturity-stage and single-industry sample. Hence, out of the contacted organizations, we selected three heterogeneous firms following replication logic and their AI maturity: *AI beginners, AI intermediates,* and *AI leaders*, operating in different industries, yet sharing a similar institutional context in Germany. A detailed description of our case companies can be found in Appendix D).

Table 13 provides an overview of our extensive data pool, consisting of both primary data (self-collected) and secondary data (existing). Our primary data consists of 17 executive interviews at Alpha, Beta, and Gamma conducted in either German or English, which we audio-recorded, transcribed, and, where necessary, translated with the help of a software. We triangulated these insights with field data notes from plant visits and workshops, as well as strategy documents, website data, and media articles on the organizations' digital change trajectories. We approached our data with qualitative coding techniques based on abductive analysis that iterated between sensitizing theoretical concepts and empirical case material and temporal bracketing (Eisenhardt, 1989; Langley, 1999), as explained in detail in Appendix E).

Further, we improved and validated our emerging AI Strategy Compass through five iteration rounds and across 27 validation points, consisting of experts from within our case companies, a set of experts from various industries beyond our case companies, and extensive author team discussions (see Table 14). This rigorous process enabled us to assess the accuracy of the Strategy Compass, exchange necessary clarifications respecting practitioners' views, and adjust where necessary (Jay, 2013). Accordingly, we are confident that the following subsections can make a tangible contribution to

managers' efforts, supporting organizations to capture and create value through AI. The first section introduces Alpha, Gamma, and Beta. The next section contrasts their individual experiences with executing AI strategic approaches as exemplary cases.

Table 13. Overview of Data Sources

	Primary Data				Secondary Data		
	Interviews	**Name (Role)**	**Plant visits**	**Workshops**	**Strategy Documents**	**Media articles**	**Websites**
Alpha	4	A1 (Head of AI)	4	2	2	4	1
	2	A2 (General manager)					
	1	A3 (Manager of technical department)					
	1	A4 (Manager of technical department)					
	1	A5 (Manager of production department)					
Beta	3	B1 (Manager corporate innovation)	1	3	3	2	1
	1	B2 (Manager corporate digital transformation)					
Gamma	1	G1 (AI coordinator and production planner)	2	5	2	15	1
	1	G2 (Manager of data innovation)					
	1	G3 (AI coordinator)					
	1	G4 (Technical expert)					
Experts (Industry)	1	E1 (Research)	-	-	-	-	-
	1	E2 (Industrial Manufacturing)					
	1	E3 (Water & Hygiene)					
	1	E4 (Manufacturing & Retail)					
	1	E5 (Polymer)					
	1	E6 (Automotive)					
	10	Part-time MBA students holding leadership or strategy consultant positions	-	-	-	-	-
Σ	**33**		**7**	**10**	**7**	**21**	**3**

Table 14. Iterations for Validating the 'AI Strategy Compass'

Iteration	Validators	Validation Format	Adjustments
01	4	Author team meeting • Testing the decision tree with several publicly known organizations	• Framework: o AI infrastructure added o Refined in-text explanation o Coherent design of figures
02	10	Extensive discussions with students in leadership or strategy consultant positions (part-time MBA course)	• ‚Momentum' instead of ‚problem' • Decision tree answers: high/low • Organizational contexts
03	5	In-depth interviews • E1, E2 (Experts) • A1, A2 (Alpha) • G4 (Gamma)	• Decision tree: o Organizational culture o External forces • Framework: Order of governance-steps
04	3	In-depth interviews • E3, E4 (Experts) • B1 (Beta)	• Decision tree: o Reduced / reordered questions o Expanded to include AI beginner to AI leader assessment • Framework: 3-levels instead of 4 (see AI maturity levels)
05	5	In-depth interviews • E4, E5, E6 (Experts) • A1 (Alpha) • B1 (Beta)	*Final round – nothing changed or added*
Σ	**27**	**Validation Points**	

3.4 Findings: Patterns of AI Strategy-Making

3.4.1 Individual-Case Snapshots

Alpha:

Alpha initiated its AI journey through bottom-up impulses rather than formal strategy. Two triggers shaped this entry: an employee-driven initiative "the initial spark… due to his disability" (A2) and concerns about knowledge loss from retirements "information drain due to retirements" (A2). Instead of developing a comprehensive strategy, the organization deliberately prioritized a simple pilot to "gain momentum" (A1), implementing an AI-based image recognition tool for quality control. The focus was on speed and visible impact rather than long-term planning, emphasizing "not … a big AI strategy … but … immediate value" (A1).

Early success led to strong employee engagement and the emergence of additional use cases. Coordination gradually evolved, with an internal AI coordinator and external partners supporting experimentation. While this approach generated rapid momentum, governance structures only developed later, as Alpha began transitioning from isolated pilots toward a more integrated AI strategy.

Beta:

Beta followed a top-down, governance-driven entry logic, embedding AI within a broader DT strategy. A dedicated unit defined a cross-functional agenda including "cultural change, Industry 4.0 … and … artificial intelligence" (B1). However, despite these formal structures, implementation lagged, with the organization acknowledging that initially "nothing had been implemented yet" (B1).

Efforts focused on planning and alignment, including workshops to identify use cases and the development of company-wide AI guidelines. While these activities created organizational clarity and structure, they did not translate into sustained momentum. Over time, the organization concentrated on a limited number of use cases, with centralized coordination and training initiatives such as "an AI course … pushed out to everybody" (B2). Overall, Beta illustrates how a governance-first approach can result in strong alignment but limited early value realization.

Gamma:

Gamma, the most mature case, also began with a governance-driven approach, initiated by a top-level strategic mandate to embed AI across the organization. A central AI unit was established early, while employees were encouraged to experiment within this structured framework. Over time, the organization increasingly emphasized measurable impact, with management highlighting that "now we want to see that it works, that it pays off" (G2).

Crucially, Gamma complemented its initial governance focus with mechanisms to generate momentum at later stages. As reflected in the strategic vision, "every Gamma product … [must be] manufactured with AI or contain AI" (G2), AI became a central element of competitive advantage. Local AI coordinators, tailored training programs, and the integration of shop-floor employees enabled the continuous identification and implementation of use cases. This combination allowed Gamma to scale AI across sites and embed it into core operations, ultimately achieving sustained AI capability

development. An extended description of the AI implementation trajectories of the three case studies is included in Appendix F).

3.4.2 Cross-Case Patterns: Journeys towards Digital Intelligence Maturity

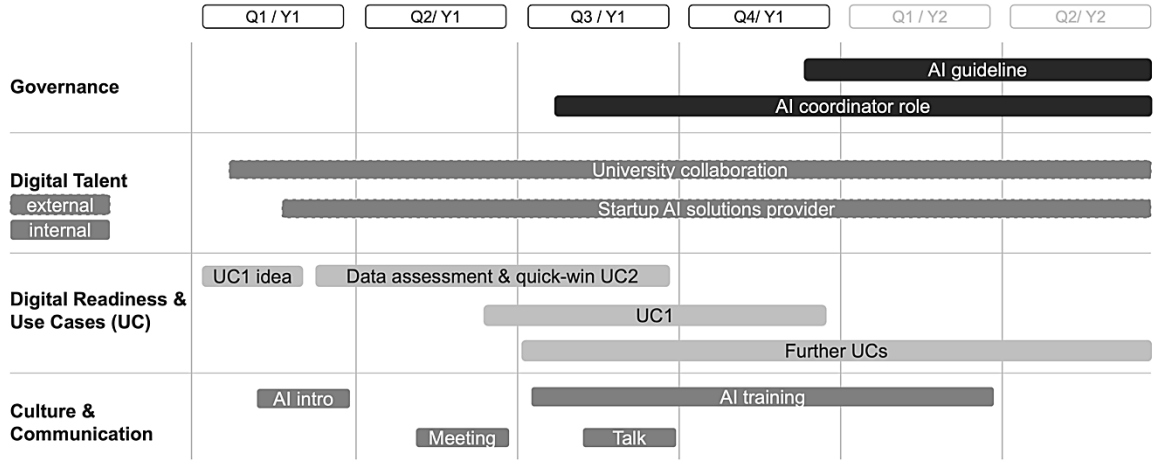
This section provides a juxtaposition of each firm's AI journey. Across every case, we identified the strategic building blocks that all organizations pursued: governance (Hess et al., 2016), digital talent (Gilch & Sieweke, 2021), digital readiness (Bharadwaj et al., 2013), and culture and communication (Proksch et al., 2024), reflecting core dimensions in contemporary literature. In Figure 6, these building blocks visualize which company pursued a governance- or momentum-driven approach. To further explain the figure: If an implementation started in June 2022, Q1/Y1 would end in September 2022. Judging by the time and depth the companies have been pursuing their Digital Intelligence Transformation for, our cases contain AI beginners (Alpha), intermediates (Beta), and leaders (Gamma) (Riedel et al., 2024).

Synthesizing these insights into a cross-case comparison, it becomes evident that two entry logics emerge (see Table 15). Alpha follows a momentum-driven entry logic, initiating AI through localized use cases and employee impulses. In contrast, Beta and Gamma adopt a governance-driven entry logic, starting with centralized strategy formulation and structural alignment.

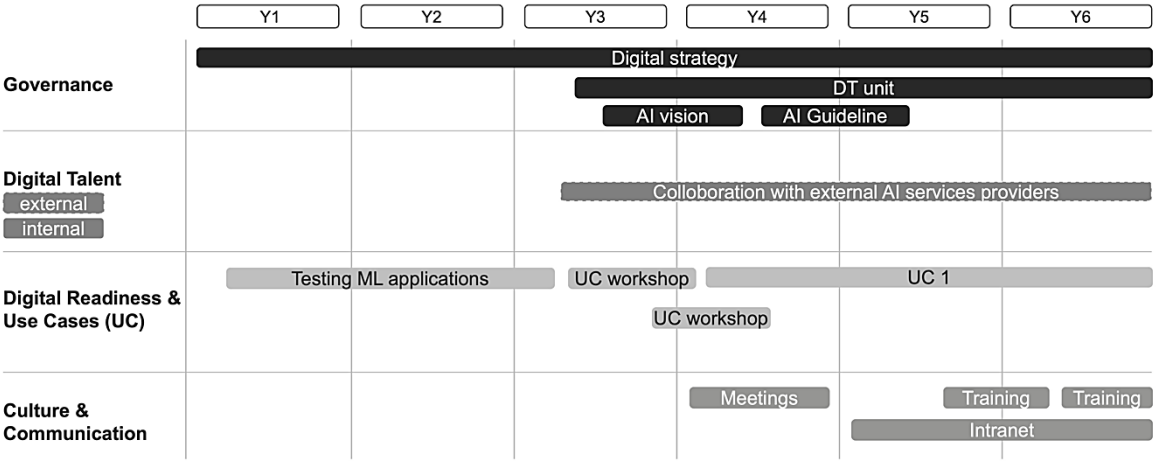
Table 15. Systematic Comparison of Cases

Dimension	Alpha	Beta	Gamma
Entry Logic	Momentum-driven	Governance-driven	Governance-driven
Trigger	Retirement (internal)	Competitive pressure (external)	Cost pressure (external)
Key Challenge	Lack of structure	Lack of execution	Integration
Outcome	Momentum	Stagnation	Digital Intelligence Maturity

Alpha: AI Beginners



Beta: AI Intermediates



Gamma: AI Leaders

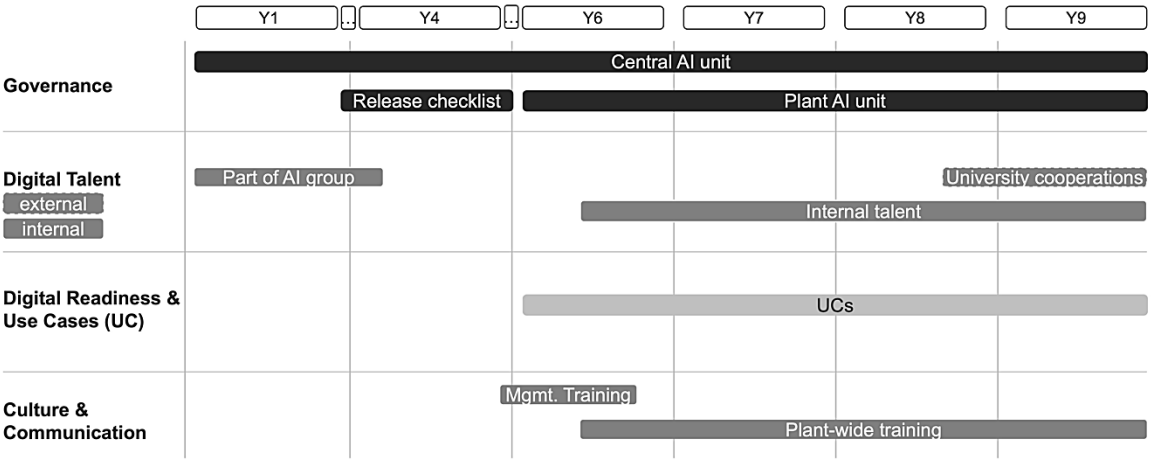


Figure 6. The Contrasting Journeys towards Reaching Digital Intelligence Maturity

In Alpha, early value creation is driven by rapid implementation of simple use cases, which generate visibility and employee engagement. This creates organizational momentum, enabling further experimentation. In Beta and Gamma, value creation is initially expected through strategic alignment and infrastructure development. However, without early implementation, this mechanism may delay tangible outcomes, as observed in Beta. The cases reveal that sustained value creation depends on sequencing both mechanisms. Gamma demonstrates how initial governance can be complemented by later momentum through localized experimentation and training. Across cases, a fundamental tension emerges between establishing organizational control (governance) and generating implementation momentum. While governance enables scalability and alignment, it may hinder early progress. Conversely, momentum accelerates adoption but risks fragmentation.

The cross-case comparison suggests that the effectiveness of each entry logic depends on organizational context. We identified differences in strategic priorities, organizational structure, and change readiness across the three cases. Centralized organizations with strong strategic alignment (Beta, Gamma) tend to benefit from governance-driven approaches. In contrast, decentralized or resource-constrained organizations (Alpha) benefit from momentum-driven entry. These insights form the basis of the decision logic embedded in the AI Strategy Compass.

3.5 A Practitioner’s AI Strategy Compass

Building on real-world data, we provide a hands-on guide for practitioners looking to implement AI in their organization throughout this section. From discovering the most suitable strategic approach to the specific steps to become AI leaders, managers will find concrete guidance for AI strategy-making. Eventually, we also discuss seven key learnings derived from our practice cases that hold actionable insight into how to avoid common pitfalls on the way to Digital Intelligence Maturity. Rather than offering another static maturity model, the AI Strategy Compass functions as a decision-support tool that helps organizations resolve the tension between governance and momentum under varying contextual conditions.

3.5.1 Selecting a Suitable Approach: Governance- vs. Momentum-Driven

Managers face the challenge of deciding whether the momentum- or governance-driven approach will better serve their organization. Especially, since “instead of being complementary, these processes may be misaligned and result in conflicts and tensions” (Poláková-Kersten et al., 2023, p. 2). To provide managerial guidance, the first part of our AI Strategy Compass forms the decision tree (see Figure 7). After iterative testing and refinement, the tree consists of four core questions to identify the suitable approach for a given firm as well as three follow-up questions per approach to assess the AI implementation maturity.

The four core questions resemble the following organizational domains decisive for AI strategy-making: *competitive strategy* (Q1), *organizational structure* (Q2), *site integration* (where applicable) (Q3), and *change readiness* (Q4). Although numbered, this order does not imply a hierarchy or relative importance. Instead, the figure serves as a structured visual guide to facilitate later referencing. The questions are phrased positively with yes/no answers, with the legend explaining the interpretation in detail.

The first question concerns the firm’s *competitive strategy*. Following strategy and management literature, market conditions shape how firms compete and thus influence strategy formation. As reflected in our cases and expert interviews, two main strategies emerge: Firms facing high-cost pressure focus on efficiency by exploiting existing processes, resembling a cost strategy (Porter, 1979) and defender behavior (Miles et al., 1978). Alternatively, firms emphasize innovation through differentiation and exploration, aligning with a differentiation strategy (Porter, 1979) and prospector behavior (Miles et al., 1978). Accordingly, Q1 asks whether firms prioritize process efficiency over differentiation; if yes, a governance-driven approach is recommended.

The second question is about *organizational structure*. Competitive strategy is often mirrored in a firm’s structural design: efficiency-oriented firms tend to be centralized, while innovation-oriented firms are more decentralized (Miller, 1987). This structure shapes AI implementation possibilities, since centralized organizations tend to rely on top-down decisions, whereas decentralized ones enable bottom-up initiatives. However, firms may also still exhibit centralized structures while shifting toward innovation. Therefore, Q2 asks whether the organization is centrally structured; if yes, a governance-driven approach seems more favorable.

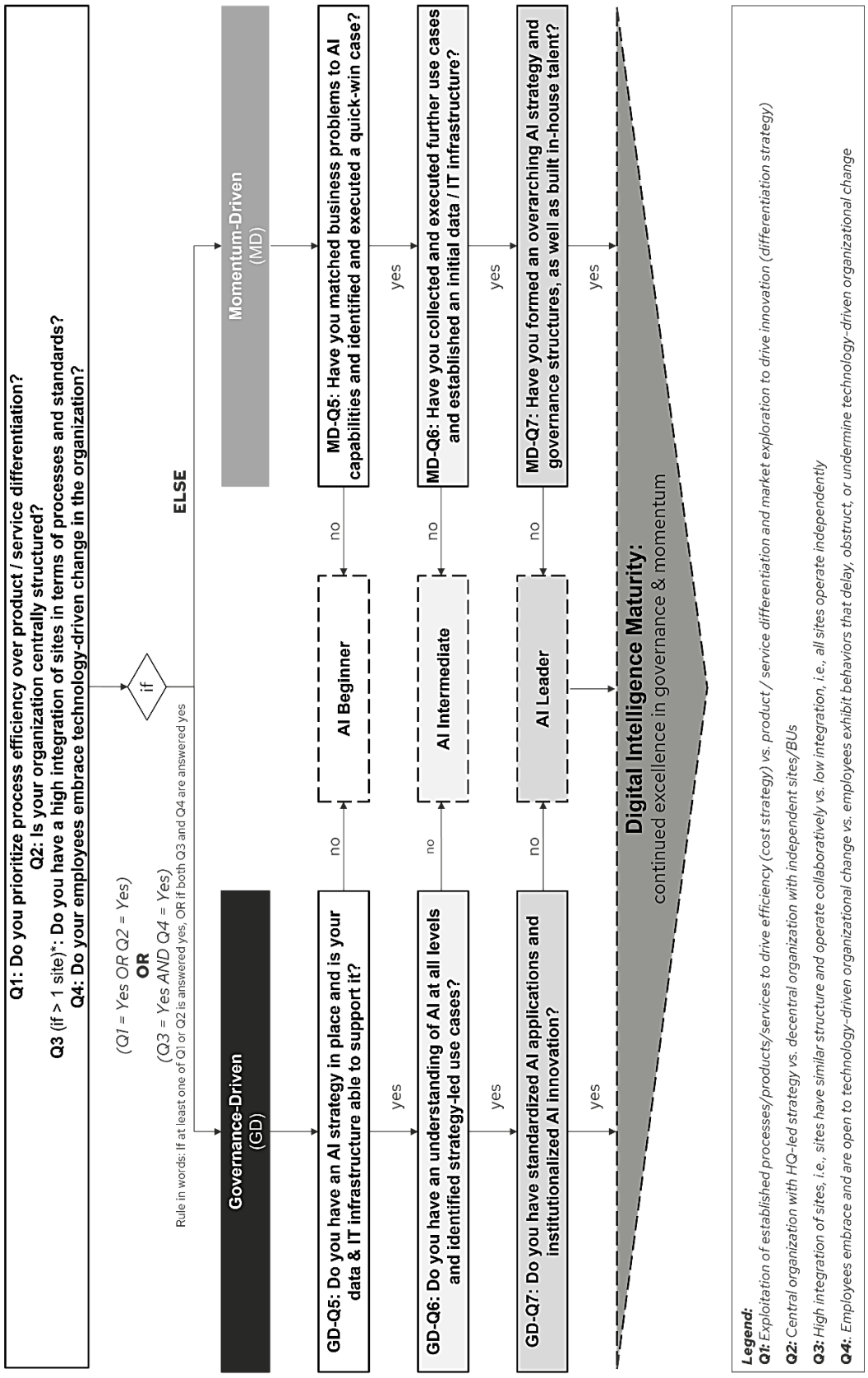


Figure 7. Strategic Decision Tree: Momentum-Driven or Governance-Driven Approach?

The third question on *site integration* applies only to multi-site organizations. We distinguish between highly integrated organizations with standardized, collaborative sites (i.e., a lead plant and other plants which copy its processes globally) and those with largely autonomous units. Prior research shows alignment between site integration and competitive strategy, where "output control and high resource sharing are associated with higher effectiveness for a low-cost strategy" (Govindarajan & Fisher, 1990, p. 259). If applicable, Q3 asks whether a firm's sites are highly integrated.

The final question addresses an organization's technical *change readiness*. Beyond structure and environment, employees' acceptance of technological change strongly affects outcomes. Acceptance may be inherent, for instance among workers who are digital natives, or it can be fostered through pioneering employees and workshops (Goto, 2021). Thus, Q4 asks whether employees embrace technology-driven change.

Summing up the decision tree (see Figure 7), answering yes to at least one of the questions Q1 or Q2 suggests a governance-driven approach, independent from other answers. If Q3 and Q4 are both answered with yes (applicable to multi-site organizations), this also indicates the governance-driven approach, independently from answers to the other questions. For all other combinations, a momentum-driven approach is recommended. In essence, this means that organizations which pursue differentiation, are decentralized, and weakly integrated across sites benefit from small-scale AI projects to build acceptance and realize value despite potential site autonomy. This holds especially true if they face change resistance, but the approach can also be pursued if employees embrace technological change in startup-like cultures.

Hence, let Q1, Q2, Q3, Q4 be Boolean variables where True = Yes, False = No, the full decision rule can be summarized as:

$$Decision = \begin{cases} Governance - Driven, if\ (Q1 \vee Q2) \vee (Q3 \wedge Q4) \\ Momentum - Driven, otherwise \end{cases}$$

Once the strategic approach is identified, the decision tree also guides the assessment of a firm's AI implementation maturity. For both approaches, organizations can be classified as AI beginners, intermediates, or leaders, ensuring our decision tree's applicability for firms at different maturity levels. While the questions GD/MD-Q5–Q7 highlight only the key steps at each level, all recommended steps at a given level in our framework should be completed before progressing to the next (see Figure 8).

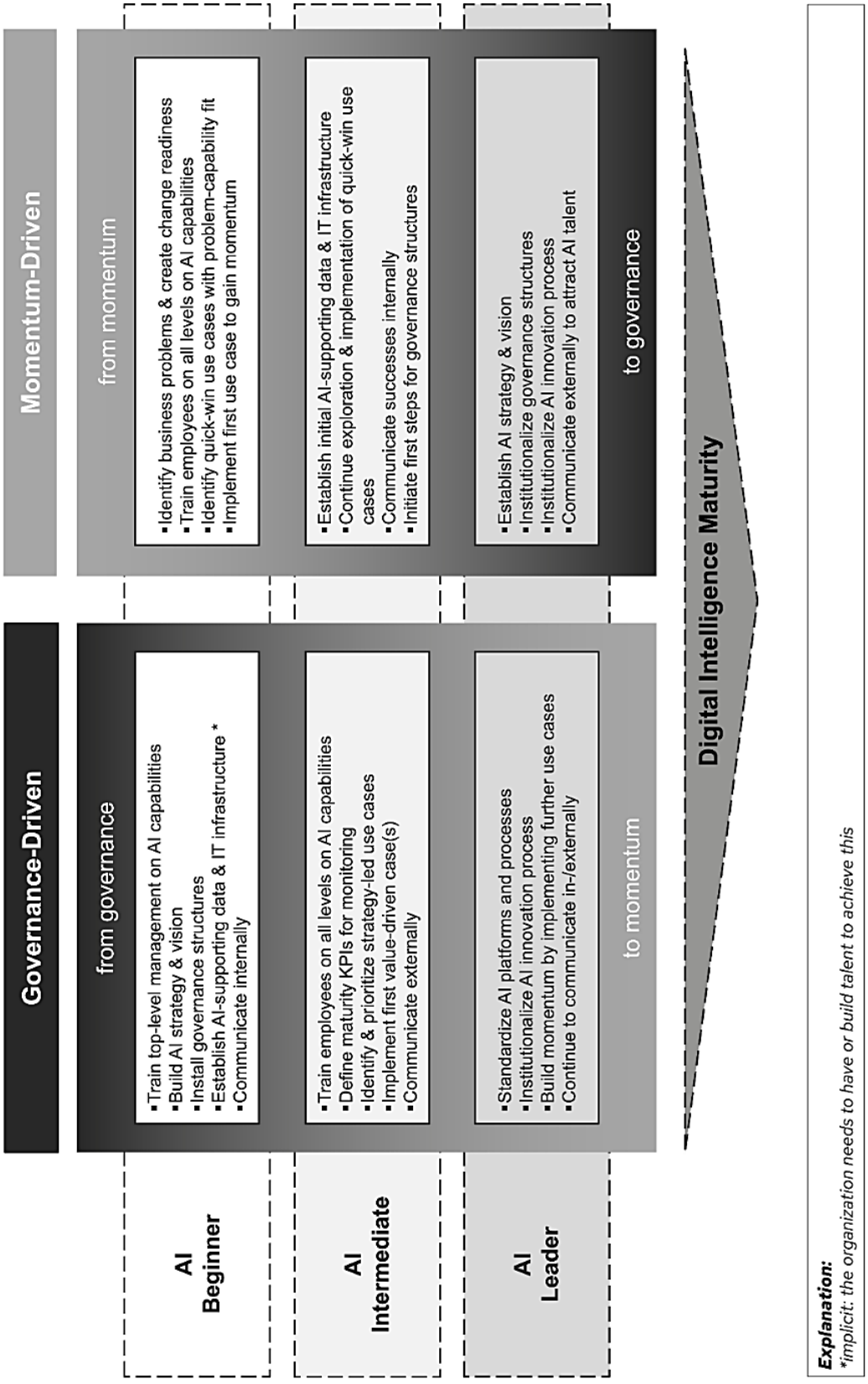


Figure 8. Digital Intelligence Maturity Framework

For the *governance-driven* approach, the first question assesses the existence of an AI strategy and supporting data and IT infrastructure (GD-Q5). Organizations lacking both are classified as AI beginners. If these foundations exist, however, the next question examines organization-wide AI understanding and strategy-driven use case identification (GD-Q6). Without this, firms remain at the intermediate level. If an AI understanding and use cases are established, the final question addresses the existence of standardized AI applications and institutionalized AI innovation, meaning a continuous and formalized approach to AI use case identification and implementation aligned with business strategy (GD-Q7). Firms that have not yet achieved this operate at the AI leader level; those that have attained all steps there reach *Digital Intelligence Maturity*, which must be continuously maintained.

For the *momentum-driven* approach, the first question focuses on having matched business problems to AI capabilities and implementing an initial quick win case (MD-Q5). Without this, organizations are AI beginners. If a first case has been realized, the next question assesses whether further use cases and data and IT infrastructure have begun to emerge (MD-Q6). If not, the organization remains intermediate. If yes, the tree further evaluates whether AI strategy, governance, and in-house AI talent have been established (MD-Q7). If achieved, the organization reaches *Digital Intelligence Maturity*; otherwise, it must pursue the missing AI leader steps. Appendix G) shows the exemplary application of the decision tree for the three case companies.

3.5.2 Implementing the Chosen Approach: Achieving Digital Intelligence Maturity

Having selected the more suitable approach and defined the AI implementation maturity level, our Digital Intelligence Maturity framework provides actionable guidance for progressing from AI beginner to AI leader (see Figure 8). Organizations can achieve Digital Intelligence Maturity by building either momentum or governance first, following the framework's steps at each level. *AI beginners* initiate implementation by prioritizing either governance through strategy or momentum through early investments. At the *AI intermediate* level, the efforts in this dimension are intensified while the complementary dimension is developed. As *AI leaders*, organizations institutionalize this second dimension to ensure sustained AI excellence. The following paragraphs describe these

steps as a guiding blueprint rather than a rigid prescription. To mitigate potential pitfalls along the way, key learnings from our case companies are discussed in section 3.5.3.

We first describe the *governance-driven approach*, which emphasizes establishing direction before investing in AI projects. At the *AI beginner level*, top management must develop an understanding of AI capabilities as a prerequisite for strategy formulation. Based on this understanding, organizations can define an AI strategy and vision, aligned with their overarching goals. Beta, for example, embedded AI as a pillar within its corporate strategy, while Gamma articulated a clear strategic mandate: “Every Gamma product is either manufactured using AI or contains AI” (G2). Next, governance structures are established, including clear leadership responsibilities and AI-related policies aligned with regulations. At Beta, they established “an AI policy … [which] took a long time to get approved with the workers council” (B2). Before being able to scale AI use cases, an AI-supporting data and IT infrastructure must be developed. As noted by a Gamma executive, “the AI strategy always sounds so grand, but one of the key requirements … was to develop an AI-enabling IT infrastructure” (G1). Reliable data collection, for example, through sensors, and an infrastructure capable of storing, connecting, and harmonizing data form the basis for AI implementation (Hess et al., 2016; Holmström, 2022). We recommend that firms make use of contemporary digital readiness assessments, particularly with a focus on technology management and required capabilities (KPMG, 2025; Nguyen et al., 2020; Schumacher et al., 2019). Additionally, building internal AI talent is critical, as it influences the speed and autonomy of experimentation (Enholm et al., 2022). In this context, in-house digital units with AI expertise enable the realization of AI strategy. Finally, early internal communication is essential to prevent employee resistance, a critical concern emphasized by our interviewees (B1, E3).

Having completed these steps, organizations advance to the *AI intermediate level*. Employees are now trained across all levels to translate governance into action, fostering the creation of a “data-driven mindset” (G1). It is important to keep the skill and experience levels of targeted employee groups in mind at this point: At Gamma, the centrally developed AI training was adapted for “the colleagues … [working] on the machines” (G1). To monitor progress, organizations should also define Digital Intelligence Maturity KPIs aligned with their strategy, such as infrastructure, quality, cost,

and delivery performance. Beta applied the “OKR method, adapted to change processes and change projects” (B1). At this stage, early momentum emerges by identifying and prioritizing strategy-aligned use cases together with individual business units or sites. Building on prior work on identifying use cases, the ‘AI use case canvas’ can help to identify, collect, and evaluate use cases at this point (Brakemeier et al., 2023). At Beta, the central team also supports “sites with use cases and different parts of the strategy to help them with their local strategy” (B2). These efforts should culminate in at least one value-driven use case being implemented, followed by external communication where appropriate.

At the *AI leader level*, the objective is to create excellence in both governance and momentum. Standardized AI platforms and processes enable scalable, value-driven implementations. At Gamma, “to develop AI models, you first define clear, clear rules and standards” (G1), enabling “centralized solutions that are suitable for all plants” (G2). AI innovation must also be institutionalized through continuous training, workshops, and central hubs that facilitate knowledge exchange. The ongoing identification and implementation of value-driven use cases remain essential at this level.

