

Integrating AI into strategic planning for a successful digital transformation. Insights from industry use cases

Maria Teresa Cuomo, Debora Tortora, Francesca Loia, Paola Zoccoli and Lorenzo Ricciardi Celsi

Abstract

Purpose – The potential of artificial intelligence (AI) is entering the strategic thinking and operations of both public and private companies, with an impact on performance, cost structure and people. At the same time, companies need organic, AI-driven plans aligned with their capabilities and business goals to successfully guide their digital transformation. This study aims to examine the significance of strategic planning in developing AI-driven digital transformation, considering the implications of data collection and the use of specific technological platforms.

Design/methodology/approach – The paper applies a qualitative methodology to investigate the AI-driven digital transformation strategy. It progresses from the particular to the general, attempting to derive meanings from the dataset collected to identify patterns and relationships, and then generalising those patterns and relationships. Nine AI-driven digital transformation projects are analysed according to the Data Benefit Index (DBI), based on three variables: (1) data consumption, (2) business value and (3) effort.

Findings – The study examines the level of maturity with which AI and data potential are being leveraged across various industries. A replicable scoring rubric is provided to reduce subjectivity by quantifying each driver's impact on data consumption, business value and effort. Scores distinguish between low (<10%), moderate (10%–50%) and transformational (>50%) returns, enabling project evaluation, AI-driven digital transformation, strategic planning, DBI, business value, data-driven strategy. Creating value from data and AI is a complex task, mainly due to the difficulty of aligning business objectives with AI-driven digital transformation. The DBI framework captures this.

Originality/value – This paper delivers a tangible managerial impact by combining managerial contributions with a knowledge-based theoretical perspective at the intersection of strategic planning and AI. It systematises a structured method grounded in the DBI model, suggesting helpful criteria for planning, implementing and evaluating AI and data-driven strategies. By linking theory with managerial decision-making, the study offers concrete guidance for organisations aiming to integrate AI into strategic processes in a rigorous and replicable manner.

Keywords AI-driven digital transformation, Strategic planning, Data benefit index, Business value, Data-driven strategy

Paper type Impact article

1. Introduction

Artificial intelligence (AI) is transforming economies and industries worldwide at an unprecedented rate. AI systems have intensified in Italy too, with continuous advances in machine capabilities and given Dall-E2 and ChatGPT exploits (Castelli and Manzoni, 2022; Peres *et al.*, 2023; Burger *et al.*, 2023). According to data from the most recent Bank of Italy business surveys, in 2024, 13% of firms with at least 20 employees had adopted experimental or task-specific AI technologies (rising from 4% in 2020). These applications tend to be strongly associated with firm size, group affiliation and innovation capacity

Maria Teresa Cuomo is based at the Department of Economics and Statistics, University of Salerno, Salerno, Italy.

Debora Tortora is based at the Department of Business and Law, University of Milan–Bicocca, Milan, Italy.

Francesca Loia is based at the Department of Economics, Vanvitelli University, Caserta, Italy.

Paola Zoccoli is based at University of Salerno, Salerno, Italy.

Lorenzo Ricciardi Celsi is based at the Department of Engineering and Sciences, Universitas Mercatorum, Rome, Italy.

Received 28 December 2025

Revised 9 February 2026

7 March 2026

Accepted 6 April 2026

© Maria Teresa Cuomo, Debora Tortora, Francesca Loia, Paola Zoccoli and Lorenzo Ricciardi Celsi. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licenses/by/4.0/>

(Bencivelli *et al.*, 2025). Currently, there is a noticeable buzz in the industrial world around emerging AI-based technologies, especially with the spread of Generative AI (GenAI) (Haefner *et al.*, 2021; Korzynski *et al.*, 2023). Recent research suggests that large-scale adoption of GenAI could increase Italy's GDP by up to 18.2% annually (AGID, 2024).

AI (Stone *et al.*, 2020; Haefner *et al.*, 2021; Mariani *et al.*, 2022) is entering the strategic thinking and operational practice of both public and private companies, with impacts on performance, cost structure and people (Rane *et al.*, 2024; Koley *et al.*, 2025).

Hence, as the potential of AI is unleashed, there is a growing need to design appropriate strategic processes that successfully direct a company's digital transformation and keep it aligned with, on the one hand, the company's capabilities or develop critical and dynamic capabilities affecting digital transformation and, on the other, its business goals.

Despite this, many companies still proceed without using an organic vision or grounding their choices in a structured understanding of their knowledge assets, data infrastructure or knowledge generation and acquisition capabilities (Teece, 2007, 2009, 2017; Chierici *et al.*, 2020; Tortora *et al.*, 2021), limiting the scalability and value of their results.

On the contrary, as Knowledge Management (KM) highlights, data, information and knowledge - in terms of data quality, data governance, knowledge-sharing routines and organisational learning mechanisms (Nonaka and Takeuchi, 1995; Grant, 1996, 2006) - represent strategic resources that determine a firm's capacity to innovate and transform (Davenport and Prusak, 1998; Alavi and Leidner, 2001). AI robustness amplifies the ability to capture, process and apply knowledge on a scale. Thus, in the present study, under the theoretical background of KM (Del Giudice and Maggioni, 2014; Del Giudice *et al.*, 2023), we posit that AI and GenAI have a strategic impact on data-driven decision-making. Therefore, AI-driven transformation requires deliberate strategic planning to ensure coherence between technological choices, organisational knowledge capabilities and business goals. By processing and analysing large volumes of data, AI algorithms can identify complex patterns and generate data-driven recommendations, thereby supporting more informed, accurate decisions in business contexts. This analytical capacity enables firms to respond more effectively to dynamic market conditions and to identify and exploit emerging opportunities (Marvi *et al.*, 2025).

In this regard, companies must answer increasing questions, ranging from defining the criteria for selecting priorities to identifying mistakes to avoid, from proper planning and execution of projects to the shrewdness needed to ensure that the chosen strategy remains relevant over time. Using an exploratory, inductive methodology, the study examines the importance of strategic planning for AI-driven digital transformation, answering the following research questions:

RQ 1. How does strategic planning shape AI-driven digital transformation?

RQ 2. What are the key drivers influencing the AI-driven digital transformation journey?

Focusing on three knowledge-centric variables – data consumption, business value and effort – the study provides a structured method to support managers in integrating AI into strategic processes, filling a practical gap and translating knowledge into professional practices. In that sense, this approach offers new perspectives for designing, implementing and assessing AI strategies.

2. The digital transformation process

In general, defining a data-driven strategy (Pirnay and Burney, 2022; Jatain, 2022; Hossain *et al.*, 2024) extends beyond technological and analytical considerations, fundamentally concerning the management of organisational knowledge. In this regard, such a strategy requires:

- articulating long-term objectives that are consistent with the firms' existing knowledge base;
- identifying activities that enable the transformation of large amount of data – i.e. big data – into actionable knowledge; and
- allocating resources to support knowledge creation and use.

Big data refers to large, diverse and fast-moving data sets that require advanced analytics technologies to enable the extraction of valuable knowledge and support organisational decision-making (Sumbal *et al.*, 2017). Following the widely adopted “5Vs” framework, big data denotes data ecosystems characterised by high volume, velocity and variety, whose usefulness depends on veracity and the ability to extract value from them (Gandomi and Haider, 2015; De Mauro *et al.*, 2016). These characteristics require advanced data architectures, governance mechanisms and analytical capabilities to transform raw data into actionable organisational knowledge. In other words, they represent knowledge assets generating value only when embedded in structured knowledge creation processes. In line with Nonaka's SECI model (Nonaka *et al.*, 1996; Nonaka *et al.*, 2005), digital technologies can facilitate the socialisation, externalisation, combination and internalisation of knowledge by supporting the dynamic interaction between tacit and explicit knowledge. However, the effectiveness of these processes is contingent upon the firm's absorptive capacity, defined as its ability to recognise, assimilate and apply new knowledge (Cohen and Levinthal, 1990; Todorova and Durisin, 2007).

Consequently, when defining digital transformation objectives, organisations must clearly delimit the scope of intervention and anticipate risks related to knowledge gaps and limited absorptive capacity. Neglecting these aspects may result in a “false start”, whereby rapid and poorly informed decisions hinder organisational learning and compromise the intended innovation trajectory. Consistent with prior research, such failures often arise from an excessive focus on technological adoption rather than on the deliberate development and governance of knowledge-related capabilities. The data-driven digital transformation process is characterised by several interrelated features (Korherr *et al.*, 2022).