The *momentum-driven approach* follows a reverse logic, emphasizing early investments and quick-wins through rather simply implementable lighthouse use cases before governance structures are fully developed. At the *AI beginner level*, organizations start by identifying business problems first to foster a readiness to change the status quo. One way to approach use case identification has proved particularly relevant when mentoring practitioners: matching one’s business problems with potential AI application areas. The technology proves highly effective in four problem domains: assignment, grouping, forecasting, and generation (Kelnar, 2019). *Assignment* refers to labeling, assigning data to known categories, or establishing the degree of connection between data points via regression tasks. A potential application would be to recognize certain patterns or logos in visual data. *Grouping* or clustering allows for, i.e., identifying social subgroups within a customer base for enhanced targeting. With sequencing time series data, future changes can be *forecasted*, i.e., predicting the probability of equipment failure in the predictive maintenance of machinery. Lastly, the *generation* of output like image, text, sounds, or voice, given an input, can for example be applied to customer service contexts including a chatbot (Kelnar, 2019). Employees across all levels are then trained in such AI capabilities, often with external partners that offer AI

knowledge and experience. At Alpha, employees received “a little [AI] training” (A1) through the collaboration with a university and an AI startup. Such training supports AI acceptance and helps identify initial use cases. Pilot cases should address pressing employee-relevant problems and be easy and fast to implement. At Alpha, they “asked internally where the shoe pinches most” (A1) and deliberately chose simplicity to “convince … [the] employees” (A1).

Moving to the *AI intermediate level*, establishing governance becomes more prominent. Organizations begin to develop a basic data and IT infrastructure while ensuring compliance with internal regulations. At Alpha, “a very extensive works agreement was proposed by the works council” (A2), increasing internal acceptance. A continued exploration of additional use cases should lead to further implementations. Workshops within individual departments can support this process, like at Alpha, where “the colleagues [got] involved in the decision-making process” (A1). Additionally, internal communication on the early success with the initial use case(s) is key. Doing so helps build trust and strengthens employee support for additional use cases, especially in large corporate constructs. Alpha, for example, presented its AI “initiatives at group level … [communicating the] roadmap and, for example, the [AI] simulation game” (A1). At this level, initial governance structures are formed, such as appointing an AI coordinator or establishing an AI team, exemplified by Alpha’s “AI officer” (A1).

Reaching the *AI leader* level, it is all about creating excellence in both dimensions. Momentum-driven organizations now need to create an overarching AI strategy and vision that can connect their silo projects and guide future AI decision-making. This is accompanied by forming a clear governance structure. It includes defining responsibilities of the AI coordinator(s), and scaling expert groups that support departments in identifying and implementing use cases. Further, initial workshops to train employees and identify use cases must be institutionalized to ensure a continued exploration of potential cases. While it comes down to a make or buy decision regarding AI, a continued communication of the organizational progress can attract AI talent, building in-house capabilities for the future. The availability of AI talent within an organization affects the speed and autonomy of AI experimentation (Enholm et al., 2022). Such expertise is critical for translating the AI strategy and vision into practice.

Regardless of whether organizations follow a momentum-driven or governance-driven approach, Digital Intelligence Maturity is achieved once all three levels are completed.

At this stage, organizations are equipped to continuously implement digital change, especially regarding AI and its evolving capabilities. Since this is not a fixed end-state, organizations must continue to excel in both dimensions to keep mature.

3.5.3 Key Learnings: How to Avoid Pitfalls

Studying the individual AI implementation approaches of the three case companies, we not only derived strategic blueprints, but we also sat down with the managers to talk about their unique challenges and best practices. After refining our interview and observational data, breaking these insights down into actionable advice, we derived seven key learnings that can be directly applied in practice. An overview of these learnings and which organization they stem from is presented in Table 16, where it also indicated whether the learning pertained to a momentum-driven or governance-driven approach.

Table 16. Seven Key Learnings to Avoid Pitfalls

No.	Key Learning	Case	Approach
1	Just get started - fail fast	Alpha	Momentum-driven
2	Create your AI ecosystem, partner up with startups and universities to learn		
3	Take your employees with you on this journey, create guidelines for safe AI use		
4	Don’t kill AI’s affordances with being overly risk-averse and bureaucratic, be bold and trust your employees	Beta	Governance-driven
5	To make a governance-driven strategic approach work, create a dedicated change management team		
6	Think of infrastructure first, use cases second, when looking to scale in large corporations	Gamma	
7	Educate your field-level employees on AI early on to find use cases, select based on scalability and potential for value creation / cost savings		

The first three learnings are derived from the case study with Alpha, which follows the momentum-driven approach and is categorized as AI beginner.

Learning 1, “Just get started, fail fast”, highlights that organizations that decide to prioritize momentum should start promptly with identifying their quick-win cases and investing in them. *“For the first one [it is important] to be really good and quick to implement, so that you don't set up a one- or two-year project, but then everyone forgets”* (A5). If the organizational culture is characterized by its general openness to change, employees will have an easier time experimenting with new technologies; they might even actively push for their application, as the initiative by the visually impaired worker’s council member at Alpha showed. Failing fast means not a lot of resources should be wasted on planning every detail; instead, minor, calculated investment risks should be taken to assess AI’s potential in this domain first-hand. This is why Alpha decided against the initially proposed idea and went for a small-scale use case first. At the beginning of any AI journey, organizations can fail fast without major consequences. At this level, employee trust is not yet at risk, and momentum can still be used effectively, even if initial attempts require restarting.

Learning 2, “Create your AI ecosystem, partner up with startups and universities to learn”, emphasizes that a strong AI ecosystem can substantially support progress. Thinking back to Alpha, the organization had little digital talent and change readiness across business units to begin with. Hence, if firms face this challenge, it is important to create an experienced network of supporters and collaborators that can support the identification and execution of use cases. When organizations prefer not to collaborate with large consultancies, which may be due to financial reasons or personal convictions, partnerships with startups and universities can provide deep expertise while remaining closely connected to the organization’s context and challenges.

Learning 3, “Take your employees with you on this journey, create guidelines for safe AI use”, accounts for the fear that might be associated with the use of new technologies like AI. Even though a momentum-driven approach is pursued, signaling a culture generally open to change, employees of all levels still need to feel secure in what to expect. Hence, establishing a solid baseline through AI guidelines is essential. In parallel to identifying the first quick-win use cases, the later AI coordinator of Alpha emphasized the following:

> *“It would be beneficial for us to establish guidelines for this issue. Since we have a directive, we should define what we are permitted to do, what we are not permitted to do, and what AI actually is, thereby establishing a framework.” (G1)*

In combination with actively involving employees, such guidelines help build trust, set clear boundaries for implementation, and provide a transparent framework. Thereby increasing the likelihood of successful AI adoption.

The next two learnings stem from the case study with Beta, the AI intermediate that chose a governance-driven approach. **Learning 4**, "Don't kill AI's affordances with being overly risk-averse and bureaucratic, be bold and trust your employees", stems from some frustration with Beta's implementation progress. A few years ago, the organization had commenced its AI journey with a clear commitment to a governance-driven approach. Considering the firm characteristics, the approach fits the context well. However, the organization currently struggles with building up the momentum dimension, as it prioritizes safety over innovation. Having built its governance structures, it struggles to translate the envisioned change into action.

> *"Data protection in Germany can be very restrictive, especially when you're a conservative company. We're … very security-oriented. Our AI environment has no internet access. ... and these are the kinds of things, the synergy effects and efficiency gains you get from AI, that disappear again. ... Sometimes, I feel like there's a lack of proportionality, and I simply wish for more courage." (B1)*

Hence, organizations should avoid being overly risk-averse or bureaucratic in their AI initiatives. Being bold and trusting employees can yield the greatest success, as this approach allows organizations to directly address employee pain points and develop solutions that target their actual needs.

Learning 5, "To make a governance-driven strategic approach work, create a dedicated change management team", ensures that the process does not stop with strategy-making. Since governance-driven approaches are recommended for efficiency-focused, centralized, or change-resistant firms, it is crucial that strategic efforts are supported by active change management. In Beta's case, employees currently feel they lack in the domain crucial for building up momentum: *"For me, this is not top-down, it's more like top-to-the-middle, and that's it. It wasn't fully broken down all the way"* (B1). Instead, a change management team should involve employees at all organizational levels, and monitor, track, and communicate efforts. This keeps the organization accountable and enables it to put strategy, ideas, and KPIs into practice.

Finally, the case study with Gamma, the AI leader that is part of a large, longstanding yet innovative firm, provided unique learnings for larger or geographically dispersed firms, especially in the field of production. **Learning 6**, “Think of infrastructure first, use cases second, when looking to scale in large corporations”, demonstrates that successful long-term AI implementation requires a strong IT and data infrastructure. In larger firms that have different sites executing similar processes, it is not economically valuable to develop individual silo projects, that may not be interoperable. Since data sharing and IT infrastructure form the foundation for AI use cases and their scalability, this basis should be strong first.

Learning 7, “Educate your field-level employees on AI early on to find use cases, select based on scalability and potential for value creation / cost savings”, refers to the importance of creating momentum after governance is established. Firms with this strategic approach, first, should not forget to install mechanisms through which valuable use cases can be found. Even if the organization’s strategists are well informed about the benefits and potential of a new technology like AI, this knowledge needs to be passed on to the field-level employees. To achieve process-optimization and innovation, these people must be enabled to spot and communicate high value cases. Second, for putting them into practice, Gamma prioritizes those with high scalability, and focuses on solutions with substantial value creation or cost-saving potential.

3.6 Concluding Remarks

Our study synthesizes the dispersed contemporary approaches to AI strategy-making, as described in practitioner and academic literature, and differentiates them into two main methods: governance- and momentum-driven. This synthesis is complemented by our empirically derived AI practitioner Strategy Compass, with which we hope to offer managers (i) the long-sought-after guidance to identify the strategic approach matching their organization’s context. Not focusing narrowly on only one industry, we determine five questions for any organization that together determine whether the governance- or momentum-driven approach can be more suitable. While our sample consisted of organizations in decade-old, traditional industries, we would argue our decision criteria are independent of organizational set-up or field of industry. Our 27 vali-

dation points including interviews with experts from various industries and organizational structures further underlined this. However, future applications and empirical studies could validate this assumption.

This study also (ii) aids in executing the selected strategic approach through the Digital Intelligence Maturity framework. For both approaches, we define specific steps to take from AI beginners to AI leaders. Eventually, it leads to having built up both the momentum and the governance dimension. Together, they ensure a continued strategy-stringent investment into AI, supported by the digital talent and digital readiness of the firm. Concurring with former DT frameworks, we also argue that maturity is not a stable end-state (Westerman et al., 2012). To achieve Digital Intelligence Maturity and stay an AI leader, it is not enough to have invested in some initial projects and to have determined governance structures in one's firm and then call it a day. Leaders must foster the organization's continuous evolvement in both domains to keep the firm mature in the long run.

Additionally, we present (iii) seven key learnings that became evident through following Alpha's, Beta's, and Gamma's AI journey. Through covering unique contexts and AI implementation maturity levels with these firms, we are confident to have surfaced the most crucial best practices and cautionary tales to enable future AI leaders to make great strategic decisions. We invite practitioners as well as researchers, however, to further study edge cases. What we learnt through our cases is that AI implementation lives from the vivid exchange within a broad ecosystem.

In summary, empirical evidence suggests that the central managerial challenge in AI strategy implementation is not strictly choosing between governance and momentum. Instead, it is learning to sequence and balance both dimensions, depending on the unique organizational context. For practitioners, the decision tree and maturity framework provide actionable guidance, through breaking down implementation in manageable steps. Further, the Digital Intelligence Maturity framework is not only helpful for top management regarding the selection and implementation of a strategic approach, "it would also be helpful for any internal communication regarding a firm's AI strategy, so that all know what comes next" (E3), as an expert emphasized. Generally, the key takeaway is that managers cannot afford to become overly focused on one dimension; they must avoid fragmentation in momentum-driven settings, and over-bureaucratiza-

tion in governance-driven ones. Hence, our study explains that Digital Intelligence Maturity requires organizational ambidexterity in both dimensions: displaying governance capabilities without extinguishing bottom-up innovation and sustaining momentum without cannibalizing strategic alignment.

Lastly, our findings also contribute to research on AI strategy by shifting the focus from general characteristics of AI as a digital technology to the strategic logic through which organizations actually implement it. Recent work argues that AI does not fundamentally challenge established dimensions of DT strategy frameworks (Hess et al., 2016; Wurm et al., 2025), and that contemporary business strategy is inherently digital in nature (Bharadwaj et al., 2013). While we agree with this general premise, our findings show that organizations follow qualitatively different pathways when translating AI potential into organizational practice. However, we also want to emphasize that the actual implementation of AI does have several steps to it that are distinct from previous implementations of digital technologies: Take, for example, the data-driven decision training of existing employees, or hiring specific AI talent. Also, the topic of IT infrastructure and data governance becomes a lot more prominent with AI applications compared to previous technological innovations. Additionally, considering the speed of innovation and competitive pressures, executing quick-win use cases may become a much more common approach to implementing AI. Our analysis reveals how organizational conditions, including structural complexity, leadership orientation, and legacy systems, influence whether firms rely on centralized governance or decentralized experimentation, and how each approach entails distinct trade-offs between control, speed, and value creation. In doing so, we extend existing research on DT by introducing a processual and contingency-based perspective on AI strategy. Rather than treating AI implementation as a uniform progression, as implicitly assumed in many maturity-oriented perspectives, we show that organizations must navigate between competing strategic logics depending on their specific context. This perspective is further operationalized through the AI Strategy Compass, which translates these empirically grounded insights into a decision-oriented framework that supports both analysis and action. In sum, while AI is indeed just another novel technology within the grand spectrum of digital change, it does warrant further, in-depth empirical study. The progress of its unique self-learning abilities offers unprecedented potential for large-scale organizational and societal impact (Hutzschenreuter & Lämmermann, 2025); but only, if

managed correctly. Taken together, our study contributes a mechanism-based and decision-oriented understanding of AI strategy, explaining not only what organizations do when implementing AI, but why different strategic pathways emerge and under which conditions they are effective.

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3.8 Appendix

D) Overview of Case Companies

Alpha

Alpha is a globally active, yet EU-focused small and medium-sized enterprise (SME) that has evolved into a leading player in the chemistry industry. The company is headquartered in Germany and employs less than 250 people. In the 21st century, it underwent two subsequent acquisitions, placing the previous family firm into the structures of a larger corporation. Now, the firm operates within a decentralized corporate structure, which grants a high degree of autonomy. Over the past 100 years, Alpha has expanded its portfolio to further application areas in the chemistry field.

The organizational structure of Alpha is characterized by a functional configuration, featuring a central management team and business units aligned with the company's divisions. Strategic oversight is exercised by the general manager in conjunction with senior management. In the past year, the company underwent a leadership transition, resulting in the appointment of a new general manager (GM). Following the emergence of AI as a topic of interest within the workforce, the GM assumed responsibility for advancing the company's AI agenda and designated the company's lead accountant as Head of AI. Since the holding company manages its organizations, including Alpha, decentrally, Alpha also adopted a similarly independent and decentralized approach when implementing the new technology within its own business unit.

> *"We don't want to do this top-down, but rather we want to provide some training for our colleagues or give them an overview of what AI is, what possibilities there are and let our colleagues deal with it. At the same time, the training will also generate ideas about where we have starting points. ... To us, it is very important not to develop a big AI strategy and generate lots of PowerPoint presentations, but … to immediately demonstrate value for our employees. How can AI relief our employees, perhaps make them better, increase productivity and speed, so that we can also work faster and improve our cost position?" (A1)*

Currently, there is no comprehensive digital strategy in place but, within the leadership board, there is an awareness that action is needed. Despite its traditional roots, Alpha has opted for a rapid entry into AI-driven transformation by initiating the first quick-win

project. The company supports its employees through a range of AI workshops aimed at disseminating knowledge and encouraging the development of new use cases. Alpha's transformation illustrates the significance of instilling a change culture among employees and highlights the critical role of their motivation in driving transformation. Overall, the company culture can be described as progressive, characterized by an openness to transformation and change, leading to Alpha adopting a momentum-driven approach to innovation and transformation.

Beta

Beta is a globally active, family-owned enterprise that has evolved into a leading player in the polymer processing industry. Headquartered in Central Europe, Beta is active in over 20 countries and employs around 5,000 people worldwide. With a history close to the 100-year mark, the firm has continuously expanded its portfolio, now serving multiple industries, including healthcare, automotive, construction, energy, and communication. As of the early 2020s, their annual revenues placed Beta among the top-tier global firms in its segment.

The organizational structure is characterized by a multi-divisional configuration, with business units aligned with the firm's application domains. Strategic oversight is exercised by a multi-member executive board. Notably, the company underwent a generational transition in its leadership team in recent years, which included the institutionalization of a dedicated digital transformation unit reporting directly to the board. Furthermore, a corporate innovation unit was also installed, leading intrapreneurship activities and startup collaborations.

> *"As part of our business strategy for 2020 to 2025, we developed a cross-functional agenda. Cross-functional means that all business areas were involved, including central departments such as Corporate Innovation, where we worked together to consider what a digital transformation or a digital Beta should look like in 2025. This essentially resulted in four elements. Cultural change, Industry 4.0, new business models with data in general, and as the fourth, I believe artificial intelligence as a separate topic."* (B1)

Before that, there was no digital strategy in place. Considering this background, Beta's transformation trajectory exemplifies the challenging duality of continuity and change in industrial-age family firms. Coming from the ethos of a traditional, value-driven industrial enterprise, the firm has recently embarked on a comprehensive renewal under

the umbrella of its 2025 strategy. However, while numerous blogposts by management and press releases underline these ambitions regarding digitalization, sustainability, and cultural change - in reality, the organization still operates mostly under the premise of top-down control and creating safety through strong leadership. Currently, the culture is still rather conservative, with the board actively strategizing for change management.

Gamma

Gamma is a regional production site of a globally active technology group. Located in Central Europe, the Gamma plant specializes in precision manufacturing of automotive parts. As part of a multinational conglomerate with over 400,000 employees, the site stands out as a flagship facility for industrial digitalization and industry 4.0 technologies. While the facilities and layouts are decades-old, the machines and systems involved are highly technology-driven. “We don’t think in departments, we think in systems” (Gamma website), remarked one of Gamma’s internal Industry 4.0 specialists, highlighting the horizontal integration philosophy underpinning g digital initiatives.

> *"Together with the team here, I have set up a complete AI-enabled IT infrastructure, which is … an essential part of our AI strategy. … The product we manufacture is not only produced at one location, but at various locations around the world, and we are trying to develop strategies and solutions that we can scale to other locations as quickly as possible. Since we are a so-called lead plant, we want to transport solutions from the lead plant to the sister plants." (G1)*

In recent years, Gamma’s transformation has been particularly driven by initiatives around predictive maintenance, real-time quality analytics, and energy-efficiency optimization through AI. One illustrative case is the deployment of a predictive maintenance system at Gamma, which included retrofitting legacy machining centers with multi-sensor setups to develop a scalable solution for tool condition monitoring. Early field results show that the approach reduces specialized steel waste by over 50 kilograms per machine annually, while avoiding excessive energy use and downstream emissions.

Gamma’s development path exemplifies how a mature manufacturing site can use its lead position in a global site network to become a technology-first organization. While

closely embedded within the broader corporate strategy, the plant maintains substantial autonomy in implementing experimental technologies. However, the overall transferability and scalability of solutions is their guiding principle of applying AI.

E) Qualitative Coding of Case Material

Considering previous literature on DT and digital change, AI strategies can be broken down into building blocks. Through qualitative coding based on abductive analysis that iterated between sensitizing theoretical concepts and empirical case material (Eisenhardt, 1989), we identified the following four main strategic building blocks: governance (Hess et al., 2016), digital talent (Gilch & Sieweke, 2021), digital readiness (Bharadwaj et al., 2013), and culture and communication (Proksch et al., 2024). Through coding within cases and cross-case comparison, we captured these blocks for Alpha, Beta, and Gamma, and structured the individual company timelines. This technique is inspired by temporal bracketing to analyze longitudinal data (Langley, 1999). The table below explains the underlying coding logic that translates into Figure 6, a visual comparison of each organization's AI implementation timeline. This chronological visualization shows whether the organization followed a governance- or momentum-driven approach, and what steps were taken on the respective paths.

Overview of Coding: AI Strategy Building Blocks

Building Block	Examples	Exemplary Quotes
Governance *(how)*	Codified visions, guidelines, strategy papers	"To develop AI models, you first define clear, clear rules and standards." (G1)
	Strategic roles, instances	"I was then officially appointed as the AI Officer, as it's formally called. And in this role, … I look at which ideas emerge bottom-up from the different units." (A1)
Digital Talent *(who)*	Internal digital expertise	"Our extensive training programs have provided us with a broad range of qualifications, enabling our value chains to implement digital solutions independently." (G2)
	External digital expertise	"At the very beginning, we had external support from the university … and made a conscious decision that we wanted to work with startups." (A1)
Digital Readiness & Use Cases *(what)*	Data, IT infrastructure	"I think I keep saying the data governance is such an important part. That's the fuel that runs the AI." (B2)
	Use case identification, evaluation, implementation	"Finding projects that work, not necessarily the most economical ones, but simply ones that have a high chance of success" (G2)
	AI training, change workshops	"We set up our own AI school because we realized that everything else out there covered too much ground and wasn't tailored to our specific needs." (B2)

Culture & Communica-tion *(how)*	Project communication	“Company-wide, we also presented our initiatives in detail for each individual use case, communicated our roadmap, and discussed the simulation game.” (A1)

F) Journeys towards Digital Intelligence Maturity

Alpha:

The AI journey of Alpha, the globally active SME and hidden champion in the chemistry industry, began in true *momentum-driven* fashion: In the first quarter of Y1, Alpha undertook two key actions initiated by employees. First, a visually impaired employee, who was a member of the works council, initiated an extension of the company's agreement on the use of AI. This initiative was motivated by his reliance on AI in daily work activities. "And the initial spark was, of course, a company agreement proposal by an employee of the work council, who, due to his disability, has apparently been working with cart systems that provide support for some time now" (A2).

Second, many highly qualified employees were expected to retire by the beginning of the second year of the AI implementation. "Some areas will experience an information drain due to retirements, and this is an issue that will certainly gain momentum in the coming years" (A2). For this reason, employees expressed the need for an AI-based solution to preserve organizational knowledge for future staff towards the general manager. To better understand the potential applications of AI within the company, a university professor was invited for an introductory presentation in the same quarter. Targeting the business unit most affected by the upcoming retirements, their knowledge management case was intended to serve as the starting point. Through the professor's professional network, the company decided to collaborate with an AI startup shortly after. In collaboration with the startup, they analyzed the processes of this business unit with the objective of identifying "quick win" use cases, as well as generating ideas for subsequent projects. Alpha deliberately chose the simpler "quick win" approach over the initial plan of knowledge preservation, to demonstrate to all employees that AI is effective and beneficial in a short amount of time. "We wanted to experiment with this ourselves first as an organization, to gain momentum" (A1). The first project started at the end of the first quarter. It involves an AI image recognition tool. In collaboration with the startup, the company found that a certain quality control process currently was a very time-consuming, manual process. They also saw that images were readily available to train the AI. So, carrying this project out with AI can be easily done while freeing up resources - a quick win for Alpha. At this level, Alpha prioritized speed in the implementation process.

> *"… it is very important for us not to develop a big AI strategy and generate lots of PowerPoint presentations, but rather to be involved in operational business, where we want to immediately demonstrate value for our employees. How can AI relieve our employees, perhaps make them better, increase productivity and speed, so that we can also work faster and improve our cost position?" (A1)*

The lead accountant of the organization, experienced in organizational transformations, voluntarily took over the role of the company's AI coordinator. In the second quarter of the first year of AI implementation, he presented the first AI use case to all employees during the firm's monthly status update. In addition, Alpha began collecting ideas for further use cases across all departments. These potential use cases were gathered through departmental brainstorming sessions involving all employees. In the same quarter, different vendors were contacted to provide assessments of implementation feasibility and to identify additional use cases in collaboration with employees. At the end of this quarter, Alpha started with their second use case, the initial idea of the knowledge preservation from the employees.

In the third quarter of the first year, Alpha conducted comprehensive AI workshops and implementation simulations for all employees; these initiatives were scheduled to continue into the following quarter. "[We did] simulation games, i.e., interactive, how can I implement AI in my company?" (A1). The objective was to educate all employees on AI, enabling them to identify additional potential use cases in conjunction with their domain knowledge. External consultancies with extensive AI expertise were engaged to conduct the workshops. In the same quarter, the university professor was invited again to provide guidance in developing an AI strategy.

Starting from a momentum-driven approach, the organization had first worked investing in quick win projects. Now, an overarching strategy is created to build governance structures as well and facilitate the successful implementation of additional use cases. Moreover, Alpha emerged as a role model for AI implementation within the parent organization. Alpha was invited to the headquarters to present its successful AI project, which went live in the third quarter of the first year. The implementation of the first use case was successful, with employees demonstrating strong engagement, support, and interest in AI.

Beta:

Beta's approach differed from that of Alpha, choosing the *governance-driven* approach. Recognizing the importance of digital change, the organization issued their first-ever, five-year DT strategy in 2020. Inter alia, the strategy entailed the formation of a DT unit. A later employee of this unit remembered: "… my boss entered the company and set up the digital transformation department" (B2). The unit became operational with three employees in the third year of Beta's DT strategy and now comprises a small yet diverse set of experts, including engineers and data scientists. Its first task was to initiate a cross-functional agenda for all business units, envisioning "what a digital transformation or a digital Beta should look like in 2025" (B1). Both specialized and central departments, like Corporate Innovation, worked together on this agenda, to come up with essential pillars for Beta's DT process. Those included "… cultural change, Industry 4.0, new business models with data in general. And … artificial intelligence as a separate topic" (B1). Through this agenda, the groundwork for implementing digital change had been laid. However, while building up extensive governance, the actual application of digital technologies including AI had not been tackled yet. "This created a vision and set the cornerstones, so to speak, but nothing had been implemented yet" (B1).

Therefore, the DT unit initiated the AI implementation process with a two-day workshop dedicated to identifying AI use cases. "In order to select the right AI environment and tools, the Corporate Digital Transformation unit organized a large workshop where we collected use cases" (B1). This centrally issued workshop was not offered by Beta alone but provided with the help of an external consultancy, which offered their initial services free of charge at the time.

> *"We essentially got a lot of AI workshops and a lot of the groundwork done for free. With a consultancy who came on site, did big workshops with us, working out use cases and what we could do with it. And then obviously we would have to pay the consultancy to implement the model." (B2)*

A smaller group of 20 managers from several departments and sites participated in this workshop. "And we got stakeholders from different departments and different sites involved. But it was definitely a convenience sample. It was like it was the most enthusiastic, best data people in the company who agreed and wanted to get involved" (B2).

During this workshop, and follow-up 3-day workshop, around 20 AI use cases were identified and assessed on a scale from one to five according to the criteria of impact, complexity, feasibility, cost, and risk. Following this workshop, Beta's management selected the first AI use case for implementation. "So, we probably identified 10 to 20 interesting use cases, and some of them were really high value, but really high complexity" (B2).

In this fourth year following the strategic initiation of the organization's digital change, Beta started to work on the first use case together with the consultancy and a solutions provider. The aim of this project was to serve as a "lighthouse project" (B2) for subsequent projects. The selected vendor also conducted an onboarding session for the tool. During this time, communication with the employees at the managerial level was done in meetings, before any information could make its way down to the blue-collar-level via channels like the Intranet.

> *"… at the so-called General Management Meeting. That is basically the strategy and annual meeting of Beta's management. It includes all site managers, business unit managers, central department managers, and also the family, the owner family, including the Executive Board. It lasts three or four weeks. … Strategy is always an important part of this … and it was already decided before it was even communicated down the line. And then it went through more official channels". (B1)*

As another critical information channel and stakeholder, the work's council kept the employees informed on the AI developments within the organization, while having a large impact on the AI guideline that must be developed following the EU AI Act. It took a year of discussion until a general AI usage "guideline was created as a further development" (B1). The guideline provided employees with instructions on the use of generative AI, and on agreements on how Beta will and will not use AI in the future.

Since the AI workshops in the third year, Beta has not collected any new AI use cases. Being in the sixth year of their AI journey, the company has taken its first use case live. As training was not company-wide available initially, some departments went to invest some of their own budget to "find a provider who could explain prompting to us, … then I organized a training session for the team" (B1). Pushed by the EU AI Act, Beta is also developing central AI training.

> *"We've got like a training platform where people can sign up and do online courses. One of my colleagues is developing an AI course for that. And that will be pushed out to everybody. Everybody will have to do that." (B2)*

Beta remains engaged in implementing those already identified, while not prioritizing internal or external communication on the matter. The central DT unit is responsible for the implementation and collaborates with the respective departments.

Gamma:

Gamma adopted a *governance-driven approach*, with the longest AI journey among the cases considered. Here, the AI journey started in year one with the strategic announcement from their former CEO, that AI should be included within their DT strategy, making it the AIoT (AI and Internet of Things) transformation. At this level, Gamma and other plants established the Project Group for AI Excellence, composed of interested employees. "So, we know this area quite well, because it's the lowest, the first level, where works are summarized, and there was an initiative there. It was a project called Project AI Excellence, with a dedicated project group" (G2). During this period, employees were granted the freedom to experiment with AI in order to explore what was effective and what was not. At the same time, Gamma's headquarters established a central AI and DT unit dedicated to research in these areas, with the aim of supporting decentralized departments. This strategy guided the company throughout the first three years of AI implementation.

In the fourth year, Gamma's headquarters released an AI implementation checklist. The checklist emphasized that AI initiatives should demonstrate both financial and productivity benefits. This development provided greater clarity to the company's AI strategy.

> *"After two years, we thought, okay, we can try this for two years, but now we want to see that it works, that it pays off. ... Then the focus was more on economic efficiency. Failure was allowed, but please tackle projects that also have an economic benefit ... At that point it was accepted as a mature technology that we use in the same way as automation or anything else, applying the same yardstick in terms of what it costs, what the benefits are." (G2)*

In the sixth year of implementation, the new CEO's strategy was strongly connected to AI, requiring that AI be incorporated into all products or into their manufacturing processes. "And it was clear that we saw this, and our research chairman at the time said that he wanted every Gamma product to be either manufactured with AI or contain AI in five years' time" (G2). At this time, the central AI unit conducted a comprehensive AI training program for all corporate managers in English. "And they also offered an AI training series at the time. Personally, I found it very good, but not practical for the employees on site, because it was in English" (G1). Gamma recognized that this training was not suitable for its employees. Consequently, an AI coordinator was appointed at the plant to organize training sessions for all employees in the local language. The primary focus was on ensuring the quality of the training. Accordingly, the AI coordinator completed a "train-the-trainer" program to maintain training quality. During these workshops, which involved all 300 employees of the plant, use cases suggested by employees were also collected.

> *"I have established the first and I think still the only AI training in German for our employees here, from the machine operator level and upwards. I think we have trained around 300 employees at our site over the last three, four years, it was a developed training over two days, on which we first tried the basic knowledge, then provide a practical example." (G1)*

During this period, the company realized the need for a dedicated plant-level AI unit, which replaces the AI Excellence Project Group. It was decided to staff this unit with engineers from the production line rather than IT specialists, with the aim of developing use cases specifically suited to production processes.

> *"We deliberately separated it from production at the time to ensure that everything was running smoothly in the right direction. Because there were quite a few ideas, we wanted to make sure that we were achieving the desired effect. We realized early on that when experts from specialist departments come in, they have great ideas, but these often don't necessarily address the problems faced in production." (G2)*

Since the sixth year, the focus of implementation has been on maintaining the plant's competitiveness using AI. In addition, potential use cases continue to be collected from blue-collar workers directly engaged in operational tasks. Moreover, all new employees continue to attend the local AI training to ensure sustained knowledge transfer.

G) Exemplary Application of the Decision Tree

Having examined the potential answers to each decision-tree question, we now turn to the practical application of the framework by evaluating the case companies, starting with **Alpha**. Alpha differentiates its products primarily through excellent customer service and therefore follows a service differentiation strategy. We learned that Alpha is organized in a decentralized manner, which means that decision-making is not enforced in a top-down way but can be established individually. Furthermore, Alpha operates multiple production sites where different products are manufactured. This results in a low level of integration across sites in terms of processes and standards. Based on these characteristics, Alpha answers questions Q1 through Q4 of the decision tree with “no,” which should direct the organization toward the momentum-driven approach. This is also the approach Alpha has chosen in practice. At the beginning of the study, Alpha was classified as an AI beginner. Over time, now, the organization increasingly aligned its business problems with available AI capabilities and successfully implemented its first quick-win use case. As a result, Alpha has progressed toward an AI intermediate state. At this stage, additional use cases have been identified and executed, while the IT infrastructure is still in the process of being established, which further supports its classification as AI intermediate.

To further illustrate the proposed decision tree, we next consider the case of **Beta**. Beta primarily focuses on process efficiency, as it operates in a highly competition-oriented industry. The organization is strongly centralized, meaning that strategic decisions are imposed top-down by top management. In addition, Beta exhibits a high level of integration of processes and standards across multiple sites. Finally, its employees are generally not strongly technology driven. Based on these characteristics, questions Q1 to Q3 of the decision tree are answered with “yes,” while Q4 is answered with “no,” which leads to the governance-driven approach as the proposed strategy. This outcome is consistent with the organization’s actual choice, as Beta opted for the governance-driven approach in its AI journey. Further using the decision tree to classify Beta’s AI maturity level, we see Beta as AI beginner: Beta has an AI strategy in place; however, its IT infrastructure is not yet sufficiently developed to fully support this strategy yet.

Lastly, we trace **Gamma**'s approach and maturity level with the help of the decision tree. Gamma primarily follows a strict process-efficiency strategy due to high cost pressure in its production environment. The organization is structured in a decentralized manner, meaning that decision-making authority resides within individual business units. At the same time, Gamma exhibits a high level of integration across sites, supported by so-called lead plants that serve as orientation points and role models for other sites. Finally, Gamma's employees have not yet fully embraced technology-driven change within the organization. These characteristics lead to the governance-driven approach, as questions Q1, Q3, and Q4 are answered with "yes," while Q2 is answered with "no." This outcome is also reflected in practice. Gamma deliberately pursued a governance-driven AI transformation, beginning with a comprehensive strategy anchored at the organizational level. A closer examination of Gamma's AI maturity level shows that the organization has an AI strategy as well as established data and IT infrastructure in place. In addition, employees possess a general understanding of AI, and strategy-led use cases have been identified. At present, Gamma is in the process of standardizing AI applications. At the same time, AI innovation has already been institutionalized. Taken together, these factors position Gamma as an AI leader.

Figure 6 provides an overview of the different paths taken by the three companies. While the organizations pursued distinct approaches, Alpha capitalized on its existing momentum, whereas Beta and Gamma adopted a governance-driven approach. The underlying drivers also differed across cases: Alpha was primarily motivated by the risk of knowledge loss due to employee retirement, while Beta and Gamma were driven by innovation imperatives and competitive pressures. All three cases have faced, or continue to face, challenges throughout their AI adoption journeys: Alpha struggles with achieving strategic alignment of its use cases, Beta encounters difficulties in scaling implemented solutions, and Gamma faces challenges in coordinating AI initiatives across the organization.

4 Ruining M&A-Based Digital Transformation: Cognitive Microfoundations of Failure

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Abstract

Digital transformation (DT) has become a strategic imperative for incumbent firms facing disruption, especially in retail where the physical and digital world are expected to blend seamlessly. Incumbents rooted in business models that are deficient in digital resources and capabilities increasingly turn to mergers and acquisitions (M&A) of complementary firms to expedite their DT. Despite apparent complementarity, many physical-digital deals fail to generate transformative outcomes. Drawing on a dynamic capabilities (DC) lens, we highlight the microfoundational role of managerial cognition creating resistance and inhibiting DT. Through the critical case of PhysicalCo, a European fashion group, and its acquisition of DigitalCo, an e-commerce firm, we trace how a non-digital mindset undermined the firm's DT despite the acquisition of a complementary digital target. Longitudinally, we examine both the historical context and the immediate pre- and post-acquisition phase through 37 interviews spanning over 2.5 years and 126 archival sources since 2005. We reveal that the manager group exhibited several non-digital thinking patterns that hindered organizational DC building over time and undermined a transformation towards omnichannel and a digital identity. Discussing our theory against rival explanations, our process model contributes to IS literature by offering a microfoundational explanation for DT failure in digital M&A. For practice, we present normative insights with measures across the strategy, due diligence, and integration phase that help top management, investors, and M&A advisors alike to foster a managerial digital mindset and exploit complementarities in physical-digital deals.

***Keywords**: Digital Transformation, Cognitive Resistance, Transformation Failure, Non-digital Mindset, Digital M&A*

4.1 Introduction

The retail industry, a key contributor to the global economy, faces an increasing pressure for digital transformation (DT): a deep-reaching change in an organization's business model or identity through digital technologies, resulting in new products, structures, and processes (Hess et al., 2016; Wessel et al., 2021). The steady growth of e-commerce has created a need for channel integration and a symbiosis of the physical and digital world in retailing (Statista, 2023; Verhoef et al., 2015). However, bound by path-dependent, organizational resources and processes, incumbent firms struggle to achieve encompassing, transformative changes on their own (Hovorka & Mueller, 2025). Hence, research and practice position mergers and acquisitions (M&A) as a key strategy stressing the opportunity to achieve strategic renewal from the outside and unfreeze previous mental maps (Dekova et al., 2023; Graebner et al., 2010; KPMG, 2024).

Incumbents have indeed recognized digital M&A as a way to drive DT through capabilities and resources beyond their organizational boundaries (Hanelt, Firk, et al., 2021; Oberländer et al., 2021). As incumbent firms are mostly built around physical business models, acquiring digital targets creates deals that exhibit complementary differences. Existing research suggests that such complementarity enables two firms to create more value together than alone (Bauer & Matzler, 2014; Bruyaka et al., 2015). From a dynamic capabilities (DCs) perspective, digital M&A can be interpreted as an attempt to acquire and reconfigure resources necessary for sensing, seizing, and reconfiguring in response to digital disruption. While studies showed that the acquisition of digital targets can entail transformative outcomes like innovativeness and increased firm performance (Hanelt, Firk, et al., 2021; Uhlenbruck et al., 2006), a staggering 70-90 % of acquisitions fail to deliver value or realize the intended objectives, including DT (Gu & Lev, 2024; Uhlenbruck et al., 2006). This raises a theoretical puzzle: If firms acquire the digital capabilities they previously lacked, why does transformation still not occur?

Research on DT and M&A phenomena has previously focused on organizational-level factors (Haleblian et al., 2009; Hanelt, Bohnsack, et al., 2021)**.** While the impact of managers on organizational-level outcomes was established early on by theories like upper echelon (Hambrick & Mason, 1984), managers have only more recently moved into the academic discourse: Here, the focus lies on managerial action-taking as crucial for realizing, i.e., projected deal value (Harrison et al., 2001; Stieglitz & Heine, 2007) and transformative outcomes (Bendig et al., 2023; D. Q. Chen et al., 2021). Research on managerial cognition, as a crucial driver of said actions, is only emerging (J. P. Eggers & Kaplan, 2009; Taylor &

Helfat, 2009). Negative cognitions towards change, an antecedent of resistance, have been widely examined at the employee level in organizational and IS research (Choi, 2011; Erwin & Garman, 2010). However, despite recognizing the importance of the managerial mindset for transformation strategies (Martin, 2017), considerably less attention has been paid to the role of managers' cognitive frames in undermining such change processes. The underlying assumption that managers must act as organizational change agents has led to a scarcity of studies on their cognitions as microfoundational source of resistance constraining organizational-level change. We therefore problematize the assumption that managers are automatically capable of leading their organization towards transformation success given the availability of the right resources. Instead, we argue that managerial cognition acts as a primary 'bottleneck' for Dynamic Capabilities (DCs). If the managerial mindset remains calibrated to a legacy logic of physical success, even the most advanced digital resources cannot be effectively seized or reconfigured to develop a new identity.

Further, few DT studies explicitly aim to understand failure (notable exceptions: Lucas & Goh, 2009; Vuori & Huy, 2016). This success bias limits learning from failure and thereby the theoretical understanding of the mechanisms that prevent transformation. Especially microfoundational processual explanations of DT and its failure drawing on longitudinal data are lacking (Poláková-Kersten et al., 2023; Wessel et al., 2025). This is surprising since DT has been conceptualized as a deep-reaching change process itself. The potential of DT and digital M&A to fundamentally change a firm's identity through digital technologies over time, therefore, warrants a more nuanced study of managers' cognitions as a crucial driver or inhibitor (Alvesson, 2011; Westergren et al., 2024). Hence, this study asks: **How does managerial cognition undermine incumbents' organizational capability to digitally transform through complementary digital acquisitions?**

Our study draws on the managerial microfoundations of organizational dynamic capabilities (DCs) as determinants of achieving organizational change (Helfat & Peteraf, 2015; Teece, 2007), and the concept of the managerial digital mindset, defined as "thinking patterns … that affect and foster the use and application of digital technologies" (Hildebrandt & Beimborn, 2022, p. 8). Through this lens, we studied a critical failure case (Flyvbjerg, 2006; Yin, 2017): A well-known European fashion group, PhysicalCo, and its acquisition of an e-commerce firm, DigitalCo. Aside from 37 interviews with members of both organizations, investors, involved consultancies, insolvency managers, and industry experts, we also analyze 126 secondary sources from financial statements to a rich media coverage of the case to triangulate our data (Eisenhardt, 2021). Refining process theories on organizational DCs and DT outcomes by applying deductive logics, we enrich these theories through "linking

micro-level processes for macro-level dynamics" (Paré et al., 2025, p. 14) with respect to the managerial mindset; a pressing issue for the IS field, where we aim to understand socio-technical phenomena surrounding digital technologies (Sarker et al., 2019).

This paper answers calls for a process-oriented exploration of the impact of top management on DT and M&A outcomes (Haleblian et al., 2009), to illuminate the acquisition of digital firms by incumbents (Hanelt, Firk, et al., 2021), and to further explore microfoundations of failure in DC research on transformation (Poláková-Kersten et al., 2023). First, we contribute to theory by linking M&A research to DT as a strategic acquisition objective and enriching both research streams through a managerial-level explanation of failure. Our process model explains how managers may contribute to the failure of M&A-based DT through hindering organizational DCs. Second, contributing to the research on the microfoundations of DCs, we identify the specific technology-related and general managerial thinking patterns detrimental to the application of digital technologies, reinforcing and undermining DCs over time. Without taking a dogmatic digital-only view, we underline how non-digital cognitions in the manager group hindered organizational sensing, seizing, and reconfiguring capabilities, preventing a symbiosis of the physical and digital world. Third, a processual view from pre- to post-acquisition phase shows how failure can manifest and reinforce over time, hindering the exploitation of the acquired complementary resources and capabilities for DT. After discussing our theory against rival explanations, lastly, we present normative insights derived from our case to help practitioners and academics alike to navigate physical-digital deals.

4.2 Theoretical Foundation

4.2.1 Digital Transformation Failure of Incumbent Organizations

We define incumbent firms as ones that "(1) are positioned in a traditional industry, (2) were established before the digital revolution, and (3) whose business models were not originally based on the use of digital technologies" (Metzler & Muntermann, 2020, p. 3). They are different from born-digital firms due to their established identity, structures and routines, and resource base (Henfridsson et al., 2014). In the digital age, they face an increasing pressure to transform to not lose market share to digital competitors (Hanelt, Firk, et al., 2021). Vial defines DT as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies (2019, p. 121). The process goes beyond simply digitalizing the status quo (Hovorka & Mueller, 2025), deeply changing a corporation's business model or identity, products, structures, and processes (Hess et al., 2016; Wessel et al., 2021). At the organizational level, the digital-first mindset as a "tendency to seek out digital solutions and systematically use technology and data for advantage" (Soule et al., 2016, p. 7) has been conceptualized as crucial to foster digital ideation, exploration, and exploitation; leading to an inclination to choose digital solutions over traditional ones (Bharadwaj et al., 2013; Weritz et al., 2024). This inclination does not mean blindly replacing physical with digital business models. Following a recent publication on digital resource primacy in DT, it rather still means "employing non-digital organizational resources, such as physical assets, labor, or traditional IT resources, when necessary" (Piccoli et al., 2024, p. 7). Practitioners need to carefully evaluate the degree of "becoming digital" that can serve their organization, especially in retail where a complementary symbiosis of the physical and digital is preferred; as researchers should equally consider the non-technological aspects of the process (Wessel et al., 2025).

As path-dependent incumbents tend to struggle with transforming their legacy structures, processes, and identities, they usually first target the digitalization of processes, then products and services, before the entire business model (Soluk & Kammerlander, 2021). For them, DT comes with unique challenges. First of all, an incumbent's resource base can be both an asset and liability in the digital era (Oberländer et al., 2021): Managers need to balance the ambidextrous exploitation of the old and exploration of the new (Gregory et al.,

2015; Svahn et al., 2017). Often, predigital incumbents are “constrained in the content and speed at which they can develop new resources and knowledge” (Uhlenbruck et al., 2006, p. 901), hampering their DT through path dependence and inertia (Kaganer et al., 2023). If an established organizational identity conflicts with a DT initiative, this can lead to perceived threats at the individual level, resistance to change, and undermine any DT efforts (Omowole et al., 2024; Poláková-Kersten et al., 2023). Further, it is often harder for incumbents with physical business models to participate in the dematerialization and near-zero marginal costs of digital goods (Hanelt et al., 2015). Lastly, digital start-ups enter the market, drawing incumbent firms out of their industries (Steininger, 2019).

Few frequently cited studies explicitly focus on DT failure cases with drivers identified at the organizational, group and individual level (see Figure 9). Failure is conceptualized as a fundamental loss of market share due to a failure to adapt to digital technologies, a tumbling stock price, divestment of core business functions, and/or bankruptcy (Lamberg et al., 2021; Lucas & Goh, 2009; Tripsas & Gavetti, 2000; Vuori & Huy, 2016). Regarding managerial cognition as an impact factor, middle managers were “unable to make a transition to think digitally” (Lucas & Goh, 2009, p. 46) at Kodak. The case of Polaroid shows how its managers’ values and the longstanding belief in their established razor-and-blade business model hindered the response to change (Tripsas & Gavetti, 2000). The authors argue that beliefs are historically developed, fixed assumptions forming a dominant logic on how the business is viewed, impacting how solutions are found. Hence, managerial beliefs can be attributed to a failure to transform and build the right capabilities (Lucas & Goh, 2009; Tripsas & Gavetti, 2000). However, currently identified beliefs in the literature refer to a specific firm’s business model or to its competitors, not drilling down into digital mindset thinking patterns and how they precisely affect sensing, seizing, and reconfiguring capabilities and DT failure over time; especially for M&A-based scenarios when previously lacking digital resources and capabilities are brought from the outside in.

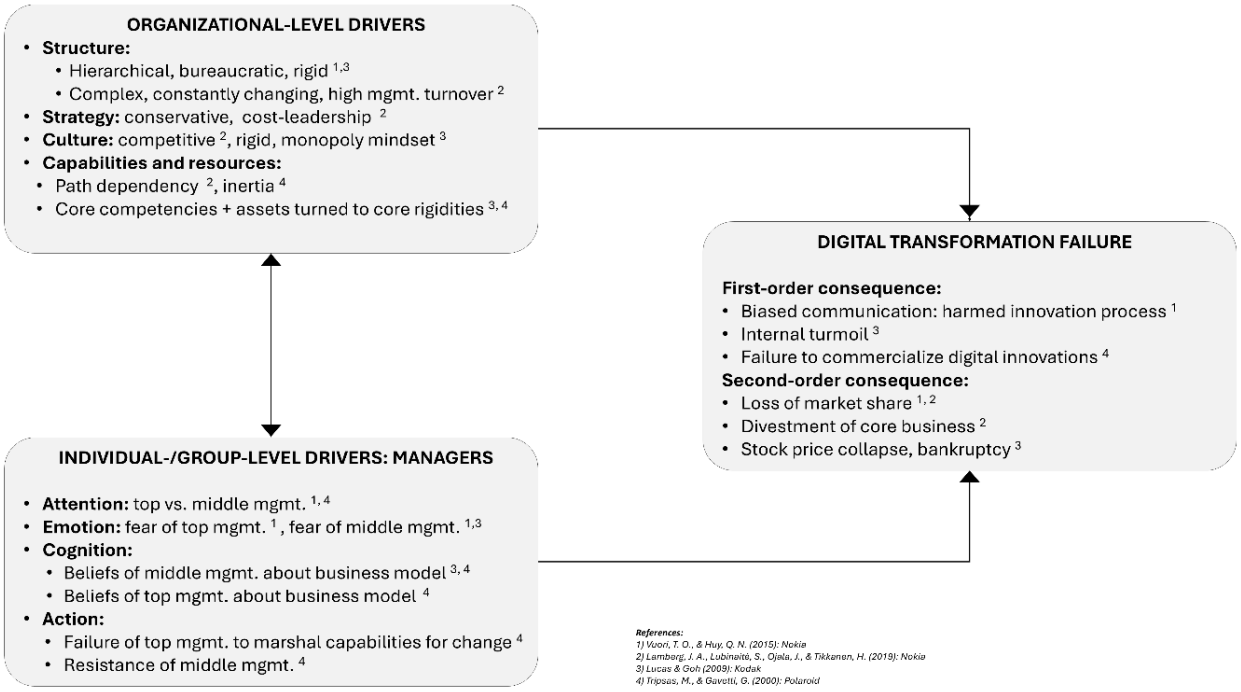


Figure 9. The Organizational- and Individual-/Group-Level Drivers of DT Failure

4.2.2 Digital M&A as Managerial Challenge

Research increasingly recognizes that DT "is not contained within organisational boundaries" (Ashrafi et al., 2024, p. 26). M&A provide a way to access critical resources and capabilities externally (Henfridsson et al., 2009; Wernerfelt, 1984). Resources can be both tangible, i.e., machinery, and intangible, i.e., knowledge, and are "tied semi-permanently to the firm" (Wernerfelt, 1984, p. 172). Organizational capabilities are a firm's abilities to deploy, coordinate, and reconfigure resources (Teece, 2007). Capabilities encompass DCs and ordinary capabilities: Ordinary capabilities include "base-level functions" to complete administrative, operational, and governance-related tasks (Teece, 2014). In a dynamic environment like today's retail sector, DCs are also needed to adapt to and drive change. They can be "disaggregated into the capacity (1) to sense and shape opportunities and threats, (2) to seize opportunities, and (3) to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring" (Teece, 2007, p. 1319) a firm's resource base. All three have "organizational and managerial processes, procedures, systems, and struc-

tures" (Teece, 2007, p. 1319) at their microfoundation. For achieving DT, research has identified several activities and routines that fall under an organization's sensing, seizing, and reconfiguring capabilities (see section 4.2.3).

Scholarly attention has recently shifted towards M&A that specifically target digital resources and capabilities, digital M&A. Such deals have been studied with regards to their positive outcomes on the market value of the acquirer (Uhlenbruck et al., 2006) or on the acquirer's innovation performance (Hanelt, Firk, et al., 2021). However, when physical firms acquire digital targets, it creates unique challenges: With business models revolving around physical goods and services, incumbents often have been on the market for decades, leading to established structures, processes, finances, and mostly physical products or services (Hanelt et al., 2015). Digital-native firms, however, tend to operate with flat hierarchies and rapid iteration cycles, displaying startup-like structures and processes (Steininger, 2019). They deal with core assets that are intangible, modular, rapidly evolving, and embedded in broader multi-sided ecosystems (Bharadwaj et al., 2013; Henfridsson et al., 2018).

Physical-digital marriages can be prime examples of complementarity in M&A: Firms that exhibit mutually reinforcing differences can create more value together than alone (Grimpe & Hussinger, 2014). Instead of similarity, "there are fundamental arguments that complementary differences are more crucial for M&A success" (Bruyaka et al., 2015, p. 98). Complementarity may be exhibited through products, knowledge, strategies, technology, markets, and industries (Bi et al., 2025; Hitt et al., 1998; Kim & Finkelstein, 2009; Makri et al., 2010; Yu et al., 2016). However, complementary differences in physical-digital deals are valuable only to the extent that they can be exploited. Since complementarity is a necessary but insufficient condition, resources and capabilities "must be effectively integrated and managed" (Harrison et al., 2001, p. 679). Especially the need for strategic direction by a firm's top management has been stressed in case of complementary resources in incumbent firms, while corresponding managerial challenges still remain a black box (Stieglitz & Heine, 2007).

Arguably, one of the biggest general challenges in M&A is integrating the human resources successfully, as an acquisition poses a significant shock to prior positions, structures, and processes (Dorling, 2017). If not carefully managed, research has shown that employee resistance, "defined as the individual and collective opposition of employees to the combination and subsequent integration of the joining firms, is associated negatively with M&A performance" (Larsson & Finkelstein, 1999, p. 6). The impact of managerial agency through, i.e., communication and sensegiving, interventions to manage cultural distance, or transformational leadership to combat employee resistance have been discussed (Steigenberger,

2017). Much contemporary research, however, implicitly follows the assumption that managers must act as change agents. Hence, the field has not reflected on managers and their cognitions as potential locus of resistance yet (Alvesson, 2011).

When it comes to M&A failure, it is often defined through either deteriorating post-acquisition performance and value destruction, or unmet goals (Cartwright & Schoenberg, 2006; Datta & Roumani, 2015; Koi-Akrofi, 2016). Research in management and IS has predominantly focused on factors at the organizational level, including financials, structure and integration, strategy, culture, and capabilities and resources (see Appendix I). Regarding managers, managerial hubris and overconfidence, as well as confirmation bias have been associated with unsuccessful deals (Y. Friedman et al., 2016; Krishnan et al., 2007). Despite these insights, what drives and hinders managers' agentic roles for digital change at the cognitive level is poorly understood. Since people form the very heart of every organization, research must offer these micro-level perspectives to holistically understand failure (Poláková-Kersten et al., 2023). Further, more research is needed to illuminate varying performance outcomes of acquisitions as offensive paths to DT (Hanelt, Firk, et al., 2021; Margiono, 2020).

4.2.3 Managerial Mindset at the Microfoundation of Dynamic Capabilities

DCs generally refer to an organization's ability to orchestrate its resources in response to a quickly changing business environment (Teece, 2014). Not only have DCs been connected to transforming the business model of acquirers in digital M&A (Čirjevskis, 2019), researchers also found they play a crucial role in the DT of incumbent firms (Warner & Wäger, 2019). DC theory itself stresses that DCs "reside, in part, with individual managers and the top management team" (Teece, 2014, p. 332). At the microfoundational level of organizational DCs, good managers should be able to "think creatively and act entrepreneurially" (Teece, 2014, p. 333). Since managerial cognition drives action (Tripsas & Gavetti, 2000), the heterogenous distribution of, i.a., managerial cognition partially explains differing managerial actions. Managerial cognition is conceptualized as managerial beliefs and mental models which provide a frame for how a situation is perceived. This frame, which may be biased, forms the basis for managerial decisions and business performance (Adner & Helfat, 2003). Nonetheless, most prior research had a tendency to conflate managers with organizations or treat them as independent of them (Alvesson, 2011; Foss & Mazzelli, 2025). More recent work, however, has focused on managerial cognitive frames. A study on IBM's successful transition surfaced how mechanical cognitive frames initially impeded the managers' ability

to link new technology to complementary resources (Taylor & Helfat, 2009). Also, CEO attention to technologies has been shown to guide incumbent entry into a radical new technological market (J. P. Eggers & Kaplan, 2009). Building on these insights, Helfat and Peteraf (2015) explicitly connected managerial cognition to organizational DCs, explicating the heterogeneous capability of managers to anticipate, interpret, or respond to their changing environment. They put forward illustrative managerial cognitive capabilities, that predominantly pertain to one of the Dynamic Managerial Capabilties (DMCs) sensing, seizing, or reconfiguring and drive organizational DCs and overall firm performance (see Table 17).

Table 17. Managerial Cognition Driving Organizational DCs (adapted from Helfat & Peteraf, 2015)

Illustrative Managerial Cognitive Capabilities	- Perception - Attention	- Problem-Solving - Reasoning	- Language and Communication - Social Cognition
Dynamic Managerial Capabilties	Sensing	Seizing	Reconfiguring
Impact on Strategic Change	- Opportunity Recognition - Creation	- Strategic Investment - Business Model Design	- Strategic Asset Alignment - Overcoming Resistance to Change

Mental processes like perception, problem solving, or communication describe how people think in ways that are relevant for the general context of change management (Foss & Mazzelli, 2025; Hock-Doepgen et al., 2025). Since DT goes beyond traditional organizational change, by fundamentally altering value creation, structures, a firm's identity, and the people within through the use of digital technologies, managerial cognition in this context requires a more nuanced understanding (Vial, 2019; Westergren et al., 2024).

To understand managerial action in the context of digital change, managerial cognition and, more specifically, the underlying concept of the 'digital mindset' appears as a suitable construct. The psychology literature defines mindset as a "cognitive orientation that promotes task completion" (Gollwitzer, 1990, p. 63). Figure 10 shows a synthesis of current literature, explicating how, for managers, general managerial cognitive mechanisms have been linked to organizational DCs and digital change (Helfat & Peteraf, 2015; Teece, 2007), while the concept of the digital mindset has been introduced as driving change at the employee and professional level (Hildebrandt & Beimborn, 2022; Solberg et al., 2020).

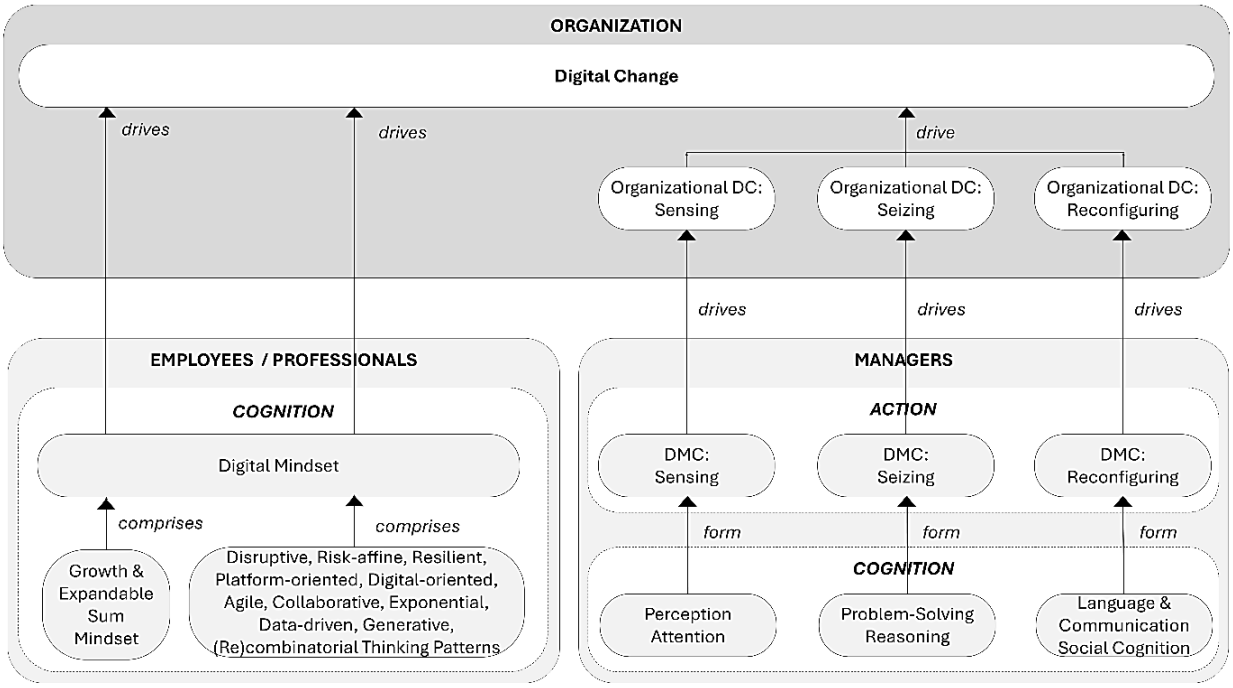


Figure 10. Managerial Thinking at the Microfoundation of Organizational DCs for Digital Change (based on Helfat & Peteraf, 2015; Hildebrandt & Beimborn, 2022; Solberg et al., 2020; Teece, 2007)

Management research conceptualized the digital mindset as beliefs about personal technological ability and situational resources (zero- vs. expandable-sum beliefs) in the context of digital change (Solberg et al., 2020). In the IS field, the digital mindset of organizational actors has recently been identified as a fundamental factor to realize successful digitalization outcomes (Hildebrandt & Beimborn, 2022). It is defined as “thinking patterns, epitomized through cognitive processes, filters, and core convictions of humans constituted of cognitive mechanisms and knowledge structures that affect and foster the use and application of digital technologies and cope with their consequences in contexts of individuals, organizations, or society” (Hildebrandt & Beimborn, 2022, p. 8). Eleven underlying thinking patterns were put forward for the context of digital innovation, which the authors closely relate DT under the umbrella of digital change (see Appendix J). Following Drechsler et al. (2020), DI research explains how digital technologies enable novel recombinations and innovations, while DT research explains how organizations restructure around these innovations. Hence, it is valuable to use thinking patterns as sensitizing device throughout our analysis. While five of these patterns, like risk-affine or collaborative thinking, reflect more *general managerial thinking patterns*, we view the other six as specifically *technology-oriented ones*: platform-oriented, digital-oriented, exponential, data-driven, generative, and recombinatorial thinking. While previous research identified thinking patterns and these mechanisms based on success cases, this paper focuses on identifying the cognitive drivers within the management team that may act detrimental to change and hinder a successful M&A-based DT.