Firstly, digital transformation is an iterative knowledge creation process. Its inherent complexity renders linear, waterfall-style project management approaches inadequate. Consistent with the Cynefin framework (Snowden and Boone, 2007), complex environments require continuous sense-making and learning rather than predefined solutions. Through successive iterations, organisations revise their actions based on insights derived from data, thereby strengthening processes of knowledge creation and refinement. This iterative cycle supports both the conversion of data into actionable knowledge and the development of organisational absorptive capacity, understood as the ability to recognise, assimilate and apply new knowledge (Cohen and Levinthal, 1990). Achieving a balance between flexibility and structural stability is therefore essential for sustaining effective and scalable transformation (Natarajan and Pichai, 2024). Secondly, digital transformation is a progressive capability-building process. Although organisations may articulate a clear strategic vision, transformation unfolds incrementally through successive stages. This gradual approach is particularly relevant given the cultural and organisational implications of digital initiatives. In line with KM theory, maturity models provide a structured means to assess the organisation's current knowledge base and absorptive capacity (Tortora *et al.*, 2024), while guiding the systematic development of knowledge-related capabilities over time (Ramirez, 2024). Thirdly, the process is deliverable-oriented, emphasising the production of clearly defined outputs that embody organisational knowledge. Beyond identifying technical resources and analytical skills, particular attention must be devoted to knowledge-based deliverables, such as shared insights, codified practices and decision-support artefacts. These deliverables operationalise the outcomes of SECI-based knowledge conversion processes and ensure alignment between data-driven activities,

knowledge governance mechanisms and operational business objectives. Therefore, a sustainable digital transformation that maximises AI benefits (De Mauro, 2020; Gatti and Danese, 2022; <https://blog.panoply.io/the-big-data-stack-powering-data-lakes-data-warehouses-and-beyond>) can be structured as a four-step data-driven strategy:

1. Selecting the big bets;
2. Enabler planning;
3. Execution and monitoring; and
4. Replanning.

The initial phase – Selecting the big bets – involves identifying AI projects that can most effectively leverage available data to create value. This process relies on data capability assessment (Yu *et al.*, 2025), which evaluates the potential economic value of each data source. Step 1 is inherently collaborative, often implemented through ideation workshops and structured selection tools, reflecting the socialisation and externalisation phases of the SECI model, where tacit knowledge is shared and formalised into actionable project ideas.

The second step – Enablers planning – involves designing the organisational, technological and cultural enablers (Kumar, 2024) necessary to extract value from data and amplify AI impact. Organisational structures, workflows and skill development are aligned to facilitate combination and internalisation of knowledge, ensuring that insights from data are embedded into business processes.

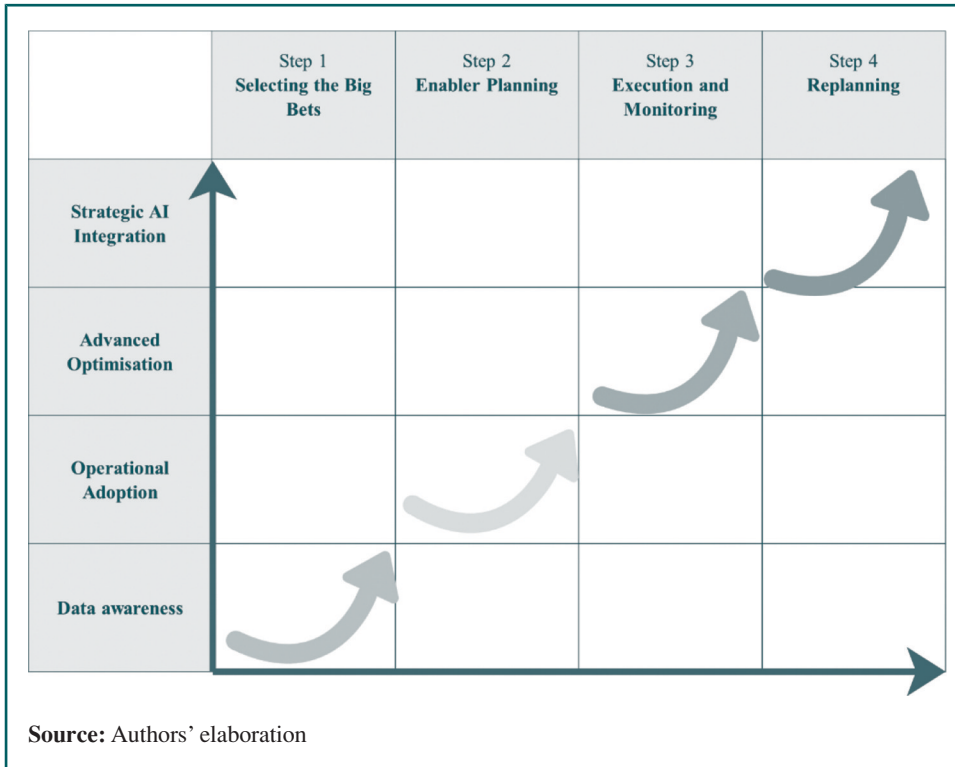
AI projects are implemented and continuously monitored, with a focus on measurable business impact. The third phase – Execution and monitoring – emphasises knowledge codification and transfer, supporting learning loops that allow the organisation to refine algorithms, data architectures (Big Data stack; Panoply, 2025) and human capabilities in real time. Governance tools, including the ALTAI (Assessment List on Trustworthy Artificial Intelligence) checklist and AI Act compliance mechanisms (Fedele *et al.*, 2024; Mueck *et al.*, 2025), ensure ethical and reliable application of knowledge.