4.3 Methodology

This study integrates and extends the literature on the DT of organizations and digital M&A from a microfoundational process perspective. Our objective is to shed light on how incumbent acquirers that target complementary digital firms still fail to digitally transform, zooming in on its management. We chose a qualitative case study design, since this method is ideal to uncover underlying processes and keep up with relationships in flux, as is the case for organizational transformations (Monteiro et al., 2022). We explore a critical failure case in Europe’s retail sector, because we understand it as an analytical opportunity to make mechanisms visible that unfold over time during a failure process (Flyvbjerg, 2006; Pettigrew, 1987, 2012). We chose this sector as one of the key contributors to the global economy, where millions of enterprises offer their goods and services to billions of consumers (Sabanoglu, 2024). The traditional sector, facing adverse economic conditions and the

steady growth of e-commerce, is under an enormous pressure to digitally transform (Statista, 2023). Sectors where coping with fast-paced change is key to succeed present an ideal setting to study processes around DT first-hand (see Brown & Eisenhardt, 1997).

In our case, we investigate the acquirer PhysicalCo, active as store-based retailer and wholesaler, and its digital target DigitalCo, a digital venture active in fashion e-commerce. The chosen case is particularly interesting, because it encompasses a clear complementarity of acquirer and target (see Table 18), which is established as an important success factor in the literature (Bauer & Matzler, 2014). PhysicalCo thereby intends to acquire digital capabilities and knowledge via DigitalCo to expand its physical business model. Moreover, the M&A-based DT intention is made very explicit by PhysicalCO, as our collected materials show. However, although these elements commonly associated with a positive outcome were present, the transformation nevertheless failed. This failure makes it particularly interesting to study the underlying cognitive managerial mechanisms. Henceforth, our unit of analysis is the management team and their cognition as it unfolds and becomes embedded in organizational decisions over time, like we saw reflected in managerial accounts, strategic choices, and interaction patterns. We are not treating the case as a single undifferentiated observation but rather analyze how managerial thinking patterns are expressed across managerial roles, organizational contexts, and critical decision phases or events throughout the intended transformation process (Flyvbjerg, 2006).

4.3.1 Case Introduction

We adopted elements of the historical research approach (Land, 2010; Porra et al., 2014), which allowed us to reconstruct a timeline and contextualize managerial cognition within broader industry shifts and PhysicalCo's long historical trajectory. Figure 11 provides an overview of the timeline, where the arrow at the top represents the time axis. The events in the grey box below list exemplary, important industry and technology trends towards digitalization, i.e., the release of the first iPhone in 2007 and the subsequent rise of mobile commerce (m-commerce).

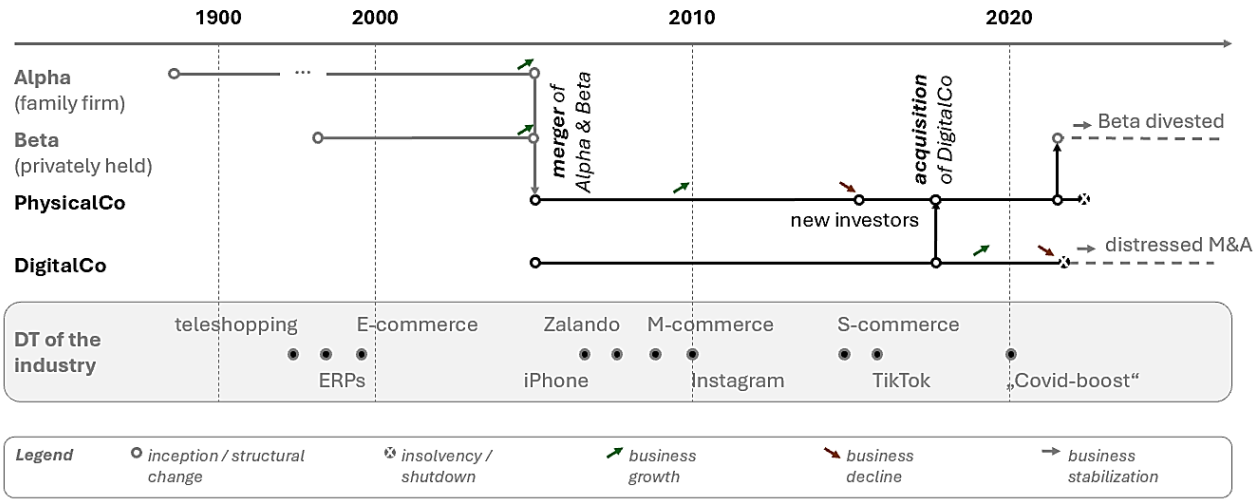


Figure 11. Case History

The origins of PhysicalCo date back to the late 19th century when the family firm Alpha was formed. It acquired a partial stake of Beta in the 1990s, before the firms merged in the 2000s to become PhysicalCo. Soon, fashion e-commerce started to grow with the advent of mobile technologies (Piotrowicz & Cuthbertson, 2014). PhysicalCo under Alpha's family management, however, expanded to 20 countries, restricting digitalization to back-office functions. Regarding customer-facing processes, its online shop has gained little traction. When the majority ownership shifted to a financial and a strategic investor in the 2010s (see Appendix M), the business was streamlined and DT became a central goal. Newly appointed managers at the time almost all held previous positions in the firm (see Appendix N). Soon after, PhysicalCo acquired DigitalCo, an e-commerce first mover with a proprietary ERP system and broad marketplace coverage.

Table 18. Firm Complementarity of PhysicalCo and DigitalCo

Domain	PhysicalCo	DigitalCo
Market	Retail: Germany, Austria, Switzerland Wholesale: additional EU countries	EU-wide
Product	*Low-price*; resale and own brands	*Low-to-mid-price* resale brands
Channel	*Retail*: ~ 400 physical stores; underperforming webshop *Wholesale*: ~2000 points-of-sale	*Online*: listed on >25 platforms
Strategic Focus	*Lower*: broader portfolio; risk-averse, family-firm-influenced	*Higher*: narrower portfolio; more agile, founder-centric
Structure	Hierarchical	Flat hierarchies
Growth Capabilities	*Moderate*: through acquisitions	*Low*: investment needed
IT / digital Capabilities	*Low*: mostly outsourced; SAP	*High*: in-house; proprietary system developed by founder
Physical Capabilities	*High*: store management; high-end logistics / warehouse management	*Low*: logistics at / over capacity

The double-digits deal promised complementary synergies: PhysicalCo would gain digital expertise and online access, while DigitalCo sought liquidity, logistics, and physical channels. For the same industry deal (Kim & Finkelstein, 2009), Table 18 shows the complementary resources and capabilities that both firms brought to the table. Despite these formally complementary profiles, they not only widely failed to materialize potential synergies, PhysicalCo did also not succeed at its DT. On the contrary, the organization continued to struggle with its physical-first strategy, hindering its customer-facing DT towards omnichannel and the formation of a digital identity. Facing headwinds on the market and financially, it resorted to divesting the Alpha unit and gaining liquidity through DigitalCo, until all involved organizations eventually filed for insolvency. The full case history is found in Appendix L).

4.3.2 Data Collection

The reality of many organizations failing to acquire and transform stands in stark contrast to the focus of contemporary research on success cases. Despite the popularity and urgency of the phenomenon, we find little theoretical explanation at the individual or group level on

why M&A-based DTs fail to produce transformative outcomes. Through business contacts, we first entered a research agreement with DigitalCo in 2023. Realizing the potential of exploring the critical case of its acquirer PhysicalCo, we allowed our focus to shift flexibly to the most interesting phenomenon at hand (Eisenhardt, 1989). This critical case offers the unique opportunity to access "retrospective … accounts by those people experiencing the phenomenon" (Gioia et al., 2013, p. 19).

Table 19. Overview of Primary and Secondary Data Sources Ensuring Data Triangulation

Data	**Primary**	**Secondary**				
Type	Interviews	Press releases PhysicalCo	Networking profiles PhysicalCo managers	Media articles	Official sources (i.e., Insolvency Portal, Commercial Register, NorthData)	Publications of involved companies
Time Frame	2023 – 2025	2010 – 2022	current	2005 – 2024	2015 – 2024	2015 – 2023
Count	37	8	15	69	24	10
Sum of Sources	**37 primary**	**126 secondary**				

To capture the interpretations and sensemaking processes of managers, we ground our analysis in informants accounts of events, decisions, and experiences (Gioia, 2021) as well as an extensive secondary data pool dating back to 2005 (see Table 19). Building on Eisenhardt and Graebner (2007), we talked to numerous informants in- and outside the focal companies to limit potential bias through, i.e., convergent sensemaking. For PhysicalCo and DigitalCo interviewees, our semistructured interview guidelines first allowed for a broad introduction of the firms and their history, before zooming in on PhysicalCo's digitalization efforts and the acquisition integration with a focus on the management perspective. For the others, we aimed for informed outsider perspectives on the case and M&A-based DT in general. The interviews were conducted from January 2023 to August 2025. Some of our interview partners agreed to repeated interviews, leading to 37 interviews and 1313 minutes material. The interviews were conducted via Zoom and in German, audio-recorded and transcribed using a software with our participants' consent and pseudonymized before the analysis. We also used pen and paper to make notes and circle back on interesting observations.

Table 20. List of Interviewees

Interviewee	Position	Interviews (mins)	Company	Role of Company
PCo1	Manager (post-phase)	1 (34)	PhysicalCo	Acquirer of DigitalCo
PCo2	Branch Manager (pre-/post-phase)	2 (53)		
PCo3	Manager (pre-phase)	2 (48)		
PCo4	Manager (post-phase)	1 (37)		
DCo1	Founder and manager	2 (62)	DigitalCo	Target of PhysicalCo
DCo2	Manager	14 (486)		
DCo3	Manager	2 (100)		
DCo4	Middle Manager	1 (36)		
DCo5	Middle Manager	1 (32)		
DCo6	Middle Manager	1 (44)		
WCo	Founder	3 (131)	WebserviceCo	IT services for PhysicalCo and DigitalCo
AdCo	Partner	1 (40)	AdminCo	Insolvency administrator
CCo	Partner	1 (32)	ConsultingCo	Search for buyer of distressed DigitalCo
ACo	CEO	4 (146)	AcquirerCo	Subsequent acquirer of DigitalCo
Ex	M&A Expert	1 (32)	-	-
Total		**37 (1313)**		

Researching failure cases by questioning directly involved actors is always challenging and delicate due to social desirability bias and their tendency to gloss over problems. Approaching this challenge, access to top-level employees at DigitalCo allowed us to interview these boundary spanners who are knowledgeable about the processes on both sides of acquirer and target and had a front-row seat in observing the cognitive resistance at PhysicalCo during the acquisition. However, we probed DigitalCo managers' informed outsider perspectives extensively about their collaboration and interactions with PhysicalCo before, during, and after the merger. We cross-validated these accounts with PhysicalCo and related third-party interviews (e.g., insolvency administrators, service providers, subsequent acquirers). This allowed us to gain a deep understanding from contrasting perspectives in our primary data source already (see Table 20).

Moreover, we systematically triangulated the interview data with longitudinal archival sources (see Table 19) to back our claims on managerial cognition through multiple data points; especially for the pre-acquisition phase where we aimed to complement our interviewees' accounts of the past. For the triangulation of our data, we relied on publicly available documents, following a systematic search and selection process for media articles (see Figure 12).

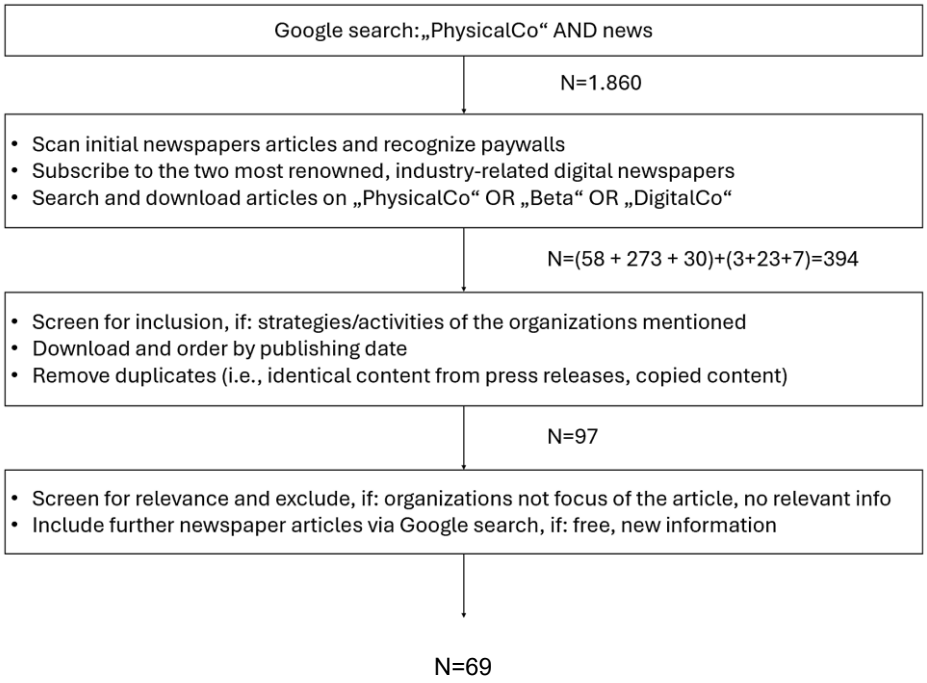


Figure 12. Search and Selection of Newspaper Articles

After an initial Google search and recognizing paywall restrictions, we subscribed to two of the most popular newspapers in the industry. After applying certain in- and exclusion criteria, we drilled down our final sample to 69 articles in the time frame from 2005 to 2024, mostly in German. For confidentiality, secondary sources like newspapers are cited generically (e.g., Newspaper A, 2019).

Together, our primary data sources (interviews) and secondary data sources (press releases of PhysicalCo, networking profiles of PhysicalCo managers, an extensive pool of media articles as well as official sources (i.e., Insolvency Portal, Commercial Register, NorthData) and publications of involved companies), allowed us an in-depth elaboration on the managerial digital mindset in the context of transformation failure. Through this data triangulation, generating various sources of evidence (Yin, 2017), we could not only cross-

validate and juxtapose our interview data but also strengthen the validity of our study (see Wimelius et al., 2021).

4.3.3 Data Analysis

Since limited theory was available to understand failure in M&A-based DT from a managerial, microfoundational perspective, we developed an in-depth process understanding through an abductive analysis, iterated between empirical case material and sensitizing theoretical concepts. All our material was coded with the help of the software MAXQDA and data structures in Excel. A complete description of the coding procedures is provided in the appendix (see Appendix K). To avoid treating the case as a single undifferentiated observation, we conducted systematic within-case comparisons across pre- and post-acquisition phases, organizational roles (e.g., PhysicalCo vs. DigitalCo; top vs. middle management), and critical decision events.

Step 1: Inspired by historical research (Porra et al., 2014), we began by mapping turning points in the organizational history to capture structural changes and industry shifts. Starting with official sources and complimenting them with our other sources, we compiled a chronological table and constructed a figure of milestones to contextualize our case for the reader (see Figure 11). For this study, we treat the acquisition of DigitalCo as temporal anchor, dividing our case into a pre-phase and post-phase.

Step 2: We then moved towards explaining the process of failure by iteratively coding and grouping data into higher order concepts. We constantly compared emergent themes in the interviews, and existing theory (Eisenhardt, 2021), anchoring emergent patterns and relationships (Díaz Andrade et al., 2023). The aim of the entire process, regardless of whether it is called axial coding (Corbin & Strauss, 2008) or building second-order themes (Gioia et al., 2013), is producing “progressively better-defined and grounded higher-order concepts … and creating underlying theoretical arguments that connect constructs” (Gioia et al., 2013, p. 27). Through team discussions we grouped key statements into second order themes and aggregate dimensions. Across pre- and post-phase, we identified (i) a lack of previously studied digital thinking patterns and (ii) novel non-digital thinking patterns as detrimental (see Figure 13; Figure 14). While we used the approach of Gioia et al. (2013) to ensure rigor, we did not progress purely inductive but adopted an abductive, theory-informed process. Particularly, we used the DC theory (Teece, 2007, 2014) and the digital mindset concept (Hildebrandt & Beimborn, 2022; Solberg et al., 2020) as a critical sensitizing device

during our iterations between data and theory. This helped us so that our higher-order concepts and themes would not emerge in a theoretical vacuum but were systematically mapped to micro-foundational building blocks of organizational transformation.

Step 3: Eventually, we translated the data structures into a theoretically grounded process model (see Figure 15) to illustrate how individual-level cognition contributed to the unfolding of organizational, M&A-based DT failure through lacking DCs.

Step 4: Finally, we elaborated on alternative explanations for the M&A-based DT failure trajectory: Having identified financial issues, business model incompatibility, and IS integration as potential explanations, we explicitly collected additional and re-analyzed existing data to discuss them in section 4.5.2. Throughout the analysis, we iteratively revisited our emerging explanations against discrepant data and negative cases to refine the robustness of our emerging process insights.

4.4 Results

4.4.1 The Emergence of Failure in a Physical-Digital Deal – Setting the Scene

With its roots in a century-old, family-led wholesale (Alpha) and a decade-old retail business (Beta), PhysicalCo in the 2010s is the blueprint of an incumbent firm that is about to be disrupted by digital technologies. While the organization is diligent in digitalizing its back-end, the typical process-digitalization of incumbents (Soluk & Kammerlander, 2021), it struggles to transform its customer-facing business in the front-end. After failed initiatives and a declining business performance, the majority ownership is transferred to a financial and a strategic investor. While it looks like the management team is newly formed, almost all actors held previous positions within the organization (see Appendix N). In a press release on the deal, PhysicalCo underscores its will to respond to the increasingly digital market environment through fresh capital: “With strong partners at our side, we can grow and thus respond to structural changes in the industry, such as the rapid growth of online retail and changing consumer behavior” (Press release, 2016). Streamlining and transforming the business move to the center of attention, so that after restructuring, the acquisition of DigitalCo should finally enable the business to spur its DT.

> *“Through the strategic acquisition and future close integration with DigitalCo, PhysicalCo will achieve its goal of “digital transformation” more quickly and effectively. This will further accelerate growth in the important e-commerce business segment, especially in the emerging online marketplace business.” (Press release, 2018)*

Both firms promise significant complementarity: Aside from their markets, products, structure, and capabilities, especially PhysicalCo's and DigitalCo's channels (physical vs. digital) stand out as complementary (see Table 18). Looking back, managers on both sides stress these reciprocal strengths and the potential to transform PhysicalCo:

> *"On the one hand, that PhysicalCo's logistics, which are quite extensive, could be utilized. And on the other hand, that old stock can be sold much better offline in physical stores than online. … PhysicalCo … had the opportunity to buy a functioning online channel for a manageable investment. And the synergy effects that they also saw is additional channels to sell goods." (DCo2, Int. 1)*

> *"This acquisition will also provide us with a high level of know-how transfer, enabling us to use the algorithms that DigitalCo works with to intelligently control the product range structure. This is a further step in advancing the digital transformation in the wholesale business." (Press release, 2018)*

The projected complementary synergies remain largely aspirational. The target is not integrated as discussed, and an encompassing change towards an omnichannel business model and a more digital identity is not achieved, even several years after the acquisition. In a retrospective evaluation, "they missed the chance to digitally transform their business, on customer side" (DCo2, Int. 11). The failure of PhysicalCo is also recognized in the media:

> *"The retail unit of PhysicalCo wanted to grow, primarily in the online sector and especially in the digital marketplace business. … But then, sales declined." (Newspaper D, 2022)*

As a PhysicalCo manager at the time noted, "the difficulty of digital transformation is … the mindset towards it" (Newspaper C, 2018). Hence, our study focuses on the cognitive factors that contributed to the process of organizational DT failure at the management level. Legacy thinking patterns from the pre-phase have had a considerable impact on the organizational DCs and status of DT at the time of the acquisition and beyond. To understand how failure could unfold despite formal complementarity, we examined the digital mindsets of managers as drivers of organizational processes and outcomes before and after the acquisition.

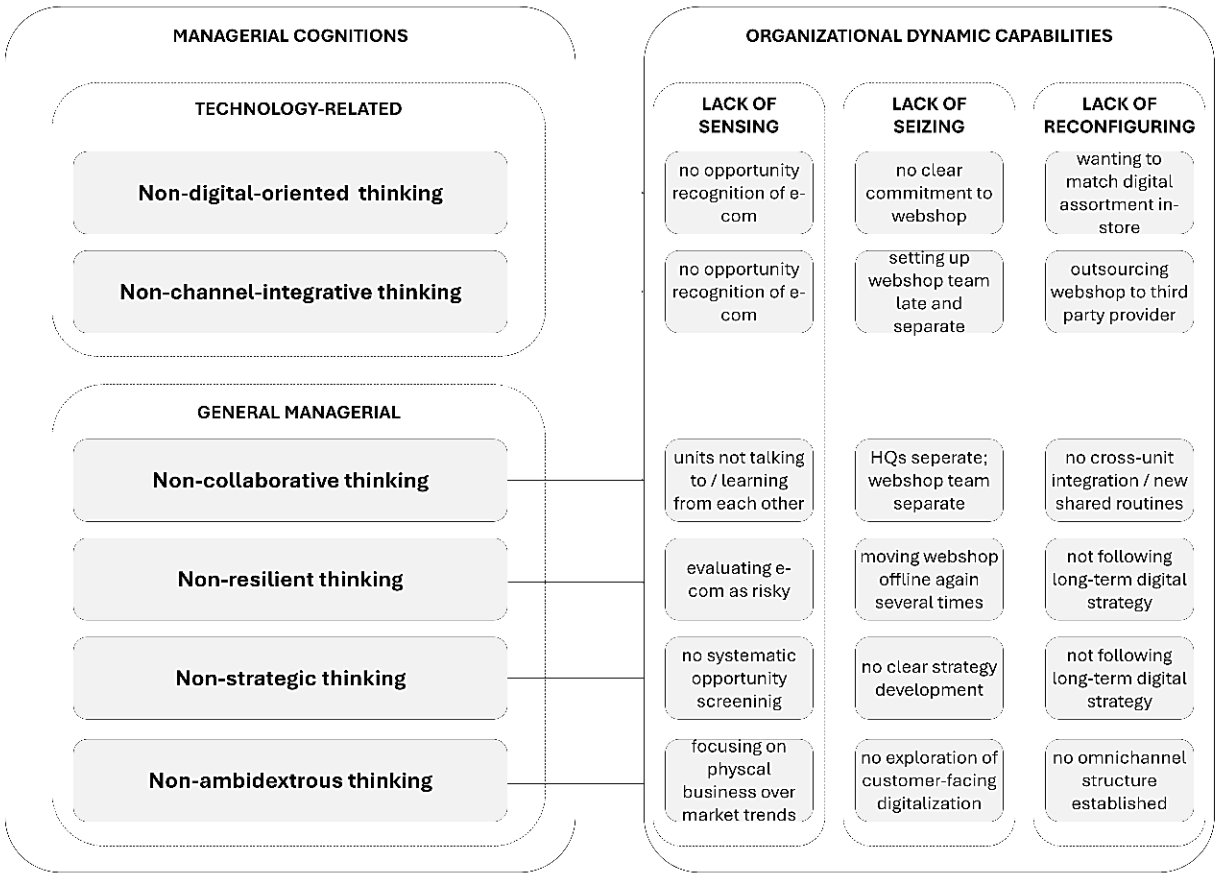


Figure 13. Detrimental Pre-Phase Thinking Patterns Hindering Organizational Sensing, Seizing, and Reconfiguring

4.4.2 Non-Digital Mindset as Microfoundational Issue in the Pre-phase

Figure 13 presents our findings for the pre-phase. In the appendix, we show the data structure derived from our coding, where the aggregate dimensions reflect the detrimental thinking patterns (see Appendix O). A *lack of digital-oriented, channel-integrative, collaborative, resilient, strategic, and ambidextrous thinking* were the microfoundational issues that led to an underdevelopment of sensing, seizing, and reconfiguring capabilities necessary for an organization-wide DT.

Non-Digital-Oriented Thinking

In the 2000s, firms like Zalando, Zappos, or Revolve entered the picture and formed the fashion e-commerce scene. “This was the beginning of an era – of selling things online. These times felt like a goldrush for the firms taking advantage of it” (WCo, Int. 1). The con-

venience of out-of-home shopping and the sheer mass of products available changed consumer preferences radically. Despite noticing this trend, management derived the following implications for stationary retail:

> *"Customers are demanding more and more choice. … consumers expect a selection of 10, 15 or 20 options. This is certainly a result of the online boom. … brick-and-mortar retailers have to follow suit. That's why the stores are getting bigger and bigger." (Newspaper D, 2013)*

This statement clearly reflects managers' **physical-world thinking about digital trends**. Seeing the developments in e-commerce, the managers decided to match the digital trends in the physical world. Some years later, when PhysicalCo had launched and relaunched their underperforming online shop, PhysicalCo's share of the e-commerce business was still half of the e-commerce share in the German industry "at around 20 percent" (Newspaper C, 2018). The channel was not seen as crucial contributor to PhysicalCo's performance and "insignificant" (Newspaper C, 2018), as a manager stated.

Furthermore, **physical-first thinking for business strategy** inhibited any effort to integrate and foster the small online unit of Beta. While the stores were well connected to each other, no sales incentives were given to store managers for selling online stock.

> *"But did the store manager personally benefit from this [selling an item online]? No, we decided that they did not. … Because we only earn from the turnover we generate at the terminals." (PCo4)*

This prioritization of the physical business at the top led to the neglect of the online business by middle-management in-store. A store manager not even remembered when PhysicalCo launched the Beta webshop: "I don't even know when ... That wasn't important for us" (PCo2, Int. 2). The prevalence of physical-first thinking is further solidified by an interview with a manager.

> *"The PhysicalCo executives, like many others in the market, prioritized physical expansion and expanded too quickly with locations that were ultimately unprofitable. This had a very negative impact on the company." (Newspaper A, 2019)*

Non-Channel-Integrative Thinking

The neglect of the online business further became evident through **channel separation thinking**. The central IT team, for example, was not responsible for the Beta's online shop. They had a separate team for the online shop, "which had virtually nothing to do with them

at all" (PCo3, Int. 1). Also, the technical setup and maintenance of the online shop was outsourced to third parties (Partner website, 2016). Managers were unable to view both channels as integrated units.

> *"And the topic of management: Online and offline need to be managed neatly together, which did not happen. They were viewed as individual business units or channels." (PCo1)*

Non-Collaborative Thinking

This lack of collaborative thinking did not only pertain to the physical vs. digital channel, but it was also sensible in an **antagonistic thinking of units.** Since the Alpha-Beta merger, this general conviction had undermined any efforts to work in cross-functional teams and profit from each other's expertise. The 'anti' mindset on both sides had prohibited the opportunity to seize synergies through collaboration, as a manager recalls: "They thought of that [the interaction] as a huge issue, issue. Exactly, which is why the interaction and collaboration between the two areas was not good at all" (PCo1).

Non-Resilient Thinking

With online shopping gaining more traction, **fear-based thinking** regarding 'the digital' took over. Especially middle managers began to fear for their jobs, "afraid that they will become superfluous at some point" (PCo3, Int. 1). This fear-based approach to the digital world did not only pertain to middle managers. Fear and finger-pointing was an issue that came from the top, with managers painting fear-inducing pictures for physical retailers.

> *"Shop rents in prime locations in large cities have been rising rapidly for years. … more store operators will give up. … And what's even worse is that we brick-and-mortar retailers pay business tax on our stores, while online retailers don't. I fear that's a glaring injustice." (Newspaper D, 2013)*

Despite this evident fear, managers still thought of e-commerce as an unsure bet. **Risk-averse thinking** was also detrimental to PhysicalCo's efforts in consequently moving online.

> *"At the beginning they said, yes, come online, we'll jump on board, … then they saw that it wasn't going to fly and an unsure thing, and they ended it - and that was definitely the wrong time. That was still under the aegis of the Alpha Family CEO, and when the financial investor took over, they said, guys, we also have to think about the future, everyone is going online." (PCo3, Int. 2)*

This unsure and risk-averse behavior also became evident through several newspaper articles on the online shop being taken online, offline, and relaunched multiple times (Newspaper B, 2010; Newspaper A, 2014; Newspaper E, 2016). One PhysicalCo manager reflects on the risk-averse thinking, and the negative consequences from a customer perspective.

> *"You can never be the first mover in discounting, you can never be the first mover in such strategic decisions, but ultimately you have to be a follower. … If you go to the Beta online store and suddenly, they decide it's no longer there for a year, your trust in the company doesn't really grow." (PCo3, Int. 2)*

Non-Strategic Thinking

PhysicalCo's management did not think strategically about using digital technologies. They lacked a digitalization strategy, until they were late in asking "how do we move forward?" (PCo3). The **unfocused strategic thinking** of management became evident in their lack of clear communication where the organization was headed, regarding the entire business strategy after the merger, as well as a DT strategy. According to a later manager, "they never managed to develop a uniform concept that they could ultimately communicate the network, the branch network, but it was always a bit unclear, they had no clear direction" (PCo3).

Non-Ambidextrous Thinking

Lastly, by **thinking of current over future success drivers**, managers faced the classic exploitation vs. exploration dilemma. Only concentrating on where they had excelled in the past and being critical of the potential of e-com, they did not prioritize the digital business as a longstanding former manager recalls.

> *"We knew that the online sector was becoming more important. On the other hand, we also knew that no one is making money online. … I personally would never have acquired a company like DigitalCo." (PCo4)*

Summary of Pre-Phase Effects

The non-digital mindset of managers during the pre-phase manifested through a lack of (i) technology-oriented (*non-digital-oriented, and non-channel-integrative thinking), and (ii)* general managerial thinking patterns (*non-collaborative, non-resilient, non-strategic, and non-ambidextrous thinking)*. While prior research describes DCs as enacted through concrete managerial activities and routines, such as systematic opportunity scanning, cross-functional experimentation, or deliberate resource reconfiguration, our case data reveal that

such activities were largely absent in PhysicalCo during the pre-phase. Instead, managers' non-digital thinking patterns prevented the emergence of activities associated with sensing, seizing, and reconfiguring capabilities.

4.4.3 Non-Digital Mindset as Microfoundational Issue in the Post-Phase

After PhysicalCo had new investors and fresh capital, the complementary DigitalCo was acquired. The acquisition was an attempt to connect to the digital world of e-com and spur PhysicalCo's DT. Looking at the composition of the management team, most managers had been involved with the firm for many years before the acquisition and continued to stay after (see Appendix N). With some patterns continuing and others newly emergent in the acquisition context, the managers showed *non-digital-oriented, non-channel-integrative, non-capability-oriented, non-collaborative, non-resilient, non-strategic thinking, and non-agile thinking patterns*. Negatively affecting the development of sensing, seizing, and reconfiguring capabilities, PhysicalCo's non-digital managerial mindset led to DT failure. Figure 14 details the non-digital thinking patterns as the aggregate dimension.

Non-Digital-Oriented Thinking

Even though the decision to acquire DigitalCo was pushed by the new investors, a non-digital managerial mindset persisted in the organization. Like beforehand, the **physical-world thinking about digital trends** was still a major issue: Online shopping on social media platforms like Instagram, **s-commerce**, was a newly emerging trend that was expected to roll out soon in Europe. Despite that, PhysicalCo's management purely focused on the issues they identified in the physical marketing world.

> *"I asked him [PhysicalCo manager] what he thought were the biggest strategic risks. His answer was … an advertising campaign in print-media a competitor is running. I almost fell off my chair. … shoppable Instagram is coming to market, no word about it. … Sure, to say digital is everything - that's not it. But this complete ignorance." (DCo2, Int. 11)*

Likewise, PhysicalCo's managers still could not get around their **physical-first thinking for business strategy**. DigitalCo felt that its digital resources and capabilities were neglected by the acquirer (DCo2, DCo4, DCo5), which was confirmed by the later acquirer of DigitalCo.

> *"You simply have a very, very nice basis there [DigitalCo], which perhaps wasn't used quite as much in the past by the investor, simply because the core of the company, PhysicalCo, was primarily focused on stationary retail." (Aco, Int. 3)*

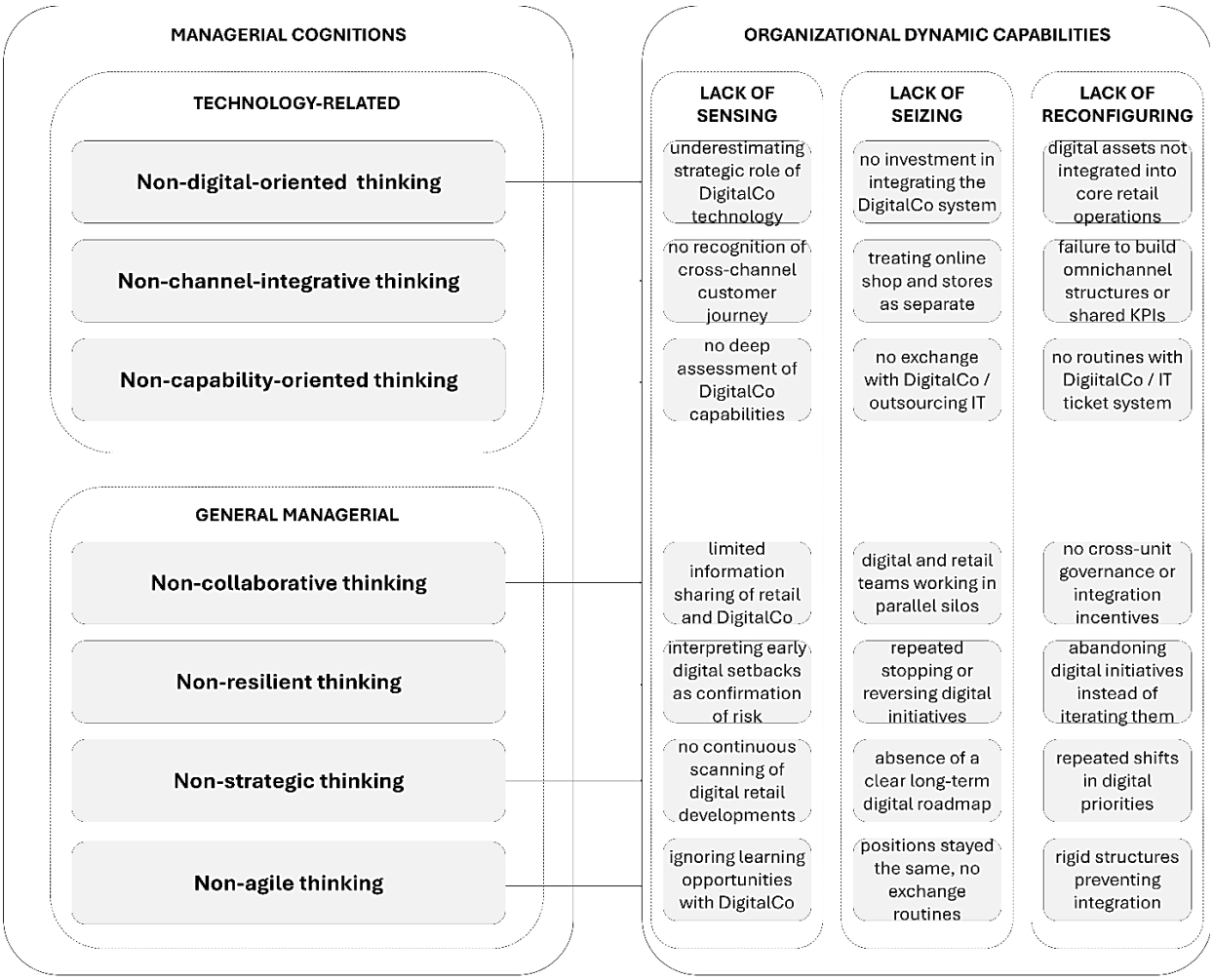


Figure 14. Detrimental Post-Phase Thinking Patterns Hindering Organizational Sensing, Seizing, and Reconfiguring

Non-Channel-Integrative Thinking

Managers also followed a pattern of **non-reconfigurative thinking**; thinking in channel versus product types. They put “DigitalCo and online from Beta together and the physical wholesale and retail business together” (PCo3, Int. 1). However,

> *“the connection between the companies was wrong. Ultimately, we should have said, we'll take the stationary wholesale area and link it much more with DigitalCo. And on the other hand, I have the Beta retail area with the stores and the Beta online shop.” (PCo3, Int. 1)*

The organization practiced the opposite, not being able to integrate independent of channel type. It shows the inability to let go of old beliefs and to think of new business models, i.e., omnichannel operations.

Non-Capability-Oriented Thinking

Further, PhysicalCo's managers showcased their **IT-capability-agnostic thinking** when they did not draw on the digital capabilities that DigitalCo brought into the marriage. Also, they outsourced their IT center. As evident in the media, PhysicalCo planned "staff changes and the migration of the data center. … the new Head of IT wants to set up a demand IT organization" (Newspaper E, 2019). Problematic about this idea was the loss of technical expertise, as managers confirmed in our interviews.

> *"[We] set up a completely new IT team at headquarters, which would then only do process and project management. So, no more programming ... And that's when the trouble began." (PCo1)*

Indeed, in a later interview, a manager even acknowledged that "the former colleagues took most of the head knowledge about our processes with them" (Newspaper E, 2022), leading to severe capability gaps.

Non-Collaborative Thinking

After the acquisition, the non-collaborative thinking extended to DigitalCo, resulting in a new pattern of an **antagonistic thinking of units**. From the perspective of PhysicalCo, a manager perceived the acquired company was always "doing its own thing" (PCo3, Int. 1). From the perspective of DigitalCo, however, no real business interest from the acquirer was shown: "They were actually rather quiet managing directors, too. … it came across as if there was no business interest in us" (DCo4). Reflecting on DigitalCo's subsequent investors as being much more present, this middle manager also noticed a real difference in the top managers' behavior at DigitalCo. Now, the "managers go to more planning meetings for strategy. … I didn't notice that at all before at PhysicalCo" (DCo4). PhysicalCo managers were actively excluding DigitalCo's digital resources or capabilities from their business operations.

Non-Resilient Thinking

Still, managers' cognitions were comprised of **fear-based thinking** patterns regarding digital change, especially in Beta's middle management.

> *"There was always a bit of a fear, and they still have it today in retail, that online and offline are not seen as linked by the managers in the stores, they are always afraid that online will steal our sales … then my store will be closed, and I'll be unemployed." (PCo3, Int. 2)*

PhysicalCo managers also cared immensely about face-saving, making **defensive thinking** another issue that impeded DT efforts. DigitalCo managers observed first-hand that 'fail fast' approaches were not at all present in the mental frames of PhysicalCo's executives.

> *"So, failing, somehow admitting it, talking about it, asking someone for help - I thought that was incredibly frowned upon. Everyone had to act as if they were the super crack who knew everything and could do everything." (DCo2, Int. 10)*

As opposed to younger and startup-like firms like DigitalCo, often based on "fail fast" approaches (DCo2, Int. 10), these managers followed a 'no-failure' culture which restricts a digital mindset.

Non-Strategic Thinking

The managers with their legacy convictions had a different strategy than the new financial and strategic investors, leading to **unfocused strategic orientation**.

> ***"****The interests then diverged significantly. The investor at the time wanted to invest heavily in the online sector. See DigitalCo. I would have wanted to expand differently." (PCo4)*

The manager of AcquirerCo explained that he often sees organizations taking shortcuts: Once they recognize the need to become active regarding DT, they are often many years behind. New investors then tend to buy digital firms, without thinking about how to create value from these. This may lead to neglect and integration failures.

> *"You know you have to do something along these lines, but what? Then you buy something else. But what do I have to do now? How do I integrate something like this? Into my core strategy? And then let it run a bit on the side." (ACo, Int. 3)*

Non-Agile Thinking

Lastly, instead of risk-aversion like in the pre-phase, the management now showed non-agile thinking through **ignoring learning opportunities** from the outside. A DigitalCo manager recalled how meetings with PhysicalCo had always been centered around day-to-day business, not forward-looking or learning-oriented.

Table 21. Detrimental Digital Mindset Thinking Patterns for M&A-Based DT (building on Hildebrandt & Beimborn, 2022)

(Technology-oriented Thinking Patterns)*

Thinking	*Established description: (+)*	New description: (-)	Cognitive frames (-)
Digital-oriented *	*A generic open-minded way of thinking, affinity and tuning towards the usage and application of digital technologies to sense, exploit as well as explore possibilities.*	A preference of physical vs. digital solutions; no openness towards the use and application of digital technologies; thinking that is guided by physical business realities.	**Pre- / Post-phase:** Physical-world thinking about digital trends; Physical-first thinking for business strategy
Channel-integrative *	*n/a*	No capacity to think of and explore options to integrate and blend physical and digital world; no expandable-sum thinking but cannibalization view.	**Pre-phase:** Channel separation thinking **Post-phase:** Non-reconfigurative thinking
Capability-oriented *	*n/a*	Lack of thinking about competence and capability building regarding the in-house mastery of digital technologies.	**Pre-phase:** *n/a* **Post-phase:** IT-capability-agnostic thinking
Collaborative	*Describes the openness for communication, cooperation and collaboration to support problem-solving. Includes awareness about own synergy effects, can pertain in inter- or intradisciplinary collaboration.*	No openness for communication, cooperation and collaboration to support problem-solving towards other parties (business units, acquired firms, …).	**Pre- / Post-phase:** Antagonistic thinking of units
Resilient	*Ways of thinking that include tolerance for failure, thinking of failure experiences as learnings and describe in general the cognitive ability to recover quickly from failures.*	Thinking that is primed on fear, defensiveness and face-saving; thinking that tries to avoid risks; no tolerance for failure or cognitive ability to recover quickly from failures.	**Pre-phase:** Fear-based thinking; Risk-averse thinking **Post-phase:** Fear-based thinking; Defensive thinking
Agile	*Comprises thinking in principles of the agile manifesto, but also willingness to learn, thinking in flexible, adaptable, uncertain ways including possibility of failure.*	Thinking that follows fixed structures is not adaptable and tries to avoid uncertain outcomes; an unwillingness to learn new things.	**Pre-phase:** n/a **Post-phase:** Ignoring learning opportunities; Fixed thinking
Strategic	*n/a*	Thinking that lacks long-term orientation or intentionality in the use of digital technologies for transformation or integration.	**Pre- / Post-phase:** Unfocused strategic orientation
Ambi-dextrous	*n/a*	Thinking that focuses on current facts over future chances; preferring exploitation over exploration.	**Pre-phase:** Thinking of current over future success drivers **Post-phase:** n/a

> *"I was there for a year, and I asked the group why I hadn't even been asked a single question yet. … Except, why had sales gone down this week? I came from a very responsible position with incredibly valuable knowledge." (DCo2, Int. 13)*

A middle-manager recalled the company-wide meeting with a 1,000 people introducing DigitalCo. "They didn't present them as part of us, and since then, we have not heard or thought about them much" (PCo2, Int. 2). This laissez-faire approach manifested in the managers' **fixed thinking**.

> *"They were very, very, very comfortable in their positions and in the way they had apparently set themselves up so far. … that was a bit 1985 [management] style" (DCo2, Int. 13)*

To achieve transformative outcomes, however, our experts stressed that having the right personnel with the right mindset is crucial. If at the top, "no one is thinking differently, then it [the effort] probably won't translate" (M&A expert).

While our casa data shows a coherent picture of managerial cognition, we acknowledge that, at times, there were also voices in the management team that argued for a better integration of DigitalCo's expertise: "I was given permission to analyze DigitalCo, I said from the outset ... for cost reasons and for reasons of risk and expertise ... we have to integrate it. That was relatively clear to me" (PCo1). However, this was never accomplished as dominant logics in the team prevailed.

4.4.4 Thinking Patterns in a Non-Digital Mindset

Based on our findings across pre- and post-phase, Table 21 defines the eight detrimental, non-digital thinking patterns we identified. To contextualize our insights, the second column includes already established definitions of identified thinking patterns for a positive DI outcome (see Hildebrandt & Beimborn, 2022). Hence, the entirely new identified patterns are underlined. The third column provides the new descriptions of the thinking patterns if they are absent. The last column lists our corresponding cognitive frames (second-order themes).

4.4.5 From Pre- to Post-Phase: Linking Thinking Patterns to DC Gaps and DT Deficits

To synthesize how failure unfolded in this complementary, physical-digital acquisition, we integrate the two temporal phases analyzed above into a unified process model (see Figure 15). This model illustrates the recursive relationship between individual-level mindset deficits undermining DMCs, leading to the organizational-level inability to develop DCs, culminating in DT failure despite digital M&A. Our data show that the non-digital mindset at PhysicalCo persisted across both phases and built the microfoundation of five mechanisms that eventually hindered organizational-level change. In the pre-phase, we saw a *lack of digital-oriented, channel-integrative, collaborative, resilient, strategic, and ambidextrous thinking* of the managers.

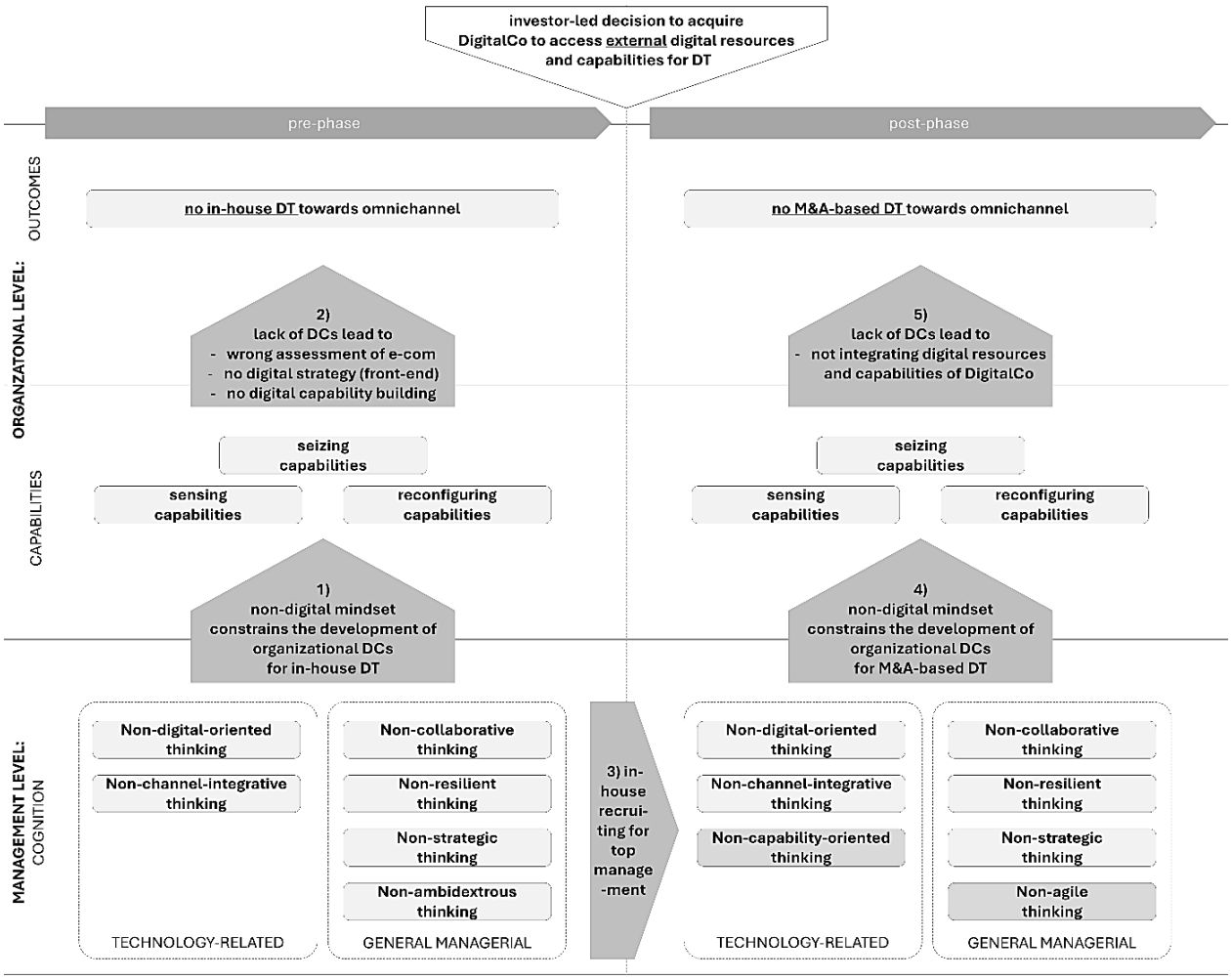


Figure 15. Microfoundational Process of DT Failure Despite Digital M&A

This constitutes the first mechanism from management-level to organization-level capabilities, showing how (1) the non-digital mindset constrains the development of organizational DCs for in-house DT. This manifested at the organizational level in a lack of DCs, which then led through (2) a wrong assessment of e-com, no digital front-end strategy, and no digital capability building to a failure to achieve an in-house DT towards omnichannel. With new investors joining, the organization went for digital M&A as a corrective mechanism. However, the (3) recruiting for top management positions was mostly sourced from within. The acquisition of DigitalCo, therefore, did not constitute a genuine turning point: Many of the *same mindset deficits* consisted in the management team*: we found an absence of digital-oriented, channel-integrative, capability-oriented, collaborative, resilient, strategic, and agile thinking.* This constituted PhysicalCo's management's non-digital mindset, that (4) constrained the development of organizational DCs for M&A-based DT, and, in turn, (5) hindering the integration of the digital resources and capabilities that DigitalCo brought into the marriage. Management failed to articulate a coherent integration logic and continued to view online and offline businesses as separate entities, leading to untapped complementarities and an erosion of transformative potential. These findings reveal a recursive failure mechanism: the legacy managerial mindset at PhysicalCo shaped organizational structures and routines, leading to a lack of sensing, seizing and reconfiguring capabilities. Even when the new investors entered the stage, these gaps inhibited the adoption of new cognitive frames. Rather than acting as change agents, even the two newly appointed managers seemed to follow previously established thinking patterns, because past decisions and existing structures made it hard to go the opposite way.

In sum, while physical-digital deals promise the condition of firm complementarity in several domains, many deals still fail to produce the intended outcomes (Gu & Lev, 2024; Uhlenbruck et al., 2006). Previous IS research has mainly focused on organizational level factors, neglecting the impact that individuals in positions of power can have. Our data demonstrates how non-digital thinking patterns, persistent and reproduced over time, serve as microfoundational inhibitors of DT, even after acquiring a digital venture. By tracing how these cognitive structures evolved over time and hampered the formation of DT-DCs, we contribute a processual explanation for transformation failure in digital M&A. These insights set the stage for the subsequent normative insights as well as the theoretical discussion, where we position our findings in light of current M&A and DT literature.

4.5 Discussion

4.5.1 Insights into a Microfoundational Process Model of DT Failure

Our findings suggest that the mere presence of complementary resources in digital M&A is insufficient to enable DT. Prior research often assumes that once firms acquire external digital capabilities, these resources can be recombined with existing assets to create value. However, our case shows that such complementarities must first be cognitively recognized and strategically activated by managers. When managerial cognition remains anchored in legacy business logics, the organization fails to sense digital opportunities, allocate resources toward them, and reconfigure existing structures accordingly. In this sense, complementarity is not automatically realized but depends on what we term the cognitive activation of complementarity, i.e., the ability of managers to interpret acquired digital capabilities as integral to the future of the organization and mobilize them through dynamic capabilities.

Our study advances the literature by foregrounding *managerial cognition as microfoundation of organizational DCs*. Specifically, we show the mechanisms through which the *absence* of digital mindset thinking patterns at management level reinforced over time and hindered the organizational creation of DCs needed for both internal DT and external, M&A-based DT. Our analysis suggests that managerial cognition did not operate as a standalone factor but as the mechanism through which strategic priorities, resource allocations, and integration decisions were interpreted and enacted. In this sense, cognition shaped how existing structural conditions and acquired digital resources were interpreted and mobilized. We thereby add to previous literature on general managerial cognition like perception, attention or problem solving where only general contexts of change have been studied (Foss & Mazzelli, 2025; Hock-Doepgen et al., 2025) and introduce are more nuanced understanding of thinking that specifically guides the use of digital technologies and organizational DT.

Further, we extend the digital mindset concept from a successful digital innovation context to a DT failure context: By differentiating between technology-related and general managerial thinking patterns, we add explanatory depth to research on cognition explaining general organizational change, and thinking that specifically constitutes DT. We showed that the absence of *digital-oriented, collaborative, resilient, and agile thinking patterns,* identified as crucial for digital innovation (Hildebrandt & Beimborn, 2022), proves equally critical for M&A-based transformations. For a non-digital mindset, we also identify and define novel cognitive

deficits; *non-channel-integrative, non-capability-oriented, non-ambidextrous, and non-strategic thinking*, as particularly detrimental in our context. To ensure a shared understanding, we also provide clear conceptual definitions for the negative thinking patterns identified, positioning them against their positive counterparts where possible and providing examples of their manifestation during pre- and post-phase (see Table 21).

In the pre-phase, *non-channel-integrative thinking* led to a lack of organizational DCs, so that e-com opportunities were not scanned or recognized, the own webshop was set up late with a team separated from other units, and the technical support for it was outsourced. Contemporary research has emphasized that recombining digital and physical elements is crucial for successful digital change (Verhoef et al., 2015; Yoo et al., 2010). *Non-ambidextrous thinking* of PhysicalCo's managers skewed their mental frames toward efficiency- over innovation-centered. However, ambidexterity has been shown to be critical for the digital change of incumbent SMEs (Cenamor et al., 2019), balancing the exploitation of the old and exploration of the new (Drechsler et al., 2020; Gregory et al., 2015; Svahn et al., 2017). Hence, identifying and defining managerial cognition detrimental to pushing ambidextrous action at organizational level is crucial for our understanding of failure. From a managerial lens, lacking ambidextrous thinking constrains DCs, leading to a physical business focus, no exploration of customer-facing digitalization, and no omnichannel structure. Lastly, managers lacked the capacity to deliberately align digital resources with long-term transformation goals. The role of *strategic thinking* for IT strategy-making has long been stressed by researchers (Mason, 1991). On an organizational level, the importance of management and its micro-capabilities like strategic vision, change management, and strategic thinking were recently underlined (Baiyere et al., 2025). On a managerial level, strategic thinking has also been connected to an organization's absorptive capacity, "as well as to each of its four components – acquisition, assimilation, transformation and exploitation" (Srivastava & D'Souza, 2019); but its absence has not been linked to detrimental DT outcomes. For the post-phase, we saw the continued absence of the aforementioned thinking patterns, while *non-ambidextrous thinking* was replaced by *non-agile thinking*. Now that the impetus for ambidextrous thinking was imposed through the investors who pushed for an acquisition, managers showed their inability to think in agile ways: Learning opportunities from and with DigitalCo were ignored, the people's positions stayed the same without creating exchange routines, and no integration took place.

Our novel *process model* from pre- to post-phase issues (see Figure 15) highlights *a recursive failure mechanism*: our study reveals the temporal endurance of a non-digital mindset

despite changes in ownership. Our process model clearly illustrates how deep-rooted thinking patterns shape a lack of sensing, seizing, and reconfiguring capabilities at organizational level. As a result, even newly acquired digital assets can fail to spur a transformation, because they were absorbed into lacking DCs at the organizational, and into a lacking digital mindset at the managerial level. This illustrates how cognition, resistance, and organizational-level inertia co-evolve, producing a form of capability trap that can lock firms into non-digital trajectories (Wimelius et al., 2021). While structural and financial conditions shaped the context of the transformation attempt, our longitudinal evidence shows that managerial cognition systematically guided strategic priorities, resource allocation, and integration decisions. In this sense, cognition functioned as the mechanism through which contextual conditions translated into organizational outcomes. In the following section, we therefore evaluate alternative explanations frequently associated with failed M&A and DT initiatives.

Lastly, we follow Teece (2014) in his recommendation that, in companies with an inert culture, novel resources and capabilities “may need to be acquired rather than developed in-house” (p. 334). We see this trend with incumbent, pre-digital organizations acquiring the digital assets externally all the time. However, our results offer a nuanced perspective on the assumption that “the resulting acquisitions [should be] managed separately in a way that minimizes conflicts with incumbent units” (Teece, 2014, p. 334). A *separate management of digital assets*, in the case of physical-digital deals, does not seem to foster *synergy creation nor transformative outcomes* for the acquirer. Managing the digital target largely separately, which happened in our case, would mean that its transformative potential remains untapped. A loose coupling may protect both parties’ structures and culture, but it might not be strong enough for deals that are intended to entail transformative outcomes. Without integrating the digital target and making a true attempt to change the organization’s business model and identity, the acquisition almost appeared symbolic: now, the company could appear as digital-oriented to the outside, without attempting to transform. Since no mindset change towards welcoming the digital was achieved on managerial level, they, in fact, were not eager to put the new, digital assets to transformative use in their own company. This reminds of Meyer & Rowan’s (1977) seminal work on decoupling, where they warn that institutional rules may lead to isomorphic organizational structures, like facades, that lack true coordination and control in order. Translated to a digital world, researchers have recently identified organizations engaging in digital decoupling, a strategy that “allows for a misalignment of the formal and the informal and opens up for the parallel handling of the digital (new business) and nondigital (existing business)” (Magnusson et al., 2021, p. 317). One of the coping

strategies include “an expressed ambition and commitment to digital transformation that is portrayed to external stakeholders but are not reflective of what is really going on within the organization” (ibid., p. 320). Our findings suggest that internal transformation is unlikely to occur when management lacks the cognitive orientation necessary to recognize and mobilize digital capabilities.

Briefly reflecting on the literature that our case could reaffirm, *firm complementarity* remains a necessary but not sufficient condition for M&A success (Bauer & Matzler, 2014; Harrison et al., 2001). The most valuable resources and capabilities may become worthless if not integrated and reconfigured in the right way (Stieglitz & Heine, 2007). As our case could corroborate, complementary differences in physical and digital resources and capabilities are a great starting point for value creation on paper. However, our findings showed that the promise of complementarity did not materialize, since managerial cognitions on acquirer side impeded any action to develop the necessary sensing, seizing, and reconfiguring capabilities to integrate and reconfigure both parties (Teece, 2014). Our findings also substantiate early management research that highlights the central role of management in shaping organizational outcomes like the upper echelons theory (Hambrick & Mason, 1984).

Subsequent work on DMCs (Adner & Helfat, 2003) underlines that not only managerial action but their underlying *cognitions* may directly influence organizational success. In our case, the recursive non-digital thinking patterns constrained the ability to activate DT-related DCs. Extending the studied DT failure to a digital M&A setting, the findings align with prior insights that managerial action, biased attention, or commonly-held beliefs about the market or business model can obstruct transformation efforts (Tripsas & Gavetti, 2000; Vuori & Huy, 2016), as can a lack of managerial cognition hinder a successful IS integration after M&A (Merali & McKiernan, 1993). Eventually, consistent with prior DT research, our findings show that a *digital mindset* at the managerial level is critical for achieving organizational transformation and the integration of digital M&A (Hildebrandt & Beimborn, 2022; Solberg et al., 2020). Absent such cognitive orientation, incumbents tend to pursue incremental process digitalization rather than engaging in transformative change (Soluk & Kammerlander, 2021).

4.5.2 Discussing Rival Explanations for M&A-based DT Failure

Financial Issues as Main Driver

Financial distress is a common explanation for failed M&A or DT initiatives. Resource constraints can limit a firm's ability to invest in new digital capabilities or integrate acquired technologies. Therefore, financial considerations must form the basis of DT strategies (Hess et al., 2016). In retail in particular, declining margins and competitive pressures have been linked to unsuccessful DT attempts (Verhoef et al., 2021). In this case, however, the empirical evidence suggests that financial constraints alone will not explain the stalled DT directly following the digital acquisition. First, financial statements indicate that following the acquisition of DigitalCo, the organization experienced temporary stabilization: revenues increased and EBIT remained positive in the initial period. Moreover, the investment in DigitalCo itself was a clear signal that investors had the strategic intent and capacity to initiate DT directly after the acquisition. Later financial deterioration where operating cash flow declined sharply occurred later, when integration and digital capability building with DigitalCo should have already taken place. Hence, timing and trajectory of financial indicators cannot explain the initial lack of DT in the decade before the acquisition of DigitalCo, when management actively invested into store expansion over an online presence. Financials can also not explain that when fresh capital was present management decided against integrating and leveraging the acquired digital resources, hence hampering PhysicalCo's DT through their resistance.

Business Model Incompatibility as Main Driver

Business model incompatibility is another frequently discussed explanation for unsuccessful acquisition outcomes, particularly when firms attempt to combine digital and traditional operations (Floch & Scaringella, 2017). Differences between online platform models and physical retail can create conflicting value logics and operational processes, that may hinder integration. While such tensions were surely present to a degree, operating in the same industry did promise significant similarities that make it unlikely that incompatibility alone accounts for the stalled DT. The acquisition of DigitalCo was explicitly motivated by the expectation that PhysicalCo's retail infrastructure and DigitalCo's digital capabilities could by combined and create the impetus for an integrated omnichannel model. Like a manager emphasized, "it wasn't a new business model. It was just different sales channels, platforms" (PCo1). Rather than replacing the incumbent's business model, DigitalCo was intended to augment existing processes and services. The absence of systematic experimentation with integrated offerings therefore points to difficulties at personal level where an integration of both worlds was not prioritized but resisted against.

IS Integration Issues as Main Driver

Lastly, IS integration issues are frequently cited as key drivers of M&A failure, (Henningsson & Kettinger, 2016; Tanriverdi & Uysal, 2011; Wijnhoven et al., 2006). Such challenges can be particularly pronounced in technology-related acquisitions where digital capabilities must be embedded into existing organizational infrastructures. However, the evidence suggests that technical integration challenges were not the prime cause for not integrating DigitalCo. On the contrary, interviews with managers showed that even a full ERP integration with the own software had been discussed at several points later in time. “My basic strategy was to consolidate similar systems. … We also analyzed the IT systems of DigitalCo. The recommendation was very clear: integrate“ (PCo1). Hence, while IS integration challenges likely contributed to the complexity of integration, they cannot sufficiently explain why the digital resources and capabilities of DigitalCo were not used for an organization-wide DT following the acquisition without understanding managerial cognition of related opportunities.