Finally, the last phase – Replanning – closes the digital transformation cycle by reassessing organisational maturity and revising priorities. Maturity models guide this process by identifying current capabilities, mapping gaps in absorptive capacity, and directing the organisation towards the next strategic stage. Iteration at this step reflects the continuous knowledge creation cycle inherent to effective AI-driven transformation.

In summary, the four-step strategy integrates collaborative knowledge creation, structured codification, capability building and iterative learning, ensuring that AI projects deliver sustainable value while enhancing organisational knowledge and absorptive capacity. The suggested data-driven strategy is derived from a study of the relevant literature, practical insights and professional experience. Through this approach, a data-driven strategy is conceptualised and organised into a coherent, structured model that could support organisations in realising a successful digital transformation (Figure 1).

The maturity model should be interpreted as a capability ladder that is traversed through repeated cycles of the same four-step strategy. These cycles represent different levels of maturity, progressively achieved or achievable by organisations. In fact, at each maturity level, organisations execute Step 1 (Selecting the Big Bets), Step 2 (Enabler Planning), Step 3 (Execution and Monitoring) and Step 4 (Replanning). What changes across levels are the scope, sophistication, governance intensity and strategic impact of each step. In early stages, the cycle is typically limited to a narrow set of use cases and lightweight enablers, with fast feedback loops and learning-oriented evaluation. As maturity increases, the same four steps progressively incorporate broader portfolios, stronger data governance and platformisation, more rigorous performance and risk controls, and a tighter coupling

Figure 1 Maturity model for a successful digital transformation



between AI initiatives and corporate strategy. The number of levels is not defined *a priori*; it depends on the firm's long-term objectives and the resources allocated to support knowledge creation and use.

The proposed data-driven strategy requires a practical methodology to translate it into actionable outcomes.

Agile methods, which have transformed software development over the past two decades, are increasingly applied at the organisational level, promoting business agility – a shift from conventional prediction-and-control paradigms to shared autonomy and collaborative decision-making. This shift aligns closely with KM principles, as it emphasises continuous learning, knowledge sharing and iterative improvement. In particular, the most popular methodologies are Scrum and Kanban (Lei *et al.*, 2017). Scrum is used in product-oriented projects where there is a strong need for product/service development while engineering data and algorithms (Cervone, 2011; Mahalakshmi and Sundararajan, 2013; Srivastava *et al.*, 2017; Morandini *et al.*, 2021; Žáček *et al.*, 2024). Its iterative sprints and structured feedback loops facilitate the codification, transfer and refinement of knowledge, aligning with the SECI model's combination and internalisation phases. Kanban, on the other hand, is more suitable for strategy-oriented projects (Ahmed *et al.*, 2024), which are not very programmable in terms of time because they are linked to external events (market launch of an innovative product, entry of a competitor, change of operational strategy). The use of task-oriented boards facilitates, on the one hand, the management of constantly changing priorities and, on the other hand, interchangeability among team members themselves (Wakode *et al.*, 2015; Alaidaros *et al.*, 2021). In both methodologies, the emphasis on continuous monitoring, adaptive planning and collaborative problem-solving reinforces organisational learning and absorptive capacity, key enablers for successful digital transformation and AI adoption.

3. The study

3.1 The theoretical framework

To evaluate the effectiveness of a project in pursuing the above-mentioned AI-driven digital transformation strategy, the Data Benefit Index (DBI) framework introduced by [Ficara \(2022\)](#) has been used by the best practitioners in the industry today.

In fact, organisations must align data architecture with business needs while maximising the value derived from data. The DBI acts as a quantitative and conceptual tool to evaluate how effectively a particular data architecture generation fulfils this goal. From a theoretical viewpoint, it is consistent with Dynamic Capabilities Theory ([Teece et al., 1997](#)), which focuses on how firms adapt, integrate and reconfigure valuable, rare, inimitable and organisational (VRIO) resources in rapidly changing environments ([Eisenhardt and Martin, 2017](#)).

Three primary capacities of dynamic capabilities ([Teece, 2007](#)) are sensing (detecting changes in the environment, new technologies, emerging markets or shifting customer needs), seizing (mobilising resources to capture opportunities and create value) and transforming (reconfiguring assets, processes and capabilities to maintain or improve performance). In other words, dynamic capabilities are the firm's abilities to sense opportunities and threats, seize them through resource allocation, and transform its operations and assets to maintain competitiveness. The DBI acts as a measurement and feedback tool, helping the organisation sense gaps and seize opportunities effectively.

The DBI framework is based on three variables:

1. data consumption;
2. business value; and
3. effort.

In detail:

- the *data consumption* variable accounts for the number of users, the data literacy and the time to market of the project outcome;
- the *business value* variable accounts for the value generated by the proposed AI and data solutions, evaluated by income growth, effectiveness at risk management and operational efficiency; and
- the *effort* variable accounts for the work required to implement a specific architectural approach, evaluated by operational expenditure, technical debt management and data governance overhead. [Figure 2](#) shows the DBI framework.

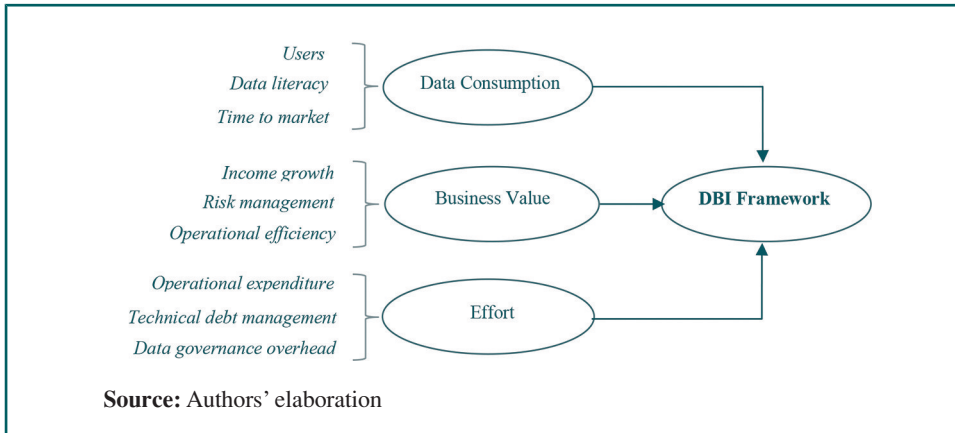
The DBI framework explicitly allows the definition of the actual capacity of a data architecture to harness the AI and data potential within the project context.

3.2 Methodology

This paper employs a qualitative, exploratory and inductive methodology to investigate the AI-driven digital transformation strategy, moving from the specific to the general and attempting to derive meanings from the collected data set to identify patterns and relationships, thereby generalising the findings. An explorative qualitative methodology ([Jebb et al., 2017](#); [Reiter, 2017](#)) comparing multiple projects seems the best option for developing empirically grounded hypotheses on emerging patterns in AI-driven digital transformation.

This is a preliminary study based on the analysis of some AI-driven digital transformation projects, according to the DBI.