Summarizing, all our discussed alternative explanations capture important contextual challenges but remain insufficient to account for the observed failure trajectory. Financial constraints emerged only after failure to transform, business model differences were limited due to operating in the same industry, and technical integration was considered but never prioritized. Hence, a common pattern emerges: the decisive barrier was not the absence of resources, compatibility, or technical feasibility, but the way managers interpreted and acted upon these conditions. This reinforces our central argument that managerial cognition plays a critical role in activating or inhibiting the DCs required for DT.

4.5.3 Key Contributions of the Study

Contributions to Theory

First, connecting the formerly separate research streams, it *links M&A research to DT* as a strategic acquisition objective. It is also one of the few studies where the *process of failure* is studied from a microfoundational perspective: We find that *non-digital managerial mindsets serve as microfoundational inhibitors of DCs.* This offers a novel, processual explanation that links managerial cognition with organizational-level failure, and explains how despite the availability of digital resources the organization was unable to transform.

Further, we could *extend the digital mindset concept* to a transformation failure context: Building on previous research on the digital mindset in DI (Hildebrandt & Beimborn, 2022), we identify the absence of seven digital thinking patterns as a root cause of DT failure. While

adapting five previously identified patterns to a new context, we also introduce two further critical thinking deficits: non-strategic and non-integrative thinking.

Third, through building a process model based on longitudinal data, we demonstrate the *temporal endurance of cognitive path dependencies*: Non-digital mindsets can persist through not building DCs but rigid organizational routines and structures, even after shifts in ownership. This adds to the literature on DT resistance that persists over time and hinders DT even though the required resources are at an organization's fingertips.

Normative Insights for Practice

Our findings suggest that even acquisitions with promising formal complementarity *may fail if top management lacks the cognitive orientation* to spur the organizational DCs to sense and seize digital technologies, and to reconfigure the organization based on that. Our findings should sensitize organizations and their top management, as well as investors and M&A advisors to the importance of assessing and monitoring managerial cognition in M&A-based DT initiatives.

Strategy Phase: Throughout the phases of an M&A-based DT strategy, we identified some crucial measures that practitioners can take to improve their success. Before a digital acquisition is made, during the strategy phase, it is of utmost importance for investors and the top management team itself to probe the willingness to break up old structures within this team and be open to digital technologies. This can be done via one-on-one discussions, roundtables, and/or anonymous surveys that also question the managers' thinking patterns. Such evaluations should especially look for the seven identified for the pre-phase are not equally absent. Based on that, the acquirer's management's future composition should be planned accordingly, and digital change must be positioned as a non-negotiable. As prior research has shown, especially in decade-old, family-firm-born organizations, CEO succession can act as a catalyst for reinventing and rejuvenating the firm, "and restore the environment-organization fit that had often deteriorated pre-succession" (Istipliler et al., 2024, p. 1604). Likewise, if old management teams are reluctant against change, it can make sense to strategically bring personnel from the outside in that offers thinking patterns in favor of digital change.

Due Diligence Phase: During the due diligence phase, further assess the technical and cognitive readiness of the acquirer top management. For those deficient in a digital mindset yet crucial in future scenarios, offer training: Develop and offer workshops or one-on-one sessions that foster a digital-oriented, channel-integrative, capability-oriented, collaborative,

resilient, strategic, ambidextrous, and agile thinking. This ensures that a future acquisition is placed into a nurturing environment.

Integration Phase: Lastly, once a suitable target is acquired, the integration phase forms the most critical, last effort: During this time, leaders must be equipped and empowered to challenge existing assumptions and allow the target to integrate its digital resources and capabilities. For this, dual leadership structures jointly from acquirer and target can help to foster this high-level exchange and integration. Retaining target firm leaders and creating executive tandems and joint leadership roles can help to break up previous mental models on acquirer side and foster ambidextrous thinking of the managers. Further, it helps to transfer knowledge from the target, and facilitate integration and transformation (Graebner, 2004). Exploiting existing knowledge of the acquirer while exploring the new possibilities of the digital target might be further fostered via temporal or structural ambidexterity and digital innovation labs (Göbeler et al., 2020). Further, the newly formed organization benefits from incentive structures that foster the integration of business units; in retail, of physical and digital channels (Herhausen et al., 2015). For example, store managers may receive credit for selling shoes online that they did not have in-store to foster a channel-integrative mindset. Throughout integration, firms and investors alike must be aware of symbolic decoupling: publicly signaling DT while lacking genuine cognitive and structural integration. These tendencies must be monitored and spotted early, so that countermeasures can be taken from interventions to replacing overly resistant legacy-led managers.

4.6 Conclusion

This study, based on the critical case of a failed M&A-based DT in European retail, set out to understand why such initiatives fail to trigger the intended transformation of incumbent firms. Drawing on longitudinal, historical data from 126 secondary sources and 37 interviews, we show how persistent managerial thinking patterns can undermine the development of transformation-relevant DCs from pre- to post-phase. Linking a non-digital managerial mindset, deficient in technology-related and general managerial thinking patterns for change, to sensing, seizing, and reconfiguring capabilities, our study contributes to DT research by providing a microfoundational explanation of how cognitive frames shape organizational responses to change. Through defining the absence of digital-oriented, channel-integrative, capability-oriented, collaborative, resilient, strategic, ambidextrous, and agile thinking as cognitive barriers to organizational DCs and (M&A-based) DT, we extend existing research on DT and M&A. Acquisition outcomes motivated by DT are therefore not only

determined by structural integration challenges but also by the cognitive frames through which managers interpret and mobilize newly acquired digital resources. Our findings also offer practical implications: Even before the acquisition of digital firms, incumbent acquirers, investors, and M&A advisors alike must critically reflect on the managerial mindsets of the current top management team. Without cognitive openness toward physical-digital complementarities, collaboration with digital actors, and experimentation with new business models, acquisitions may remain symbolic rather than transformative. Firms attempting M&A-based DT should therefore pay closer attention to leadership constellations, and plan the integration through governance mechanisms, and incentive systems accordingly.

While some criticize qualitative case research regarding the generalizability of findings, we emphasize that instead of aiming for statistical representativeness, our goal is analytical generalization. We develop theoretically grounded insights into the mechanisms through which managerial cognition can undermine M&A-based DT through a critical case (Eisenhardt et al., 2016; Flyvbjerg, 2006; Gioia et al., 2013). Furthermore, we mitigated retrospective bias as best as possible through cross-informant validation from several involved organizations, repeated interviews, and extensive triangulation with 126 archival sources spanning more than two decades. Since the thinking patterns identified in this study emerged from one retail context, this opens several avenues for future research: Future studies should examine whether other thinking patterns become relevant in different industries, geographies, or phases of acquisition. Especially channel-integrative thinking is expected to predominantly be relevant in a retail context. Further, it should be explored whether the simultaneous absence of these thinking patterns contributed to the failure, or if some patterns have a more detrimental effect than others, through, i.e. Fuzzy-set Qualitative Comparative Analysis (fsQCA). In addition, quantitative research could build on these insights by developing validated instruments to capture thinking patterns and test their influence on DT and digital M&A outcomes across larger samples, so that practice may be able to benefit from management surveys based on these insights.

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4.8 Appendix

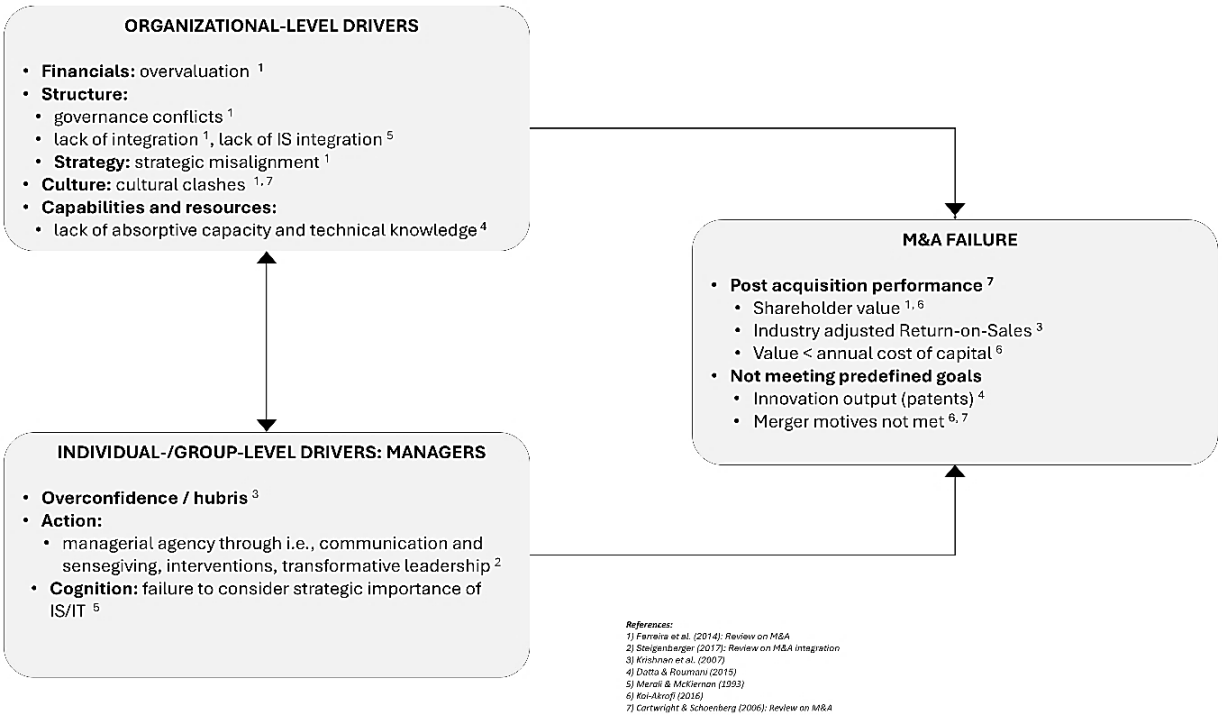
H) Activities and Routines for Organizational Sensing, Seizing, and Reconfiguring

Sensing	Seizing	Reconfiguring	Author
– **scanning** – **creating** – **learning** – **interpreting**	– addressing sensed opportunities or possibilities through – **new products,** – **processes,** – **services,** or – a combination of these alternatives	– **transforming organizational structures and assets** as the firm grows and the environment changes	Teece (2007)
– **exploratory phase: scanning** (i.e., CEO reviewing environment regarding B2C e-commerce; e-commerce mentioned at Board meeting); **learning** (i.e., CEO having many conversations with new Head of Digital); calibrating (i.e., formulating B2C strategy) – **building phase: scanning** (i.e., T&Cs of external platform providers)**; learning** (i.e., feedback for customization)	– **exploratory phase: creating**: Head of Digital position and hiring – **building phase: selecting** (i.e., pros/cons of outsourcing)**; committing** (i.e., CEO authorizing in-house capability)**; designing** (i.e., specifying requirements of in-house platform) – **extending phase: creating** (i.e., additional roles/position/size of digital department); **leveraging** (i.e., integrating growing B2C processes with B2B processes); **releasing** (i.e., moving employee from sales to digital department)	– **exploratory phase: designing** (i.e., identifying processes and resources that could be used for B2C); **committing** (i.e., Board and CEO approve resources for five-year plan) – **building phase: creating** (i.e., a digital department); **accessing** (i.e., h Hiring and managing vendor); **leveraging** (i.e., improved data transfer from ERP system to B2C system) – **extending phase: s**electing (i.e., dentifying where to go full B2C ecommerce and where to hold back); **designing** (i.e., specifying extent of stock for B2C); **committing** (i.e., decision to go slow on roll-out)	Yeow et al. (2018)
– **cross-industrial digital sensing**: identify new digital opportunities, also outside network of partner firms – **inside-out digital infrastructure sensing**: routines to evaluate the demand for	– **digital strategy development**: semi-continuous adaptation of increasingly digitalized strategy, aligned with (changing) environment and (flexible) overall business objectives	– **decomposing digital transformation into specified projects**: prioritize digitalization projects based on alignment to digital strategy and reevaluate resource and team member allocation during exploration phases	Ellström et al. (2021)

digital infrastructure and search for new solutions	– **determining enterprise boundaries**: routines to determine what to do in-house and what to outsource	– **creating unified digital infrastructure**: integrate digital solutions into unified digital infrastructure and make it accessible to entire organization

I) Organizational- and Individual-/Group-level Drivers of M&A Failure

The Organizational- and Individual-/Group-level Drivers of M&A Failure



J) Digital Mindset Thinking Patterns

Digital Mindset Thinking Patterns for Digital Innovation (adapted from Hildebrandt & Beimborn, 2022)

Disruptive	Constant questioning of existing solutions and imagination of how digital technologies could induce alternative scenarios that include fundamental pivots e.g. in the first principle how problems are solved.
Risk-affine	Comprises the readiness of individuals to take calculated risks regarding the digital technologies and business domain.
Resilient	Ways of thinking that include tolerance for failure, thinking of failure experiences as learnings and describe in general the cognitive ability to recover quickly from failures.
Platform-oriented *	Ways of thinking that apply the platform concept and its belonging phenomena like network effects on traditional tasks, products or businesses through the availability of digital technologies.
Digital-oriented *	A generic open-minded way of thinking, affinity and tuning towards the usage and application of digital technologies to sense exploit as well as exploration possibilities.
Agile	Comprises thinking in principles of the agile manifesto, but also the willingness to learn, thinking in flexible, adaptable and uncertain ways that include the possibility of failure.
Collaborative	Describes the openness for communication, cooperation and collaboration to support problem-solving. It includes awareness about the own synergy effects and can pertain in inter- or intradisciplinary collaboration.
Exponential *	Recognition and awareness of scalable and exponential characteristics of digital technologies. It includes technological predictions and visions.
Data-driven *	Turning away from reliance on gut feelings, recognizing potentials of data and constantly taking these into account in decision making or product development and thinking in computing ways of problem solving.
Generative *	Thinking that fosters procrastinated binding and solution exaptation typically for digital solutions by integrating abstraction and modularity during development.
(Re-) combinatorial *	Constantly integrating the recombinatorial characteristics of digital technologies in solution-finding to broaden the potential solution space by creatively combining independent digital technologies.

Legend: * technology-oriented (own classification)

Since innovation triggers DT, DI and DT do have overlaps. However, DI concentrates on creating and sensing new things, “whereas a digital mindset for digital transformation rather focuses on the transformation of “old” things” (Hildebrandt & Beimborn, 2022, p. 2). Hence, for a M&A-based DT context, for example, generative thinking is less likely to be important. Rather, thinking patterns that foster organizational M&A integration capability (Benitez et al.,

2018), transformation capabilities (Weritz et al., 2024), and strategic vision and change management (Baiyere et al., 2025) may be thinking patterns that foster DT.

K) Data Analysis

Detailed Description of the Data Analysis

Step 1: Since this case is complex and involves different firms, organizational structures, and decision-makers, we initially focused on identifying turning points in the organizational history, i.e., structural changes. Before studying our data intimately, we extracted those key events from information on company websites, press articles, and our interview data (Eisenhardt et al., 2016). To better understand the context in which the organizations operated at given points in time, we also captured key industry trends towards digitalization, like the rise of ERP systems in the 1990s. From a chronological table, we then constructed a figure that provides all important milestones (see Figure 11). This helps the reader to quickly grasp the circumstances under which PhysicalCo evolved since the 19th century.

Step 2: Now, moving towards explaining the process of failure, we needed "to identify the generative structures that enable and constrain it" (Pentland, 1999, p. 722). While we did not copy the exact steps of the original, grounded-theory approach (Glaser & Strauss, 1967; Suddaby, 2006), we still followed the principle of an iterative organizing and grouping of raw data into more and more abstract conceptualizations. During this inductive phase, an open mind to embed observations in existing research is called for. We constantly compared emergent themes in the initial interviews, further interviews conducted, and existing theory (Eisenhardt, 2021), anchoring the emergent patterns and relationships (Díaz Andrade et al., 2023). The aim of the entire process, regardless of whether it is called axial coding (Corbin & Strauss, 2008) or building second-order themes (Gioia et al., 2013), is producing "progressively better-defined and grounded higher-order concepts … and creating underlying theoretical arguments that connect constructs. Ultimately, the core interest is strong theory" (Eisenhardt et al., 2016, p. 1114).

Further, it is important to note that the change in PhysicalCo's ownership structure, when financial and strategic investors joined, was several months before the acquisition of DigitalCo. In our data, we treat these two incidents as one anchor point. This anchor point divides the timeline of this case into a pre-investor and -acquisition, and a post-investor and -acquisition phase. Hence, we speak of pre-phase and post-phase from now on, enhancing the readability of the paper. In the middle of coding first-order issues in pre-phase and post-phase, this comment by PhysicalCo's then-CEO caught our attention:

> *"The difficulty of achieving digital transformation is not primarily the technology or the know-how, but the mindset towards it within the organization. I have seen this in the various industries in which I have worked to date." (Newspaper C, 2018)*

Hence, as the interviews and the analytical process continued, we paid special attention to the thinking patterns of the managers. Our new understanding also facilitated "the formulation of yet more questions, to be pursued in later interviews" (Gioia, 2021, p. 25), putting an increasing focus on mindset issues. To minimize individual bias in data interpretation, we had multiple coders in our research team (Gioia et al., 2013). (i) The lead researcher started by openly coding over 400 DT issues and observations pre- and post-phase in our data. In true fashion of interpretive or hermeneutic research, these codes were closely reflecting our informants' statements and not the researchers' interpretations (Gioia et al., 2013). The focus on the mindset issues and underlying thinking patterns led us to further distill the statements we had to a manageable number of key codes. (ii) The author team discussed the suitability of the key quotes selected for surfacing detrimental thinking patterns. In some instances, we decided to shorten the quotes, focusing on the most relevant statements only. Eventually, we arrived at 15 codes for the pre- and 18 codes for the post-phase with corresponding statements that were the most informative for learning how managers were thinking. (iii) Next, the research team grouped the statements that reflected shared thinking patterns together. This could be best described as building second-order themes, following Gioia's approach, and is also related to the approach of axial coding (Strauss & Corbin, 1998). For the pre-phase, we identified nine second-order themes or thinking patterns, for the post-phase, eleven. (iv) Eventually, we abstracted further into second-order aggregate dimensions (Gioia, 2013; 2021). Following the method of constant comparison between theory and data, we found a violation of the digital mindset thinking patterns as discussed by Hildebrandt and Beimborn (2022). For example, thinking of the physical and the digital business as separate units was a clear indication that the dimension "digital-oriented thinking" (Hildebrandt and Beimborn, 2022, p. 13) was missing in these managers' thinking patterns. Also, we observed anti-digital thinking patterns unique to the study of DT through M&A: strategic and integrative thinking. Appendix O) and P) represent the data structures of both pre- and post-phase. To further increase transparency, we decided to keep word-by-word quotes instead of first-order codes in the data structure at the primary level. This approach, where we truly report informant voices at the first, and researcher voices at the second-level, "enables a more "qualitatively rigorous" demonstration of data-to-theory connections and

gives some confidence that any creative insights are rooted in the informants' experience" (Gioia, 2021, p. 24). Through this, we aim to contribute to the credibility and third-party replicability of our study.

Step 3: Coding and creating the data structures to surface the detrimental, higher-level thinking patterns regarding DT through M&A was a crucial step. Yet, this step can only display a static picture of the phenomenon we studied. This static picture or photograph "can be converted into a movie … when the data structure is "set in motion"" (Gioia, 2021, p. 26). Therefore, the final step is to create a theoretically grounded process model. Showing the reader how we carried out a systematic approach from step one to step 3, our aim is to arrive at the discovery of some "new, revelatory concepts and grounded theories" (Gioia, 2021, p. 27). Figure 15 represents this process model of failure at the microfoundational level. The next section will detail our findings before presenting our evolutionary process model of failure from individual to organizational level.

L) Case History

Detailed Description of the Case History until the Acquisition of DigitalCo

The story of PhysicalCo dates back to the end of the 19th century, when the company Alpha started out as a fashion manufacturer. Further generations internationalized and diversified the family business to licensing and managing other brands. The same-industry retailer Beta was founded in the 1970s, and soon became a well-known brand for consumers in the low-price segment. In a growing number of B2C stores as well as through wholesale, Beta sold its private labels and a diverse set of other brands for the entire family. When Beta was offered for sale in the 1990s, Alpha became partially invested in Beta, together with a private person. Eventually, both organizations merged to become PhysicalCo in the 2000s, with plans to grow by up to 100 new stores and shop floors within the next year. The merger entailed shared ownership for both parties, and a family member of Alpha managing the business operatively.

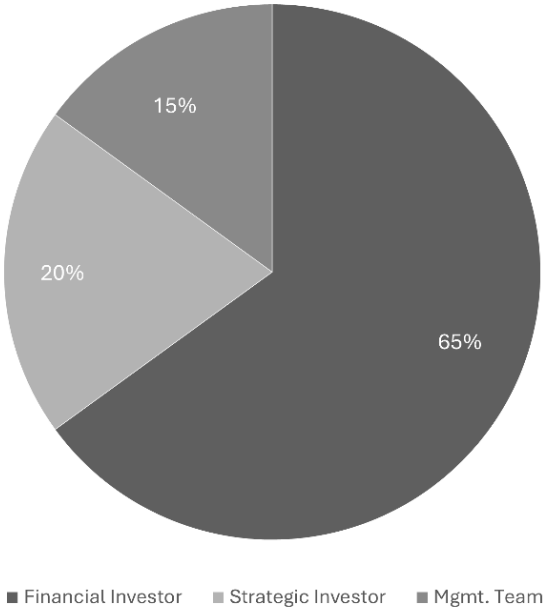
In the same decade, fashion e-commerce got a boost by advancements in technologies, "such as smart mobile devices (smartphones and tablets) and related software (apps, mobile payments, e-valets, e-coupons, digital flyers, location-based services)" (Piotrowicz & Cuthbertson, 2014, p. 6): m-commerce was born. Our interviewees spoke of a "goldrush" (DCo1, Int. 1) when the first marketplaces entered the picture. PhysicalCo, however, focused its growth on a store-based concept, reaching an international presence in 20 countries. Its digitalization efforts were mostly concentrated on its back-office. Despite early investments in its own online shop, the channel never managed to get enough external traction and internal recognition. Around this time, the organization began to struggle: Changing consumer preferences collided with internal, organizational issues around strategic direction, growth, and financing. The ownership of the organization was eventually transferred from the private person and the Beta family, to financial and strategic investors, as well as the management team. The business had to be streamlined, leading to divestments in R&D, IT, and logistics, and store closures. Also, the distant headquarters of Alpha and Beta were eventually fused in one location.

With the financial and strategic investors taking over, DT came into the spotlight. Soon, the decision to acquire the majority shares of DigitalCo was made. DigitalCo was one of the first local movers in e-commerce: Its proprietary ERP system enabled the organization to partner with new marketplaces quickly and efficiently. Soon listed on more than 20 marketplaces internationally, the digitally-mediated company (Steininger, 2019) started to struggle with

physical resources: Outgrowing its demand and logistics, it entered the deal with PhysicalCo. Communication about this deal in the double-digit million numbers emphasized PhysicalCo's ambitions of spurring its DT through this strategic acquisition. Also, both firms hoped to create synergies between the physical and digital world: PhysicalCo wanted to access online marketplaces, more brands and digital talent, DigitalCo aimed for liquidity, physical channels, and logistics services.

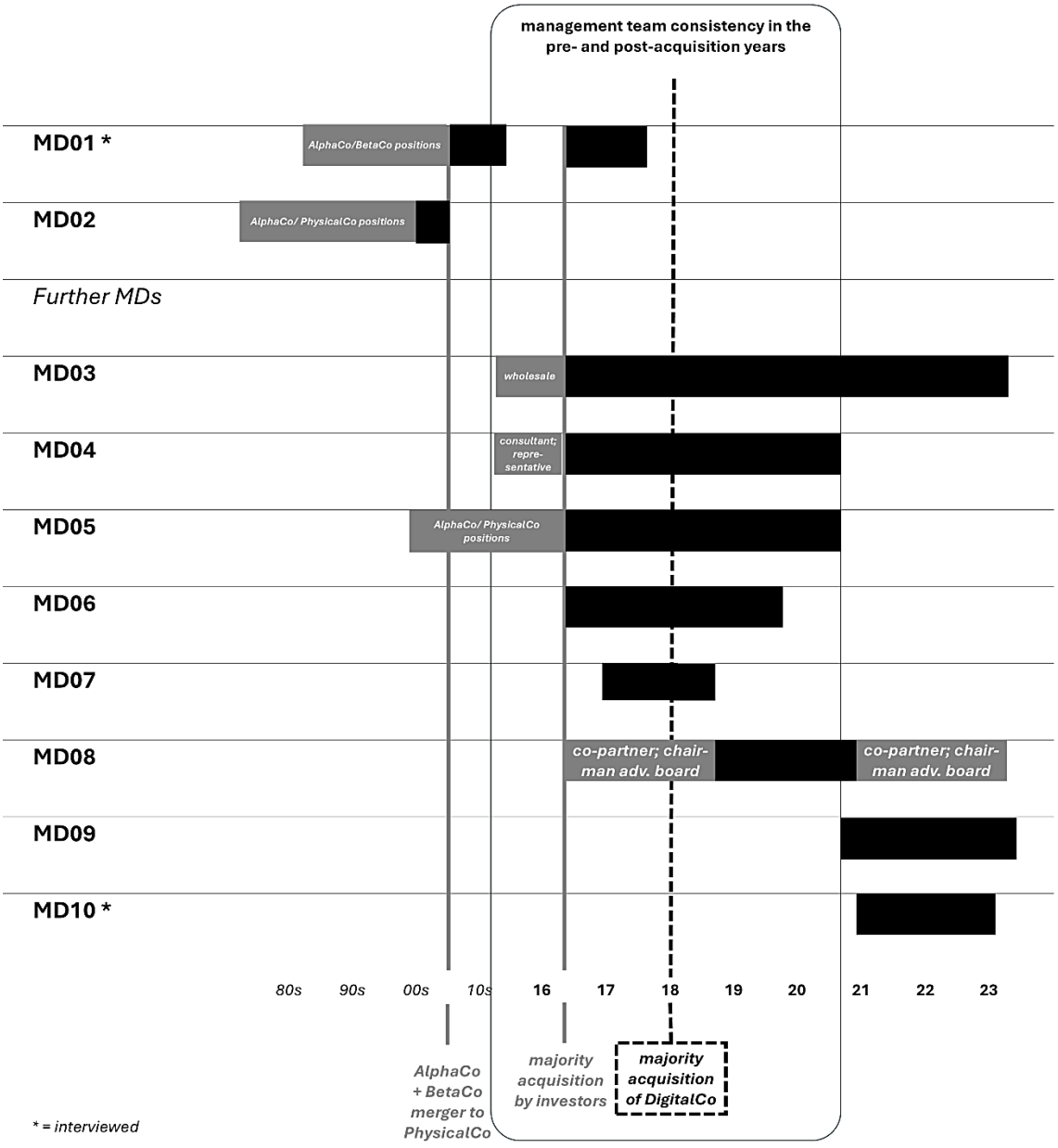
M) Ownership Structure

Ownership Structure after the Acquisition of PhysicalCo by a Financial and Strategic Investor in 2016



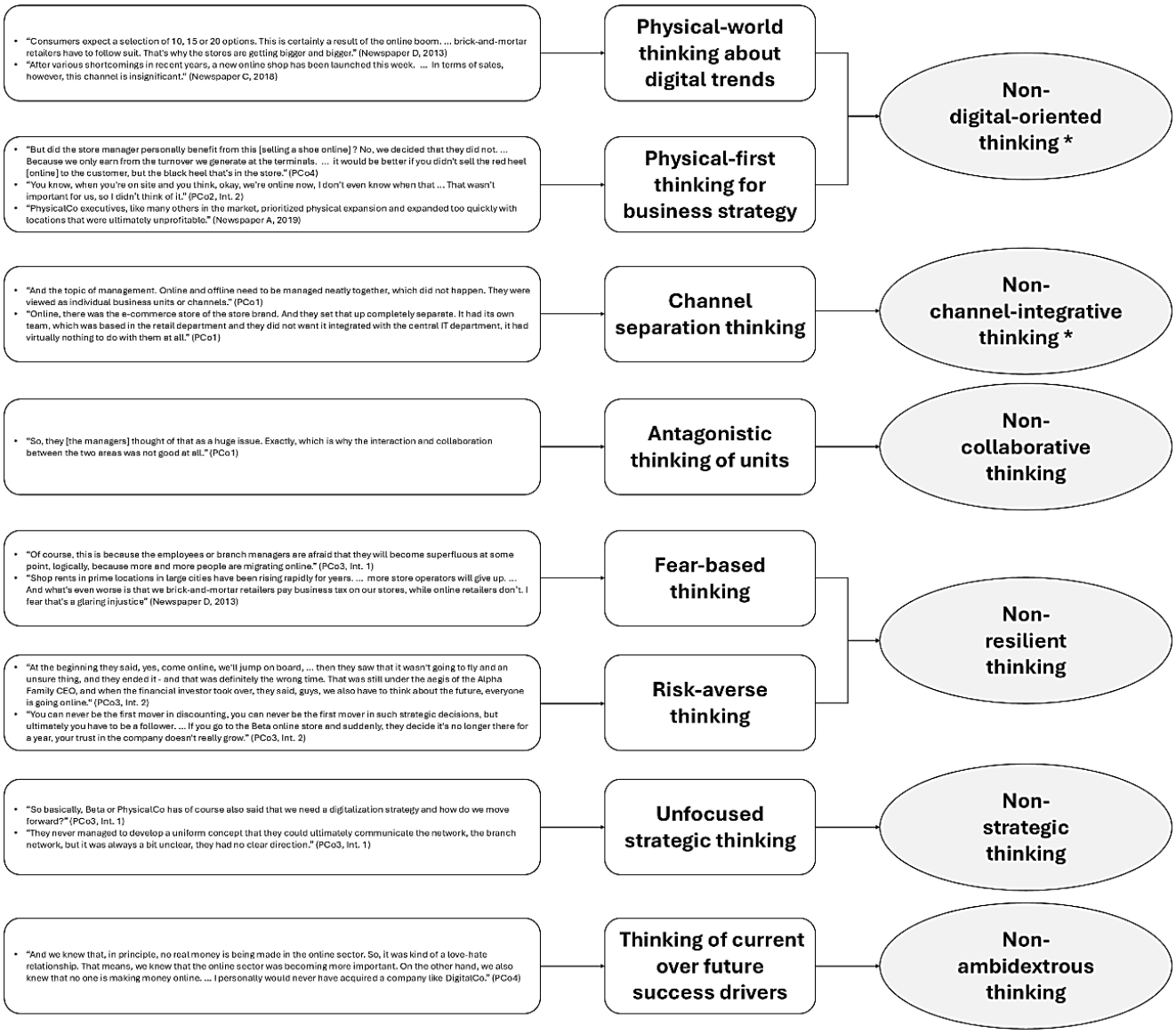
N) PhysicalCo Manager History

PhysicalCo Managers (black) and their Previous Firm Involvement (grey)



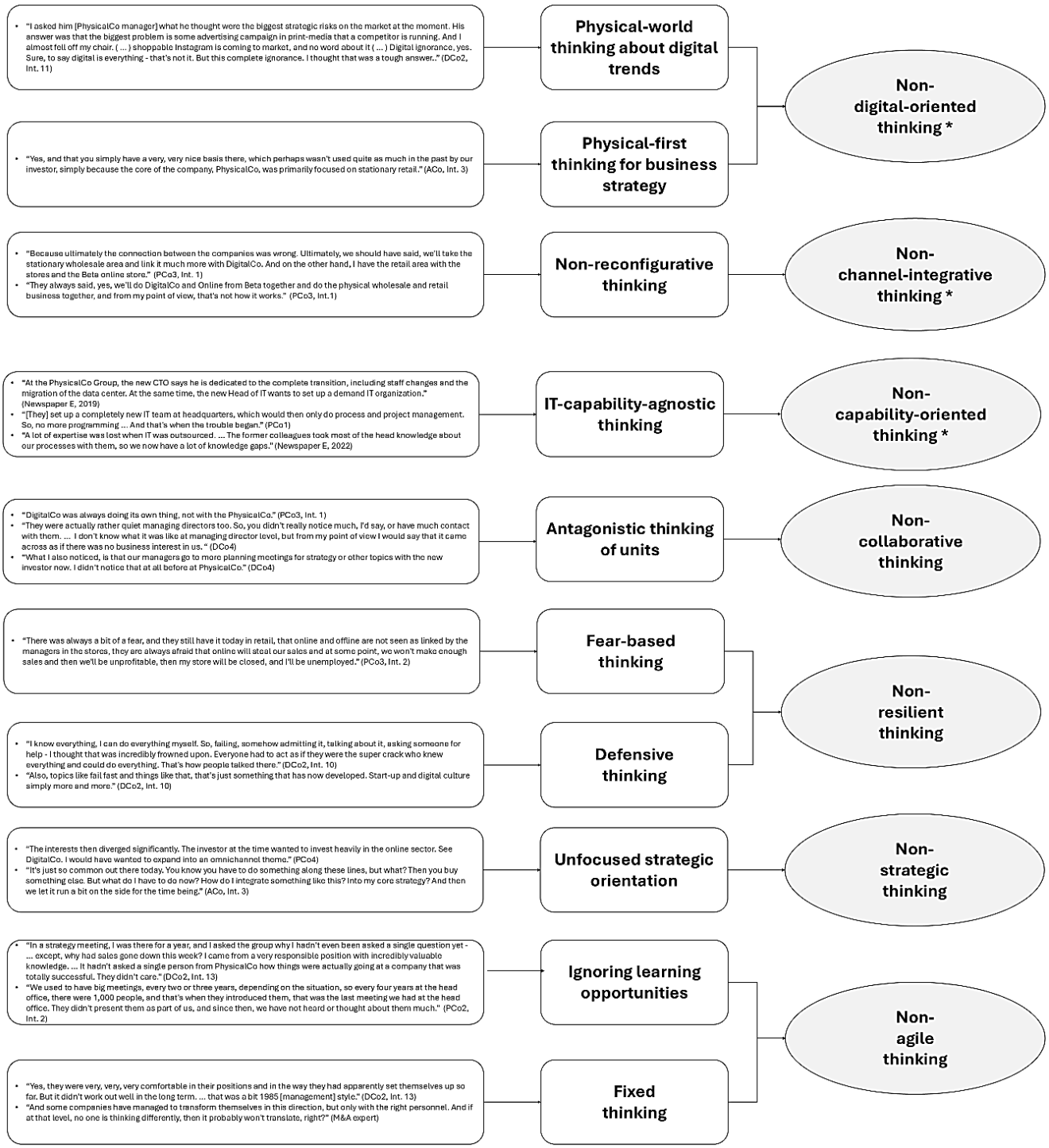
O) Pre-Phase Thinking Patterns

Data Structure: Detrimental Pre-Phase Thinking Patterns (* Marks Technology-related Thinking Patterns)



P) Post-Phase Thinking Patterns

Data Structure: Detrimental Post-Phase Thinking Patterns



5 From Knowledge Loss to Knowledge Leverage: How GenAI Affordances Transform Post-Merger IS Integration

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Abstract

Post-merger IS integration often threatens the human-centered and IT-embedded knowledge of acquired firms. Drawing on the knowledge-based view of the firm and a technology affordance lens, we examine two consecutive acquisitions of the same digital M&A target to explain how an emerging technology reshapes IS integration choices. While the first acquirer pursued a disruptive "rip-and-replace" strategy for the target's proprietary ERP system, the second adopted a "retain-and-revive" approach, enabled by newly discovered GenAI affordances. In particular, LLM-supported affordances like learning system knowledge through chat increased knowledge transferability, knowledge aggregation, and efficiency, reducing prior assumptions about system intransparency, personnel dependence, and conversion costs. Our findings show how GenAI reconfigures perceived knowledge challenges, alters integration logics, and expands feasible paths for value capture. The study contributes to M&A and IS integration literature by revealing how affordance actualization can shift strategic choices between the replacement and retainment of target systems.

***Keywords**: Generative AI Adoption, Mergers & Acquisitions, Post-Merger IS Integration, Knowledge Integration Challenges, Technology Affordances and Constraints*

5.1 Introduction

While mergers and acquisitions (M&A) activity is rising, the majority of M&A deals still fail (Robson et al., 2025). One of the most pressing issues is an insufficient organizational focus on post-merger integration and value creation (Kengelbach et al., 2024; Trichterborn et al., 2016). Integrating knowledge resources is particularly critical for value creation in M&A. Stemming from a firm's technologies and capabilities, an acquirer may target a firm "for its tacit, socially complex, and idiosyncratic knowledge, but the very fact that it is tacit and socially complex suggests that it may not survive the acquisition" (Ranft & Lord, 2002, p. 423): Merging two distinct organizations creates a high risk that knowledge becomes fragmented, lost, or obsolete (Alaranta & Martela, 2012).

Information Systems (IS) serve as the backbone through which organizational knowledge is created, stored, and accessed. Hence, IS are central to M&A knowledge integration (Datta & Roumani, 2015; Stylianou et al., 1996). Integrating the IS of two companies involves "the software components (applications that support business processes and databases), the hardware components (computers and networks), and the organizational ones (personnel and skills)" (Giacomazzi et al., 1997, p. 291). Integrating IS is therefore not purely a technical challenge; it represents the crucial task of connecting the explicit and tacit knowledge held by individuals and digital systems, and the meta-knowledge of knowing whom to ask and where to look (Yoo et al., 2007).

Consequently, IS integration has received considerable attention in research thus far (see Henningsson et al., 2018). Extant literature suggests that the decision to keep the target's system intact and separate, or to integrate it fully or in parts, should be aligned with the degree of business integration (Henningsson & Kettinger, 2016). Integration becomes more difficult and costly when the underlying architectures, data structures, and system logics of both firms are distant, creating serious obstacles to post-acquisition integration and realizing acquisition value (Lee et al., 2022). Acquisition practice shows that acquirers tend to impose their systems on the target, absorbing the target IS into their own, unless a major reason not to exists (M. Mehta & Hirschheim, 2007). This rip-and-replace logic is especially expected in acquirers with a higher IT capability than their targets (Tanriverdi & Uysal, 2015). If acquisition targets operate on legacy or proprietary systems, it adds to the integration complexity. Such systems are often poorly understood and managed in M&A (Johansson et al., 2023). In an effort to cut

costs and enable quick post-merger business integration, acquirers tend to streamline the hardware, software, and IT functions of the target. However, research reports that replacing existing systems and key personnel not only requires immense up-front investments, it is also associated with considerable knowledge gaps and value destruction in the merged firm (Alaranta & Martela, 2012; Stylianou et al., 1996).

Emerging AI capabilities may render some integration challenges malleable. Contemporary AI introduces new action possibilities that can alter the feasibility and economics of post-merger IS management. The focus on AI affordances has recently gained traction in the IS community, with calls to further explore the topic (Juell-Skielse et al., 2025; Yang et al., 2024). Especially Generative AI (GenAI) offers acquirers a huge potential for, i.e., large language model (LLM)-assisted retrieval of tacit system knowledge even when key staff exit (Sira, 2024; Weisz et al., 2022). System constraints that used to mandate costly absorption, associated with target knowledge and capability loss, may now be managed through AI-supported integration paths. Therefore, this study asks: ***How do GenAI affordances reshape strategic choices in post-merger IS integration?***

To answer this question, we studied a revelatory M&A setting through an embedded, multiple case study (Yin, 2017): Our longitudinal data collection focused on the same digital target (TargetCo) in the retail industry which experienced two consecutive acquisitions; first, through BetaCo, second, through GammaCo. Separated by the adoption of GenAI, the former followed a rip-and-replace strategy for the target's system, the latter, retain-and-revive, keeping the system in place and developing it further through AI-supported practices. Because both acquisitions were executed by a similar group of people and are anchored in the same target, the case offers a compelling cross-case comparison to study "the processes that acquirers use to seize value" (Haleblian et al., 2009, p. 490). 39 interviews served as our primary data, triangulated by a large secondary dataset, i.e., online media articles of 20 years. Applying a knowledge and technology affordance perspective, we respond to recent calls in research to study the sociotechnical phenomenon of post-merger IS integration (i.e., Juell-Skielse et al., 2025; Majchrzak & Markus, 2012). Our framework explains how the affordances of GenAI reconfigure knowledge challenges stemming from cryptic systems and departing key personnel. We add novel insight to (i) IS innovation and

adoption research by showing how the adoption of GenAI reshapes organizational integration strategies and drives M&A value capture; (ii) technology affordances research by theorizing how GenAI affordances alter an acquirer's action potential regarding human-centered and IT-embedded knowledge challenges; (iii) M&A IS integration literature by introducing an AI-assisted retain-and-revive path for proprietary systems, challenging past assumptions on complexity and cost vs. value and synergy, and offering new paths to extracting value from M&A (i.e., Henningsson et al., 2018; Lee et al., 2022).

5.2 Theoretical Background

5.2.1 Knowledge and IS Integration in M&A

Extending the resource-based view of the firm, the knowledge-based view argues that a firm exists primarily as an institution for integrating individual knowledge (Grant, 1996). Competitive advantage arises from superior mechanisms for knowledge integration rather than the ownership of physical or financial assets. Organizational knowledge should offer the following three characteristics to make it valuable: (i) *Transferability*, which is harder and costlier for tacit knowledge than explicit, codified knowledge, since the tacit one can only be observed. (ii) The *capacity for aggregation*, which depends on the recipient's ability to add new knowledge to an existing base and can be increased through common language. (iii) *Appropriability*, which is hard to enforce since little knowledge is protected by patents or copyrights, making it inappropriable by means of market transactions (Grant, 1996).

Knowledge can be conceptualized in two general forms: As *content*, referring to explicit and tacit knowledge held by individuals, as well as embodied in digital IS, and as *connection*, describing the meta-knowledge of knowing who and where (Yoo et al., 2007). Knowledge and information are clearly related, since “information is converted to knowledge once it is processed in the mind of individuals and knowledge becomes information once it is articulated and presented in the form of text, graphics, words, or other symbols” (Alavi & Leidner, 2001, p. 109). The IS of a company consists of software and hardware components as well as personnel and skills (Giacomazzi et al., 1997). As such, organizational knowledge creation, transfer, and application is supported by an organization’s IS. As seen in Figure 16, merging two distinct firms requires

some degree of IS integration to realize knowledge integration and the creation of absorptive value from an acquisition (Datta & Roumani, 2015). Hence, M&A represent both an opportunity and high risk: value can be created when firms effectively integrate complementary knowledge bases; and destroyed when this integration fails (Alaranta & Martela, 2012). While a higher IT intensity of the merging firms may indicate greater potential for value creation, it can also increase the likelihood of conflict between the management teams and drive costs (Weber & Pliskin, 1996).

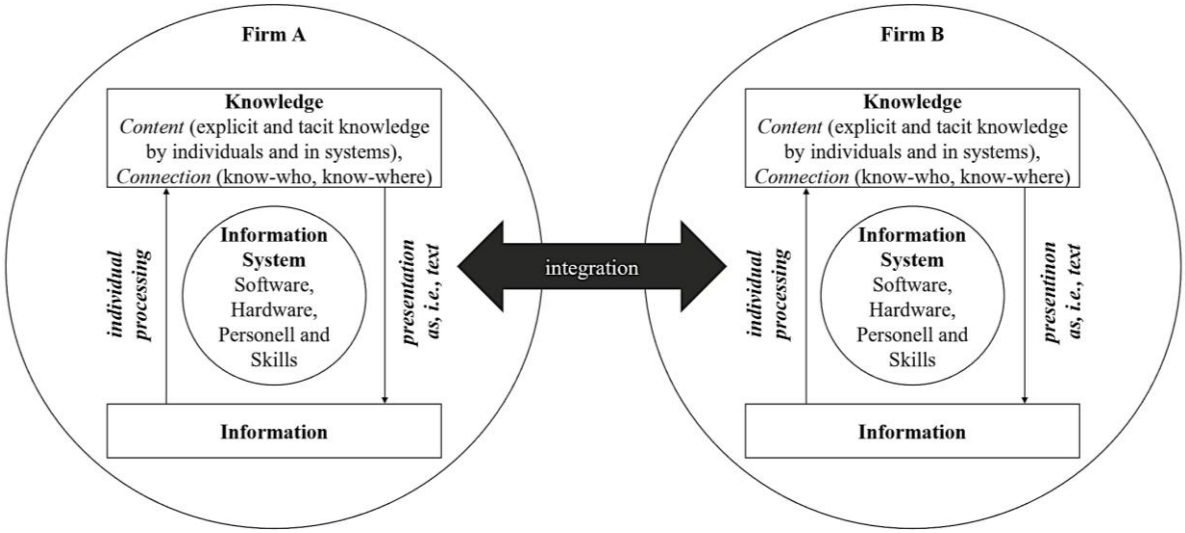


Figure 16. The Integration of IS and Knowledge when Merging Two Separate Firms

According to research, IS and business integration strategies should be aligned (Henningsson & Kettinger, 2016), with IS integration generally following one of four strategies: absorption, co-existence, best-of-breed, or new creation (Johnston & Yetton, 1996; N. Mehta et al., 2007). Generally, the strategy "depends on a mix of both technical and organizational factors that force the new asset designers to consider the impact of the strategic objectives of the transaction on the integration cost in term of financial, information, and human resources" (Giacomazzi et al., 1997, p. 297). A scoping review of acquisition and related IS integration strategies provides an overview of their effects (see Table 22).

Often, integration decisions are led purely by the acquirers imposing their systems and standards, unless they see "a significant reason (e.g., cost-savings from adopting target systems) not to do so" (M. Mehta & Hirschheim, 2007, p. 164). Such an absorption

strategy of the acquirer can reduce integration complexity if the IT configurations of merging organisations are deemed incompatible (Stylianou et al., 1996). In most acquisitions, legacy systems of the target are neglected, including short-term solutions like “building API’s to connect IT stacks from both organizations and harvest the necessary information” (Johansson et al., 2023, p. 624) until integration is completed. However, rip-and-replace strategies centred around full system replacement have been associated with a loss of unique knowledge stemming from the target (Tanriverdi & Uysal, 2015).

Table 22. Literature Synthesis on IS Integration Decisions (based on Johnston & Yetton, 1996)

Acquisition Strategy			**IS Integration Strategy**				**Effect** (+ increase / - decrease)				**Contingency / Further Information**
Independent	Cost reduction	Value-add / Synergy	Absorption	Co-existence	Best-of-breed	Renewal	Risk / Complexity	Cost	Time	Synergy / Learning	
x				x			-	+	-	-	Often occurs in acquisitions of unrelated or geographically distinct businesses
	x		x				-	-	-	-	IT configuration to be absorbed needs to be initially maintained until conversion can be completed
		x			x		+	+	+	+	IT compatibility high: initial gestalt already exists and synergies can be realised by incremental adjustments
		x				x	+	+	+	+	IT compatibility low: configurations are incompatible, as was the case for the national and regional banks, there would be high costs associated with the long period of misfit and re-alignment

Depending on the context, IS integration strategies may also be emerging instead of executed as planned before: In a study on a legacy target system, the short-term project of the acquirer focused on infrastructure investments to stabilize the old infrastructure and cut costs, while the long-term project then focused on the transformation of the system to drive added value. During the initial “open-heart surgery”, the retention of specialists for the legacy system was deemed critical (Busquets, 2015). Overall, IS integration success depends on “prior merger experience, IS participation in merger

planning, the quality of merger planning, the criteria used for setting IS integration priorities, and a high level of data sharing across applications" (Stylianou et al., 1996, p. 203). However, personnel changes and programming language incompatibilities were found to have a negative impact on IS integration success (Stylianou et al., 1996). Hence, integration disruptions often arise from incompatible technologies, inconsistent data structures, and poorly documented legacy systems, with software conversion typically driving most of the associated costs (McKiernan & Merali, 1995). The greater the IT distance before the acquisition, the stronger the negative effects if tight integration is required (Lee et al., 2022).

5.2.2 Affordances of GenAI

Current AI technologies, including "natural language processing (NLP), and virtual agents of all sorts, are being deployed in an astounding variety of problem domains" (Berente et al., 2021, p. 1433). While the underlying technology of machine learning is decade-old, contemporary AI differs from previous IT artifacts through its autonomy, learning capability, and inscrutability (Berente et al., 2021). When it comes to GenAI, LLMs introduce new potential: While prior work in NLP trained language models on a single domain of text like Wikipedia, LLMs use web scraping as a source of diverse and nearly unlimited text. Leveraging extensive datasets and neural network architectures, LLMs can generate human-like text, understand context, and provide relevant responses (Juell-Skielse et al., 2025; Radford et al., 2019). Since its release at the end of 2022, the LLM-interface ChatGPT took the world by storm, offering assistance for both private and professional use. Especially its impact on programming has seen a surge of publications in computer science journals, i.e., exploring functionalities for a variety of programming-related tasks like code completion and correction or the impacts of AI-generated code-prototyping on productivity (Almanasra & Suwais, 2025). Aside from increased productivity, the chat-based interaction with code improves individual learning and democratizes programming (Dohmke et al., 2023). Recent work has emphasized the impact of GenAI on knowledge workers, specifically software developers: not only can programming tasks be outsourced, allowing them to work more efficiently, but GenAI is also significantly changing work practices and team compositions as it is gradually replacing human team members, entailing significant social and economic effects (Kirchner et al., 2025).

To understand the complex relationship between humans and IT artefacts in M&A integration, we adopted the technology affordance and constraints theory as a lens (Yang et al., 2024). Initially coined in ecological psychology by Gibson (1977) to describe what the environment offers to an animal, the IS field has used the concept of technology affordances and constraints as "the action potentials or potential stumbling blocks" (Majchrzak & Markus, 2012, p. 3) people or organizations encounter when dealing with a technology or IS. Both affordances and constraints should not be conflated with technology features, like automatic calculations in a system, and "human and organizational attributes such as tasks, needs, and purposes" (Majchrzak & Markus, 2012, p. 2). Instead of viewing technology as a bundle of features, technology use is often emergent, dependent on a situated context (Faraj & Azad, 2013). For example, ChatGPT's *feature* of natural language generation has an "emergent *property* [emphasis added] to produce novel ideas and synthesise knowledge during its interaction with users" (Yang et al., 2024, p. 4). While affordances and constraints are independent of human perception, "their enactments emerge from intertwinements among the … IT artifact, user, and context" (Mesgari et al., 2023, p. 32).

The affordance lens is recently gaining traction for the study of AI phenomena in the IS field: At the organizational level, studies have identified affordances like standardising and automating processes in auditing (Yang et al., 2024), or cowriter-ability and recommendability in redesigning customer service routines (Juell-Skielse et al., 2025). While these studies represent the potential and the growing importance of the affordance and constraint lens for GenAI, a connection to M&A research and IS integration decisions may surface unique action potential. Considering the three domains that together afford or constrain certain outcomes, namely, IT artifact, user, and context, our case represents a uniquely informative setting: Across two instances, from (i) BetaCo's attempted system replacement to (ii) GammaCo's decision to deploy GenAI to keep the system, the scope of viable actions for IS integration was redefined. Conventional integration theories are often cost-driven and grounded in notions of IT distance and compatibility. In the age of GenAI, an affordance lens directs attention to how technologies offer new action possibilities to resolve knowledge integration challenges regarding proprietary systems and key personnel.

5.3 Method

5.3.1 Methodology

Qualitative case studies are particularly appropriate for capturing the fluid and relational nature of contemporary IS phenomena (Monteiro et al., 2022), like IS integration practices in M&A. Adopting an interpretivist stance, we studied two revelatory acquisition cases of the same e-commerce target, TargetCo. Our longitudinal data collection started in 2023, when initial access to the case was obtained for a study on investor relations; at a time, when TargetCo became the target of distressed M&A activity. We treated this as purposive access to a critical case. As IS integration questions emerged, we transitioned to theoretical sampling of TargetCo's previous and emergent acquisitions, iteratively adding informants and documents to follow evolving constructs (Yin, 2017). Our longitudinal perspective draws on nearly three years of primary and secondary data collection in-situ, complemented by archival material and "retrospective … accounts by those people experiencing the phenomenon" (Gioia et al., 2013, p. 19). Through this, we offer unique insights in post-merger IS integration and management from individual-case analysis to cross-case comparison (Yin, 2017). Our multiple case on two related acquisitions constitutes an interactive system of people, structures, and processes that evolved over time, providing an information-rich setting that yields portable theoretical insights (Gioia et al., 2013). The adoption of GenAI, especially for coding tasks, marks a crucial differentiator between both cases that informs theory on GenAI use in proprietary system acquisitions.

5.3.2 Case Introduction

We explore a revelatory setting in Europe's retail sector. We chose this sector as one of the key contributors to the global economy, where millions of enterprises offer their goods and services to billions of consumers (Sabanoglu, 2024). To understand the chronological events better, Figure 17 provides an overview of the origins of the involved organizations, the two subsequent acquisitions of TargetCo in 2023, and the adoption of ChatGPT by the founder of WebserviceCo in between that enabled a switch from the planned rip-and-replace to a retain-and-revive strategy.

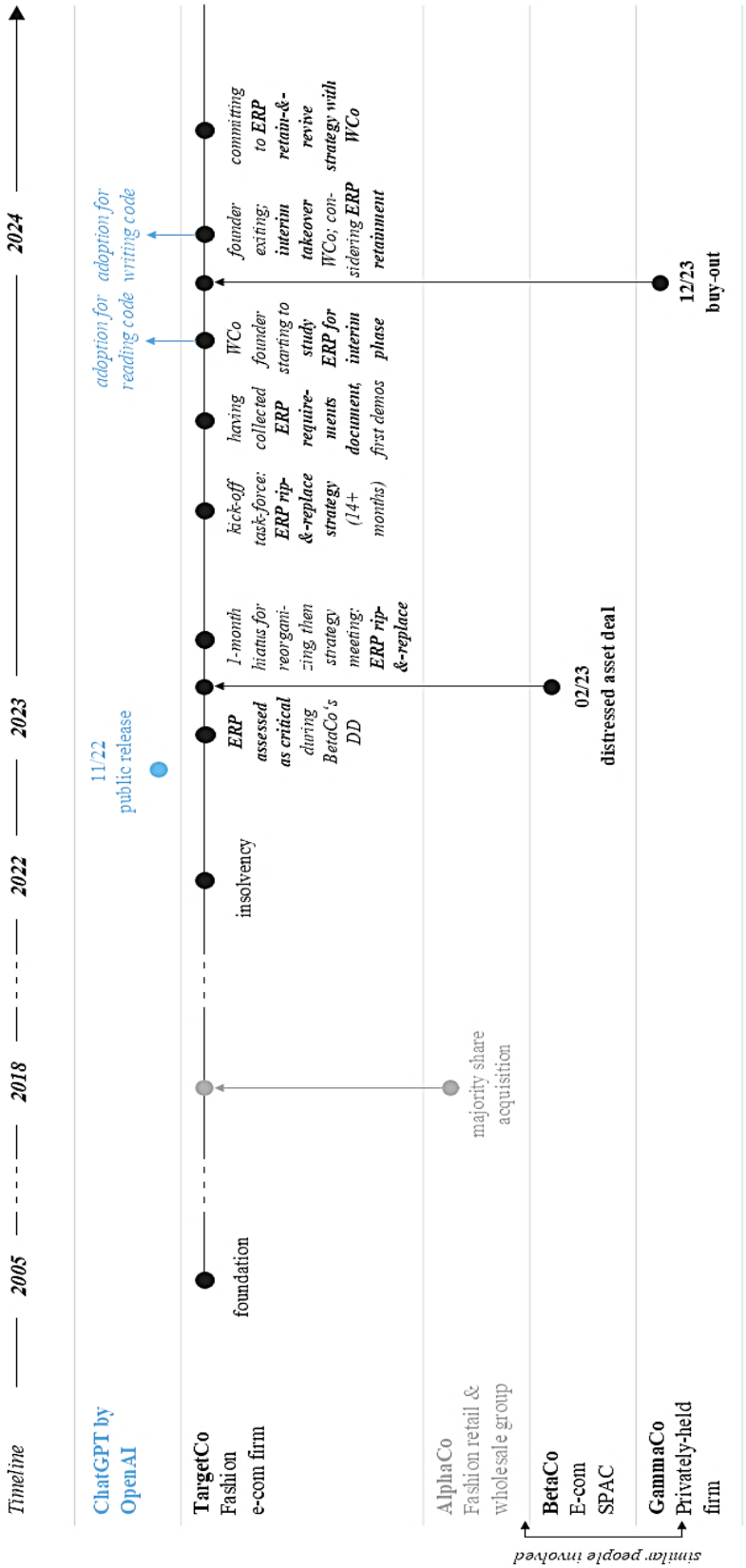


Figure 17. Case History

TargetCo history: The target of both acquisitions is TargetCo: Founded in 2005 by a tech-savvy entrepreneur, it belonged to the first movers in the European e-commerce world. Specializing in the resale of mid-price fashion brands via ebay, Amazon, and its own webshop, TargetCo soon partnered with emerging marketplaces like Zalando or AboutYou. Our interviewees remembered this time as a "goldrush" (TCo1, WCo). The "heart of the company" (BCo) formed a proprietary ERP system developed by the founder. This system was able to respond better to the needs of marketplaces than any standard solution at the time. Together with WebserviceCo, whose founder operated as a freelancer for creating marketplace APIs, the company could offer quick and efficient integrations. Once TargetCo was listed on more than 20 marketplaces, it started struggling with capacity limits. With the founder also planning his exit, the investor search began. In 2018, AlphaCo acquired 55% of shares in an attempt to create online-offline synergies between both businesses. While AlphaCo identified the founder-dependency of TargetCo's proprietary software as a clear risk, it followed a co-existence approach with system bridges only where necessary. Overall, the acquisition was no success: Together with the consumer crisis, AlphaCo's financing decisions drove TargetCo into insolvency in 2022.

Case 1 - BetaCo: Thanks to the otherwise sound business model of TargetCo, the insolvency manager LegalCo contracted ConsultingCo to find a range of interested investors for an asset deal. In 2023, the company was acquired as part of BetaCo, a special purpose acquisition company (SPAC). A SPAC is "an investment fund that is launched through an IPO, where it raises substantial cash from investors with the express purpose of reverse merging with a private company" (Floros & Sapp, 2011, p. 852), thereby taking it public without a traditional IPO process. BetaCo's goal was to use TargetCo as an anchor investment and create an e-com ecosystem with multiple brands in the fashion vertical and beyond. Wary of TargetCo's proprietary system, the investors propelled a rip-and-replace strategy, actively looking for standardized alternatives.

Case 2 - GammaCo: After several turbulent months and no further acquisitions through BetaCo, it was decided to acquire TargetCo through a privately held organization. This acquisition by GammaCo should give TargetCo more freedom to operate and restructure its business without reporting duties. The new owners were still connected to the former BetaCo ecosystem. At this time, the TargetCo founder TCo1 had

basically left the company; leaving his proprietary system behind but little of his system and business knowledge. The short-term maintenance of the proprietary system had been contracted to WebserviceCo as an interim solution, until the rip-and-replace strategy with a standard system could be finished. Instead, the managers soon agreed to continue the proprietary system instead of replacing it. With GenAI, WebserviceCo not only kept the system operative, but also developed new features and tools surrounding it. Keeping its lean structure and customized system features, TargetCo was able to avoid a costly system replacement by a standardized solution (rip-and-replace), enabling a faster financial recovery and value capture from the deal. This retain-and-revive approach is most closely related to the priorly discussed IS co-existence strategy in M&A (target system retention), while adding the aspect of developing it further (revival).

5.3.3 Data Collection and Analysis

Since limited theory was available to understand knowledge integration challenges and the impact of GenAI affordances on post-merger IS integration decisions, our aim was to inductively build theory from this case (Eisenhardt et al., 2016). Our study relies on both primary and secondary data sources (see Table 23). As we view human experience is socially constructed, we first ground our research in the “informants’ experience and their understanding” (Gioia, 2021, p. 22). Building on Eisenhardt and Graebner (2007), we talked to numerous informants in- and outside the focal companies to limit potential bias through, i.e., convergent sensemaking. Following a semi-structured guideline, interviews were conducted from January 2023 to August 2025 and transcribed and translated to English. Some of our interview partners agreed to repeated interviews, leading to 39 interviews and 1476 minutes material (see Table 24). The continued interviews with TargetCo’s CEO (TCo2) gave us a crucial insider perspective on key decisions regarding the ERP system over time, stretching from January 2023 to August 2025, as he was consistent part of management and strategy meetings during both acquisitions (BetaCo, GammaCo). To limit potential bias regardless, we also conducted several interviews at different points in time with, i.a., the TargetCo founder (TCo1), WebserviceCo founder (WCo), and the BetaCo / GammaCo CEO (BCo), among many more. On top of that, we analyzed a large secondary data set to address negative cases and rival explanations (see Table 23).

Step 1: All our material was coded with the help of MAXQDA and data structures in Excel. We started out by sketching a chronological timeline of events through the interviews, further confirming the important turning points via the collected secondary data (see Table 23).

Table 23. Overview of Primary and Secondary Data Sources

Primary Data	Secondary Data	
39 interviews	86 press articles / press releases 10 investor communication releases	Company websites and NorthData profiles of focal organizations

Step 2: We then moved towards explaining the process of IS integration by iteratively coding and grouping data into higher order concepts. We constantly compared emergent themes in our data and existing theory (Eisenhardt, 2021) eventually anchoring emergent patterns and relationships in the knowledge-based view of the firm as well as an AI affordances lens (Díaz Andrade et al., 2023; Majchrzak & Markus, 2012). The aim of the entire process was producing "progressively better-defined and grounded higher-order concepts … and creating underlying theoretical arguments that connect constructs" (Gioia et al., 2013, p. 27). Through discussions within the author team, we arrived at second order themes and, eventually, at aggregate dimensions. Table 25 provides an exemplary data structure for capturing TargetCo's business model and IS set-up. Further aggregate dimensions revolved around TargetCo's overall IS benefits, but also IS challenges perceived from in- and outside the firm. We then moved to a separate analysis of both cases, focusing on deal context and challenges, the acquirer's knowledge and IS integration challenges, and their solution strategies.