Figure 2 The data benefit index framework



The DBI is computed as follows:

$$DBI = \frac{\text{data consumption} \times \text{business value}}{\text{effort}}$$

Each of these variables is quantified by assigning a score of 1 (low), 2 (medium) or 3 (high) that comprehensively considers the drivers listed above. The final score of a component is obtained by averaging the scores of the drivers that compose the index. Depending on the resulting DBI value, we can distinguish among three different situations:

1. $DBI < 0.5$: The data and AI potential are exploited to a limited extent.
2. $0.5 \leq DBI < 1$: The data and AI potential are moderately exploited.
3. $DBI \geq 1$: The data and AI potential are fully exploited.

Each of the three variables is an average of three drivers, each scored on a 1–3 scale.

1. Maximum raw component score: the maximum score for any variable (i.e., data consumption, business value, effort) is obtained if all three drivers score 3.
2. Maximum raw numerator: the maximum product of the numerator is $\text{data consumption}_{max} \times \text{business value}_{max} = 3 \times 3 = 9$.
3. Maximum DBI without normalisation: the minimum score for the denominator is 1. Thus, the absolute maximum possible raw DBI is $9/1 = 9$.

The final DBI value is evaluated after normalising the product $\text{data consumption} \times \text{business value}$ between 0 and 1, and the *effort* at the denominator of the ratio between 0 and 1.

This implies that the calculation of the normalised DBI (or \overline{DBI}) is:

$$\overline{DBI} = \frac{\text{normalised numerator}}{\text{normalised denominator}}$$

The crucial missing detail is the maximum scaling basis (i.e. the constant used for the 0–1 mapping). Thus, we disclose in the revised manuscript that the product $\text{data consumption} \times \text{business value}$ is normalised against its theoretical maximum value of 9. Namely:

- $Normalised\ numerator = \frac{data\ consumption \times business\ value}{9}$

Also, the *effort* component is normalised against its theoretical maximum value of 3.

- $Normalised\ denominator = \frac{effort}{3}$

With the normalisation constants disclosed, the full replicable formula (normalised DBI, denoted with \overline{DBI}) is:

$$\begin{aligned} \overline{DBI} &= \frac{\frac{(data\ consumption \times business\ value)}{9}}{\frac{effort}{3}} = \frac{3 \times (data\ consumption \times business\ value)}{9 \times effort} \\ &= \frac{data\ consumption \times business\ value}{3 \times effort} \end{aligned}$$

The maximum DBI is achieved when:

$$\overline{DBI}_{max} = \frac{3 \times 3}{3 \times 1} = 3$$

As a result, by explicitly stating the scaling basis (9 for the numerator and 3 for the denominator), we confirm that DBI values can range up to 3.0, making the values exceeding 2.0 reported below in Section 4 mathematically plausible under the proposed calculation methodology.

We recall that, in terms of the aggregation of drivers into the corresponding variables, the score for each of the three main variables (Data Consumption, Business Value, Effort) is calculated as the arithmetic mean of its three respective drivers:

$$variable\ score = \frac{\sum_{i=1}^3 driver\ score}{3}$$

Namely, the three variables are calculated as:

$$data\ consumption = \frac{users\ score + literacy\ score + time\ to\ market\ score}{3}$$

$$business\ value = \frac{income\ growth + risk\ management + operational\ efficiency}{3}$$

$$effort = \frac{operational\ expenditure + technical\ debt\ management + data\ governance\ overhead}{3}$$

We opt for an unweighted arithmetic mean to reflect the equal strategic importance of each driver. In the DBI framework, a deficiency in any single driver (e.g. high user adoption but low data literacy) represents a structural weakness that should proportionally reduce the overall variable score. This approach ensures that the variable score remains on the same 1–3 scale as the drivers, maintaining consistency with the normalisation thresholds defined above.

3.2.1 Data collection. In line with a qualitative multiple-case design, aimed at exploring patterns in AI-driven digital transformation initiatives, the study examines nine projects that integrate artificial intelligence technologies within broader digital transformation programmes. The cases were identified through a structured screening process conducted between 2021 and 2024, drawing on both academic publications and publicly available industry documentation.

Case selection followed three main criteria. First of all, the initiative had to explicitly involve the deployment of AI-based analytical methods as a core component of the digital transformation process. In addition, sufficient technical and managerial information had to be available through peer-reviewed publications, technical documentation or publicly accessible reports, ensuring transparency and replicability of the analysis. Finally, the project had to be in sectors undergoing significant data-driven transformation, enabling the framework to be examined across heterogeneous organisational and technological contexts.