Step 3: Then, we compared emerging constructs and relationships across the two acquisitions in an iterative cross-case analysis, applying constant comparison logic (Eisenhardt & Graebner, 2007). Through team discussions on data visualization, the process model was refined until theoretical saturation was reached. This step allowed us to trace how both cases faced similar knowledge integration challenges across system and people. It also shows how GenAI constitutes a key differentiating element between the cases, shifting integration strategies from rip-and-replace towards retain-and-revive through affordances like code understanding, writing, and tool development.

Table 24. List of Interviewees

Company	Role of company	Interviewee	Position	Interviews (mins)
TargetCo	Acquisition target	TCo1	Founder; Ex-C-level Executive	2 (62)
		TCo2	C-level Executive	14 (486)
		TCo3	Senior Sales Manager	1 (36)
		TCo4	Marketplace Manager	1 (32)
		TCo5	Demand-Side Manager	1 (44)
		TCo6	C-level Executive *(IT)*	2 (100)
		TCo7	Buy-Side Manager	1 (53)
		TCo8	Senior Supply Manager	1 (42)
		TCo9	Junior Marketplace Manager	1 (28)
AlphaCo	First acquirer: Fashion retail & wholesale	ACo1	Branch Manager	1 (28)
		ACo2	C-level Executive	1 (34)
		ACo3	C-level Executive	2 (48)
		ACo4	C-level Executive	1 (37)
BetaCo / GammaCo	Second acquirer: E-com SPAC	BCo	C-level Executive	4 (146)
WebserviceCo	IT services for TargetCo	WCo	Founder and Manager	4 (187)
LegalCo	Insolvency manager	LCo	Partner	1 (40)
ConsultingCo	Search for BetaCo	CCo	Partner	1 (32)
-	-	E	M&A Expert	1 (32)
Sum				**39 (1467)**

5.4 Results

Before diving into both cases and their different IS outcomes, we first wanted to understand the essence of TargetCo; “as an online pure player quite an old company, active since 2005” (20230124 TCo2). It became apparent that the firm’s lean structure, both regarding its staffing and its systems architecture had been a driver of its success and growth: The WebserviceCo founder told us that “the processes were quite well thought through. That is, you could achieve quite a lot with a relatively lean team” (20240613 WCo). Aside from TargetCo’s business model and IS set-up (see Table 25), we also reviewed our interview data to delineate the unique advantages and disadvantages of TargetCo’s IS.

Consisting of the proprietary ERP system, programmed and maintained by the founder of TargetCo, as well as the API integrations to the marketplaces and data management

by WebserviceCo and its founder, the TargetCo key IS is complemented by TargetCo's longstanding employees. Reflecting on this close-knit structure, the WebserviceCo founder remembered his collaborative programming efforts with the TargetCo founder:

Table 25. Exemplary Data Structure for TargetCo (adopted from Gioia, 2013)

1st Order Concepts	2nd Order Themes	Aggregate Dimensions
• Successful in e-commerce since 2005 is special (20240207 TCo6) • TargetCo as an online pure player quite old (20230124 TCo2)	DNA: digital incumbent	**TargetCo Business Model**
• TargetCo as reseller which buys stock from brands (20230124 TCo2)	Buy-side operations	
• Receiving payment from marketplaces for the goods (20230414 TCo2) • Direct contact with the marketplaces (20240119 ACo2)	Sell-side operations	
• Run everything with little staffing (20240613 WCo) • Very low personnel expenses (20230220 LCo)	Lean structures	
• System is a proprietary creation, originally developed by the founder (20230707 TCo3) • Three levels of systems, with ERP as core (20250204 TCo2)	Proprietary ERP system	**TargetCo IS Set-up**
• Programmed everything himself for easy stock management (20230124 TCo2)	TargetCo founder	
• Orders flow into the system, get mapped and passed on in a unified format to the founder's ERP (20230405 WCo)	API integrations	
• First request for collaboration around 2005 (20230405 WCo) • Moved with TargetCo several times and worked on-site at least once a week (20230405 WCo)	WebserviceCo founder	
• With the company for over ten years and built processes up (20231024 TCo5)	TargetCo employees	

> *"From my point of view, that also made a big competitive advantage back then. If you compare other retailers … they always had much more sluggish systems, or innovations or marketplace connections couldn't be implemented at the speed that was possible at TargetCo" (20230919 WCo).*

Despite "the know-how that is embedded in the source code" (20240613 WCo), driving the system's back-end functionality, customization and speed, the ERP system today

also entails some disadvantages: The TargetCo employees often complain about a lack of functions and usability (TCo6, TCo8).

Even more critical is the content knowledge stored inside, which lacks explicitness due to missing code documentation and several programming language changes (WCo, TCo1, TCo2). Connected to the challenge of knowledge stored in systems, TargetCo's lean personnel structure also has its disadvantages: The tacit knowledge of key personnel like the TargetCo founder, WebserviceCo founder, and TargetCo key employees create a huge dependency on these individuals (see Table 26).

Table 26. Advantages and Disadvantages of TargetCo's IS

TargetCo IS Dimensions	Advantages	Disadvantages
Proprietary ERP system	– Agile adaptation – Customization to market needs – Founder knowledge on business logics inherent	– Content knowledge cryptic due to lack of code documentation and several programming language changes – Lack of end-user functions and usability
API integrations	– Lean test integrations before middleware use	– Laborious integrations due to customization
TargetCo founder	– *System knowledge-as-content:* Speed of support for ERP; Low-cost adaptation – *Business knowledge-as-connection*	– Dependency on tacit knowledge-as-content and -connection
WebserviceCo founder	– Close collaboration with TargetCo founder for integrations	– WebserviceCo founder dependency to operate business
TargetCo employees	– Lean, start-up like team – Team spirit	– Tacit knowledge concentrated in few people

5.4.1 Case 1 – BetaCo

The acquisition context in the BetaCo deal is distressed: TargetCo is acquired as an asset deal by a SPAC, "to build an e-commerce company with various divisions, including fashion. And our company fit into that concept perfectly. We were their first investment" (20230411 TCo2). Further acquisitions should follow soon, depending on TargetCo's IT infrastructure: "If the systems, ERP, logistics, inventory management,

work seamlessly together and toward the consumer, … then we could start immediately" (20230711 BCo). However, several business challenges create a demanding background for the investors and TargetCo managers: external financing (TCo2), market headwinds (TCo2), as well as the restructuring of business structure and processes (TCo2, TCo4, TCo3) demand many resources.

While the BetaCo acquirers view the ERP system as a perfectly tailored tool to the market, they also acknowledge TargetCo's IS challenges, considering that the TargetCo founder is soon to leave and "someone else will take over in the near future" (20230411 TCo1). Looking at the system,

> *"you have to update it yourself, you don't have anyone out there who supports you.… And an exorbitant, disproportionate build-up in terms of IT and programming, which you actually don't need" (20230711 BCo).*

Since TargetCo has been hugely dependent on its founder and his proprietary system, the BetaCo investors have a strong interest in managing this knowledge integration risk they identified during due diligence. Following the advice of an IT consultant in their professional network, they immediately plan to replace the TargetCo system with a standard solution. As BetaCo has no IT architecture of its own yet, we view imposing a standard solution on TargetCo as absorption-like rip-and-replace strategy, imposing the logics of a standard system on the target. While this decision was not up for debate in top-level meetings, the employees welcomed the decision, as the sales manager confirms:

> *"Everything from support to further development runs through one person. And that's risky. If that person were suddenly gone, you'd lose all your know-how, support, and ability to evolve the system. So, I very much welcome the move toward a new, external inventory management solution" (20230707 TCo3).*

While the founder's capacity is bound by organizing a logistics switch, BetaCo creates a task force to drive the search for a standard ERP system. In a file, they collect TargetCo's entire "value creation process, insofar as it is digitally supported" (20230801 TCo2). Despite the benefit of explicating systems requirements and processes, the task creates further fear of knowledge loss among longstanding employees:

> *"I must be honest, typing out these requirements, I'm panicking that certain processes won't come to mind, or that I'll forget something in the back of my*

> *head, because I do feel that a lot rests on me now. Because if the founder leaves now, I'm the second, or the next, who knows the system or our processes" (20231024 TCo5).*

While the rip-and-replace strategy is clearly pushed by the acquirer to manage risky dependencies, the project is regarded an open-heart surgery and not treated lightly: "the heart has to come out, a new one has to go in, it has to beat immediately … because we cannot afford to be offline for even a single day" (20230711 BCo). Once the requirements have been finalized, initial calls with system providers are held. Some at TargetCo view the switch critical: The demand manager expects the standard system's customization and licensing to be "unbelievably expensive" (20231024 TCo5), while the new manager TCo6 fears for costly downtimes or data issues. However, most employees using the system daily welcome the future switch, with the replacement still being propelled by the BetaCo network.

Before the new solution can be fully rolled out, that the founder will have left the company. Therefore, BetaCo needs an intermediate solution for its investment, and finds it in the founder of WebserviceCo:

> *"I believe the new solution is supposed to be introduced around the middle of next year. That means, in the meantime, it's only necessary for him [WCo] if there are any issues, bugs, or problems to know where to find and fix them" (20230912 TCo1).*

5.4.2 Case 2 – GammaCo

In the same year, the trajectory of TargetCo should change again. The TargetCo manager explains that

> *"the company has been sold… to the same people who held large parts of BetaCo.… Now, we are no longer a stock listed corporation but a GmbH [German limited liability company]" (20231215 TCo2).*

Due to internal business challenges, like a logistics switch and restructuring, as well as continued external challenges that had not allowed for further acquisitions, this new set-up should provide less distraction for TargetCo's day-to-day operations. However, further acquisitions are not entirely ruled out by TargetCo's new management, consisting of the former BetaCo board members, plus the TargetCo manager TCo2 and TCo6,

a newly appointed manager with IT expertise. “If opportunities arise, we’ll take them, but we’re not planning with that” (20231215 TCo2). The new management team is similar, still follows the same goals of value creation and faces the same IS challenges, yet, one thing is different: The founder has left the firm. The IT advisor for BetaCo had been “worried that since the founder had left with his knowledge, and what he had built was pretty much a black box, nobody else would be able to manage it” (20240419 TCo2). Referred to as a “ticking time bomb” (20240419 TCo2) from all corners, the black box system should be replaced as soon as possible. This is mirrored by the WebserviceCo founder, remembering when he signed the interim system maintenance contract:

> *“I actually did that under the condition that the proprietary system would gradually be replaced, maybe after about half a year, and that TCo5 would support us, because she had, when it comes to databases and structures, quite a lot of know-how. At some point, we then found out that she will leave. …I included a termination clause that I could also leave if it didn’t move forward or if we didn’t manage it” (20240613 WCo).*

However, over time, the perception of the system maintenance changes, and makes a continued maintenance appear an actual option. As of then, TargetCo has written “major doubts into strategy ’24 that we’ll do an ERP switch in ’24. That still has to be discussed with the shareholders” (20231215 TCo2). Also, the new set-up should be put to the test by the new CEO TCo6, whose evaluation tips towards the current solution:

> *“I’m somewhat reluctant to replace the ERP to introduce a new system, because that would tie up an enormous amount of our resources. … It’s always a matter of weighing how much money to invest. … right now, we’re in a good position where we practically have none, apart from the fee we pay to our service provider [WebserviceCo] for support availability” (20240207 TCo6).*

To understand how WebserviceCo was able to perform not only the system’s maintenance but also to develop further tools to make operations more secure and increase usability, the deal context becomes important: After the release of ChatGPT in November 2022, LLMs had become increasingly prominent in the developer community for supporting programming tasks. The TargetCo manager clearly states AI as differentiator in their IS strategy:

> *"Even maintaining our system isn't such a big deal anymore, thanks to AI support. Our partner [WebserviceCo] told us he wouldn't have been able to do that two years ago, it would've been way too time-consuming. But now, with AI helping out so much, he says it's almost easy and actually fun" (20240223 TCo2).*

5.4.3 Cross-Case Comparison

While the comparative study design allows for isolating meaningful differences through GenAI, alternative explanations merit consideration: Differences may stem from *experience* effects, where actors learn from prior acquisitions (Haleblian et al., 2009). However, while learning may have sensitized decision-makers to knowledge risks, it cannot explain the observed shift in feasible action: only the availability and adoption of GenAI enabled the actors to learn, understand, and extend the proprietary ERP system efficiently. Further, changes in structure or ownership can influence differing integration choices. Yet, the people involved stayed mostly the same, and informants consistently emphasized that the transition had "strategically and operationally, … absolutely no impact on anything within TargetCo. Zero" (20230711 BCo). Lastly, variation in resources or time pressures, common drivers of IS integration strategies (Giacomazzi et al., 1997), may have shaped decision-making. However, such constraints would typically reinforce, rather than relax, rip-and-replace logics. Our data show that GenAI affordances like learning or generating code reconfigured maintenance costs and rendered a retain-and-revive strategy viable.

To understand how GenAI, especially ChatGPT, was able to support WebserviceCo in its system maintenance and change the integration trajectory for TargetCo, we undertook a cross-case comparison. Focusing on the knowledge challenges inherent in the TargetCo IS, we identified several emerging GenAI affordances for programming and their effects on knowledge transferability, aggregation, and maintenance efficiency: chatting with code snippets in natural language (learning), error spotting, bug fixing, code generation, tool development, and time saving (see Table 27).

Table 27. Knowledge Challenges, GenAI Affordances, and Knowledge Integration Effects

Knowledge Challenges	GenAI Affordances	Knowledge Effects
– **„Cryptic“ process knowledge in system:** Lack of documentation in proprietary ERP system – **Tacit system and process knowledge in people:** TargetCo founder (exit → loss), WebserviceCo founder, key employees (dependency risk)	– **Chatting with code snippets in natural language (learning):** “if we feel we need a deeper understanding, we check to see if there is any data that must not be sent to an AI. We then use these code snippets to essentially get an overview through the AI. This gives us a deeper understanding of the sense behind” (20240613 WCo)	*Knowledge transferability:* Cryptic and tacit know ledge externalization
	– **Error spotting:** “WCo uses it a lot to send code snippets of ours to ChatGPT and say, ’Please take a look. We expect this to happen, but it doesn’t. Here’s the code, where’s the error?’” (20240521 TCo2)	
	– **Bug fixing:** “we didn’t know where anything was located or where the error might be. The challenge was finding those corresponding spots, so that we could then reproduce the issue in the source code” (20240613 WCo)	*Capacity for knowledge aggregation:* Building on and with externalized knowledge
	– **Generating code:** “Producing source code goes much faster with GPT” (20250828 WCo)	
	– **Developing tools**: “I think we can only sustain this level of innovation because we have AI-supported solutions” (20240419 TCo2)	
	– **Time saving:** “it would have taken him [WCo] four hours. With ChatGPT, he spent fifteen minutes” (20240521 TCo6)	*Efficiency* in knowledge maintenance

From this, we built a contextual model of IS integration choices (see Figure 18). While in case 1, the perceived knowledge challenges led to a planned rip-and-replace strategy with a standard software, in case 2, the interim maintenance surfaced that the GenAI affordances for WebserviceCo enabled not only the maintenance of the proprietary system, but also increased system safety and usability through developing tools sitting on top of the proprietary system; driving the retain-and-revive choice.

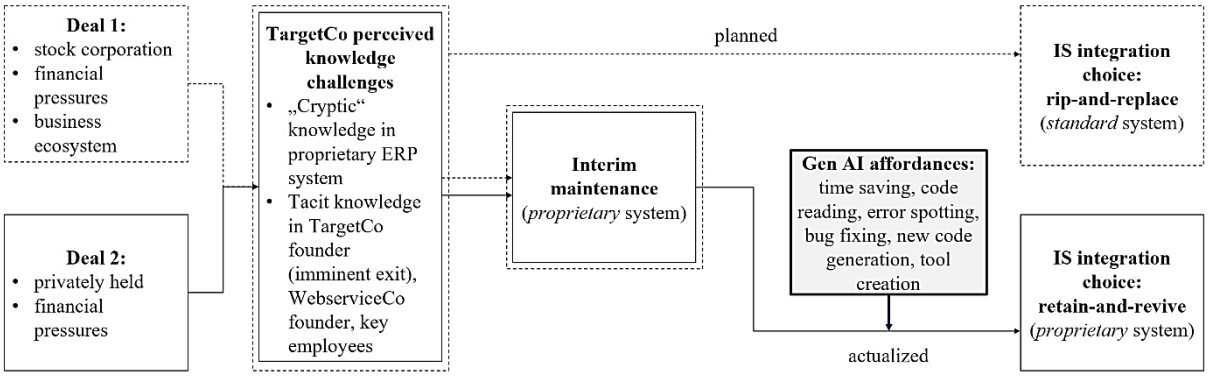


Figure 18. Deal 1 versus Deal 2: Rip-and-Replace versus Retain-and-Revive

Eventually, the WebserviceCo founder evaluates this approach positively:

> *"It has turned out that we get along quite well with the system. AI, ChatGPT and the like, gives us quite a bit of support. … without that, things would look completely different for us, it would have been significantly more difficult. Which is also why, when it became a question of keeping the system after all, I initially had some concern. But since we've been doing it with AI, that's been completely fine for me." (20240613 WCo)*

Taking these insights together, Figure 19 presents our framework. It shows how the adoption of GenAI shapes IS integration strategies and can increase deal value capture through retaining proprietary systems at relatively minimal cost even when key staff exit, leveraging the knowledge that had tacitly or cryptically been stored in systems and people. This path may render rip-and-replace strategies redundant, associated with high investments into imposing a standard system and entailing knowledge loss; enhancing viable IS integration paths for acquirers.

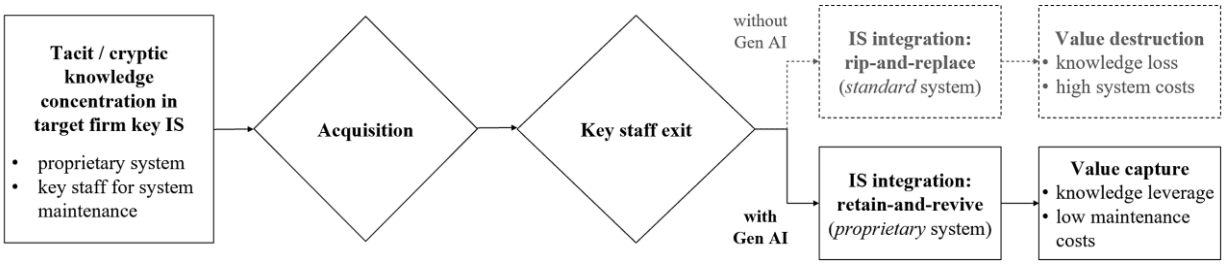


Figure 19. Framework of GenAI in IS Integration: Rip-and-Replace versus Retain-and-Revive

5.5 Discussion

5.5.1 Theoretical Implications

This research answers calls to deepen scientific knowledge in acquisition IS integration (Hedman & Sarker, 2015). Our study extends the IS integration literature by showing how GenAI affordances reshape long-standing assumptions about post-merger IS management. Prior work positioned IS integration as contingent upon technical and organizational distance, often framing legacy or proprietary systems as constraints that necessitate absorption strategies (i.e., rip-and-replace) (Lee et al., 2022; Tanriverdi & Uysal, 2015). By leveraging a unique case setting contrasting two nearly identical acquisitions of the same target, we reveal how GenAI affordances like chatting with code naturally and learning expand the perceived action space for acquirers. These affordances transform proprietary systems from “black boxes” into maintainable, evolvable assets, effectively reconfiguring the cost vs. knowledge trade-off previously driving absorption decisions (McKiernan & Merali, 1995). We also show that previously, the retention of key IT personnel during “open-heart surgery” (Busquets, 2015) was critical. Now, GenAI significantly alleviates tacit knowledge challenges connected to staff turnover, enabling a leaner and less risky integration set-up from the beginning. Theoretically, we advance the technology affordances perspective (Juell-Skielse et al., 2025; Majchrzak & Markus, 2012) for M&A settings, describing GenAI affordances as evolving in IS integration contexts. Moreover, we contribute to the knowledge-based view of the firm (Grant, 1996) by showing that AI affordances can restore the transferability and aggregation of embedded knowledge after IT personnel loss. Hence, rather

than being determined by static IT distance, post-merger IS integration can become a process of GenAI affordance actualization, potentially reshaping integration decisions for proprietary systems.

5.5.2 Practical Implications

For practitioners, our findings highlight how GenAI tools can alter the economics of integration decisions and enable retain-and-revive strategies for legacy systems once deemed obsolete. Managers should recognize that replacing proprietary systems (rip-and-replace) is no longer the default route to standardization or control. Instead, AI-assisted code analysis, documentation, and maintenance can reduce knowledge dependencies and lower integration risk (Weisz et al., 2022). In the TargetCo case, this allowed the acquirers to maintain a proprietary ERP system and enable value creation instead of spending scarce post-merger resources on system replacement, which is often found to be value-destructing in existing literature (Tanriverdi & Uysal, 2015). However, realizing these benefits requires deliberate orchestration. IS leaders must govern the responsible enactment of AI affordances, balancing automation with human oversight, and establishing quality control for AI-generated code or knowledge documentation (Berente et al., 2021; Yang et al., 2024). We recommend integrating GenAI affordance considerations early into post-merger audits and knowledge transfer planning. Rather than focusing purely on compatibility, integration teams should assess the readiness of legacy systems to be leveraged by AI tools, i.e., existing codebases, data structures, and workflows, as long as the interoperability of target systems with existing systems can be assured. GenAI is therefore positioned not as a disruptive replacement technology, but as an enabler of incremental, resilient integration in resource-constrained post-merger contexts.

5.5.3 Limitations, Future Research, and Conclusion

This study has several limitations that open avenues for future research. First, our insights derive from an embedded, multiple case in e-commerce, potentially limiting its generalizability across industries. Future studies could examine how GenAI affordances play out in other M&A contexts, such as regulated sectors or large-scale serial acquisitions. Second, while we highlight how affordances reshape integration

possibilities and are informed by interviewees on the increasing performance of TargetCo, we did not analyze performance outcomes in this paper, because the case is still unfolding. Subsequent research could measure how AI-enabled “retain-and-revive” strategies compare to traditional absorption in terms of cost, knowledge retention, or time-to-synergy. Our findings invite scholars to revisit classic IS integration models that treat systems as static, decomposable components (Giacomazzi et al., 1997) and to conceptualize integration as an emerging process of technology affordance enactment. In doing so, we contribute to a broader understanding of how digital intelligent technologies may redefine organizational learning, knowledge retention, and value realization in post-merger integration.

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6 Conclusion

This dissertation set out to examine how organizations strategically respond to digital change, and what determines whether these responses truly generate transformative outcomes. It started from a central tension of the digital age: AI and digital technologies promise substantial opportunities for strategic renewal, yet organizations frequently struggle to translate this potential into sustained transformation (Hanelt et al., 2021; Vial, 2019). This tension is particularly visible in the context of M&A, where firms often seek to acquire the digital resources and capabilities to stay competitive. However, they continue to face uncertain, inconsistent, and frequently disappointing outcomes (Lev & Gu, 2024). Against this background, this dissertation investigated DT not as a purely technological challenge, but as a sociotechnical process shaped by organizational strategies, actors and their cognitions, and emerging technological affordances (Sarker et al., 2019).

Across four interconnected papers, the dissertation contributes to IS, strategic management, and M&A research by developing a multi-level perspective on DT in the era of AI. At the meso-level, it examines how organizations can respond to digital change through AI-supported external M&A and internal AI strategy-making. At the micro-level, it investigates how managerial cognition can undermine DT even when strategic intent appears sound. Finally, by integrating a technology affordance perspective, it shows how GenAI may reconfigure the conditions under which organizations make post-merger integration decisions. Taken together, the dissertation argues that DT success depends not only on the access to digital technologies or strategic rationale, but on the cognitive, structural, and sociotechnical conditions through which digital change is interpreted, enacted, and integrated.

The first paper, ***Automating the Deal: A Literature Review on Artificial Intelligence in Mergers and Acquisitions***, addresses the external route of DT by examining how AI can support M&A decision-making across the deal cycle. Drawing on a practitioner-oriented literature review of 39 studies across finance and accounting, strategy and management, IS, and computer and data science, the paper consolidated a fragmented research field into a process-based, actionable framework (Webster & Watson, 2002). It shows that current research on AI applications in M&A is concentrated in pre-deal phases, particularly strategy, search, and due diligence, where structured and publicly available data enable prediction-oriented AI models. At the same time, the

paper reveals important blind spots: post-deal phases remain understudied, generative and prescriptive AI capabilities are only marginally addressed, and many empirically validated models are not yet ready for deployment. By mapping managerial challenges to AI models and frameworks, the paper contributes to closing the rigor-relevance gap in M&A research (Kieser & Leiner, 2009) and offers practitioners evidence-based guidance for sequenced adoption, data architecture planning, human-machine governance, and context-specific AI deployment.

The second paper, ***The AI Strategy Compass: A Case-Based Guide for Achieving Digital Intelligence Maturity***, shifts attention to the internal DT of organizations. It addresses the question of how organizations can choose and sequence their AI implementation journey in a fragmented and often contradictory jungle of frameworks (Hutzschenreuter & Lämmermann, 2025). By juxtaposing governance-driven and momentum-driven approaches (Westerman et al., 2012), the paper shows that AI strategy-making does not follow one optimal path. Instead, organizations need to select and adapt their approach based on business strategy, organizational structure, and digital readiness of their employees. Drawing on comparative case study insights from organizations at different stages of AI maturity, the paper develops a practical AI Strategy Compass that helps firms determine whether they should begin with building overarching governance structures or with creating use-case-first momentum. Firms that achieve Digital Intelligence Maturity excel in both dimensions, showing the complementary nature of AI strategy-making regardless of the chosen entry point to implementation. The paper contributes to AI strategy research by showing that Digital Intelligence Maturity is not a static endpoint, but an evolving organizational capability (Holmström, 2022). As such, it needs continued ambidexterity between strategic direction and local experimentation, governance and momentum.

The third paper, ***Ruining M&A-Based Digital Transformation: Cognitive Microfoundations of Failure***, descends to the micro-level and investigates why DT may fail even when organizations pursue seemingly appropriate strategies. Through the critical case of a physical incumbent acquiring a complementary digital target, the paper shows how managerial cognition can undermine organizational sensing, seizing, and reconfiguring within their dynamic capabilities. The findings reveal that managers are not automatically neutral carriers of strategic intent, nor do they act as change agents. Instead, a non-digital mindset may shape which opportunities are recognized, which

actions are considered legitimate, and which integration efforts are enacted towards the digital target. By identifying detrimental thinking patterns before and after the acquisition, the paper advances a microfoundational explanation of M&A-based DT failure (Helfat & Peteraf, 2015). It contributes to dynamic capabilities and DT research (Teece, 2007), showing that transformation failure may originate not only in structural incompatibility, resource or financial misfit, or integration complexities, but also in the cognitive frames through which organizational actors at the top interpret digital opportunities and constraints (Eggers & Kaplan, 2009; Tripsas & Gavetti, 2000).

Lastly, the fourth paper, ***From Knowledge Loss to Knowledge Leverage: How GenAI Affordances Transform Post-Merger IS Integration***, introduces a complementary perspective by examining how technology itself can reshape organizational action possibilities. Focusing on the post-merger IS integration of proprietary software, the paper shows how GenAI affordances may alter long-standing assumptions about such systems, knowledge loss in case of M&A, and integration feasibility (Majchrzak & Markus, 2012). Whereas traditional IS integration literature often emphasizes absorption or replacement through standardization as viable integration paths for acquirers (Stylianou et al., 1996; Yoo et al., 2007), this paper introduces a GenAI-supported retain-and-revive approach to IS integration. GenAI offers knowledge-related impacts (Grant, 1996): It can make tacit system knowledge more retrievable, improve knowledge aggregation, and reduce the dependence on key personnel. This changes the perceived costs and risk of retaining target systems. The paper contributes to M&A integration and IS research, showing that GenAI can expand the set of feasible integration choices by changing how actors manage knowledge-related system constraints.

Collectively, the four papers provide a coherent contribution to understanding DT as a multi-level sociotechnical phenomenon. The dissertation makes three overarching contributions: (1) First, it advances research on DT strategy by connecting internal and external strategic responses. Rather than treating AI adoption and digital M&A as separate phenomena, it shows that both represent complementary ways of accessing, building, and reconfiguring digital resources and capabilities. (2) Second, it contributes to a more nuanced understanding of transformation failure by linking organizational-level outcomes to the individual-level cognition of management. It demonstrates that even promising digital strategies can fail when managers lack the mindset required to

recognize, value, and enact digital opportunities. (3) Third, it extends sociotechnical and affordance-based perspectives, by showing that emerging technologies like GenAI can become impactful actors, initiating and reshaping organizational trajectories together with human actors. They do not determine outcomes on their own, but through their affordances, they can alter the conditions under which humans make strategic integration decisions.

The practical implications of this dissertation are equally important. For managers, investors, and DT or deal advisors, the findings show that DT cannot be approached through technological investments alone. Organizations need to understand where digital technology, particularly AI, can create value, what data foundations and infrastructures are required, how governance and momentum-building should be balanced, and where human cognition may become a hidden barrier to transformation. For M&A practitioners, the dissertation provides guidance on how AI can support deal processes while cautioning against premature assumptions of deployment-readiness. For firms developing AI strategies, it offers a decision-oriented framework for selecting and implementing suitable adoption paths. For top management teams, it highlights the importance of critically examining digital mindsets before and throughout digital acquisitions. Finally, for post-merger integration teams, it shows that GenAI may enable alternative integration logics that, aside from preserving and leveraging knowledge, also can save costs.

The dissertation also opens several avenues for future research. First, future studies could further examine the post-deal phases of AI enabled M&A, particularly integration and evaluation. Currently, these phases remain underrepresented in research, as are prescription and generation capabilities evolving with contemporary AI tools. Scholars should investigate how these capabilities influence deal negotiation, integration governance, synergy realization, and post-merger learning. Second, future research can study AI strategy-making longitudinally to better understand how organizations move between governance- and momentum-driven approaches over time. Such work could clarify how firms sustain Digital Intelligence Maturity under conditions of rapid environmental and technology-induced change. Third, more research on managerial cognition in DT can further illuminate the field of IS and management research, especially at the level of top management teams. Future studies could examine how digital and non-digital mindsets emerge, how they spread across managerial groups, and how they

can be changed. Fourth, the role of GenAI in post-merger integration seems a promising field: As GenAI systems become more deeply embedded in organizational work, future research should explore not only their affordances but also their risks, limitations, and governance requirements.

In conclusion, this dissertation argues that the gap between the promise and the performance of DT is not primarily a strategic or technical gap. It is a sociotechnical gap between what digital technologies offer and afford, and what organizations and the people within are cognitively, structurally, and practically able to realize. Closing this gap requires understanding DT across levels: the strategic options that are available to organizations, the governance structures that guide implementation, the managerial mindsets that shape action, and the affordance of novel technologies that reshape what can be done. By synthesizing these levels, this dissertation contributes to a richer understanding of strategy-making in the era of AI. It offers a foundation for both practical action-taking and future research on how organizations can turn digital potential into transformative outcomes successfully.

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