The chosen projects span multiple industries, including insurance, telecommunications, energy, tourism and financial services. This cross-sectoral selection enhances the study's analytical richness and enables the identification of common patterns in the strategic use of AI and data.

Data used for the DBI evaluation were obtained from three main sources: technical documentation describing the architecture and implementation of the projects, experimental results reported in the corresponding scientific publications, and publicly available performance indicators related to operational outcomes, efficiency gains or economic impact. The triangulation of these sources supports the robustness of the qualitative assessment and enables systematic cross-case comparison of the DBI variables.

4. Findings

We summarise the main characteristics of nine projects that apply an AI-driven strategy. According to the DBI, the results of each project are organised based on:

- Data Consumption - the consumption of data and analytical solutions, evaluated by the following drivers: number of users, data literacy and time-to-market.
- Business Value - the value generated by the data and analytical solutions, evaluated by the following drivers: income growth, risk management and operational efficiency.
- Effort - the work required to implement a specific architectural approach, evaluated by the following drivers: operational expenditure, technical debt management and data governance overhead.

To eliminate subjectivity – and ensure replicability too – we define the specific impact of each driver on the three main variables. The scoring criteria follow a scale from 1 to 3, where for the numerator variables (*Data Consumption* and *Business Value*), a score of 3 represents the maximum positive contribution. Conversely, for the denominator variable (*Effort*), a score of 3 represents the maximum burden (highest cost or complexity), which penalises the final DBI. [Table 1](#) functions as a replicable scoring rubric, defining each score for every driver.

We recall that Income Growth measures the direct financial return (ROI), which should be quantified as the Expected Annual Income Growth attributable to the AI solution, calculated as a percentage of the total project cost (Operational Expenditure + Technical Debt). According to ([Anderson, 2025](#)), a score of 1 (meaning expected income growth below 10% of the project cost) implies that the project barely covers its investment cost or may even represent a negative net present value (NPV) based on this driver alone. The data is under-exploited relative to the capital invested. As per ([Anderson, 2025](#)), the median reported ROI for enterprise-wide AI initiatives often hovers around 10%. Furthermore, one study found that median ROI in corporate finance departments remains around 10%. A return below this median consensus level signifies that the project is performing poorly relative to typical enterprise expectations, often achieving only limited or zero net gains after accounting for all costs, risks and the time value of money. Projects falling here are typically considered

Table 1 Scoring rubric for DBI drivers

<i>Driver</i>	<i>Score 1 (Low)</i>	<i>Score 2 (Medium)</i>	<i>Score 3 (High)</i>
Data consumption: No. of users	Solution used by < 10% of target population	Solution used by 10–50% of target population	Solution used by > 50% of target population
Data consumption: Data literacy	Usage requires advanced technical skills (e.g. data scientists only)	Usage requires specific business training (e.g. business analysts)	Intuitive usage accessible to non-technical staff (high democratization)
Data consumption: Time-to-market	Slow deployment (> 12 months), typical of rigid waterfall cycles	Standard deployment (6–12 months)	Fast deployment (<6 months), typical of Agile/MVP approaches
Business value: Income growth	Expected income growth is < 10% of project cost	Expected income growth is 10%–50% of project cost	Expected income growth is > 50% of project cost
Business value: Risk management	Standard compliance with no significant risk reduction	Improves monitoring of specific operational risks	Critical for regulatory compliance, fraud prevention or strategic risk avoidance
Business value: Operational efficiency	Marginal efficiency gains (<10% time/cost reduction)	Significant improvement in specific tasks (10–30% reduction)	Radical process re-engineering or automation (>30% reduction)
Effort: Operational expenditure	Minimal incremental costs (uses existing infrastructure)	Moderate costs requiring budget allocation (e.g. standard cloud fees).	High recurring costs (e.g., expensive GPU instances, proprietary licenses)
Effort: Technical debt management	No new technical debt introduced; architecture enhances existing system stability	Technical debt is tracked and managed with minimal impact on operations	Significant unaddressed technical debt and system instability introduced
Effort: Data governance overhead	Uses standard, non-sensitive data with existing policies.	Requires specific privacy/security measures (e.g. GDPR compliance for customer data)	Complex governance required for highly sensitive or unstructured data (e.g. health data, heavy NLP requirements)

Source(s): Authors' elaboration

cost-inefficient or technical experiments that have yet to realise meaningful financial value. A score of 2 (meaning expected income growth between 10% and 50% of the project cost) implies that the project generates a positive return that meets typical internal corporate hurdles but does not deliver exceptionally high value capture from the data. Exploitation is moderate. This range captures the performance of the majority of successful, non-transformational AI projects. It starts above the median reported ROI, indicating a satisfactory return. It aligns with the general return expectations for productivity improvements. For example, realistic planning often starts with 10%, 20% and 30% productivity improvements. Process efficiency gains are often reported in the 15–25% range in the short term. This score level represents a project that breaks even or achieves a positive ROI within a reasonable timeframe (e.g. 2–4 years, typical for complex AI) but has not yet achieved the “transformational returns” seen in high-performing projects. Finally, a score of 3 (meaning expected income growth above 50% of the project cost) implies that the project delivers exceptional financial benefits, indicating that the data and AI potential are being maximised for significant value capture, resulting in a high return on investment. A return exceeding 50% positions the project firmly in the category of AI ROI Leaders or transformational initiatives. Organisations that strategically measure and invest in their most advanced AI initiatives report substantially higher returns, with some best-practices teams reporting a median ROI of 55% for GenAI. High-performing firms define success in strategic terms like the “creation of revenue growth opportunities” and “business model reimagination”, which correspond to returns far exceeding incremental efficiency gains. This score signifies a project that has maximised the potential of the data and AI, delivering

returns that significantly outperform the median, justifying the highest rating for Business Value.

The comparative study provides different DBI values, scored by nine other projects in various contexts, thus measuring the level of maturity with which AI and data potential are exploited across different industries.

Project #1 - A deep-learning based antifraud system for car-insurance claims ([Maiano et al., 2023](#)).

This project proposes an automatic system for identifying fraud attempts in the insurance sector. Once images of an accident have been received, the system allows the extraction of information about the vehicle and the identification of similar damages within a collection of images. The solution has been validated by comparing the proposed method with two state-of-the-art solutions for image similarity estimation.

Consumption of AI and data solutions, based on the number of users, data literacy and time-to-market, can be considered as medium-level (2) for this project. Indeed, data literacy is not extremely high as the task is specifically focused on computer vision, which is still challenging when shifting from a working prototype to a profitable product. The business value, too, can be regarded as medium value (2), as the project outcome is not a game changer for the industry. Still, it would sensibly reduce processing time from claim experts, thus improving task efficiency by about 50%. Yet the required effort is considerably higher (3) by contrast with the other considered projects, especially in terms of opex (namely, the cloud infrastructure requirements for operation) and AI and data governance.

Project #2 - A quantitative exploratory analysis of household savings via segmentation ([Cuomo et al., 2023](#)).

This project aims to study the purchasing behaviour of almost 20 million individual savers to suitably profile them and propose marketing actions that can be specifically targeted to each cluster of savers. In this case, the consumption of AI and data solutions, especially relative to the number and type of users of such a tool, as well as data literacy, can be regarded as relatively high: this is why we eventually choose to assign a high-level score to the data consumption variable (3). The business value is medium-level (2), too, as it lies in the marketing actions that can be targeted to each cluster of individuals due to segmentation. Instead, the effort is relatively low (1), as operational expenditure, technical debt and data governance are not a cause for concern. Overall, it is an easy task to carry out, provided that reliable data are used.

Project # 3 - HR-Specific Natural Language Processing (NLP) for the homogeneous classification of declared and inferred skills ([Ricciardi Celsi et al., 2022](#)).

This project was carried out within the Erasmus+ I4EU project (Key competencies for a European model of Industry 4.0). It proposes a heuristic algorithm to solve two problems:

1. semantic matching among heterogeneous datasets storing the hard skills possessed by the company's employees to obtain a homogeneous catalogue, according to the O*NET and ESCO competence dictionaries; and
2. inferring the employee's soft skills concerning their declaration of interests, work experience, certifications, etc., given their curriculum vitae.

Such a solution is expected to yield some benefits for the Human Resources Department of a large company. First of all, it will avoid the manual, and often subjective, collection of employees' training needs. It will also minimise the manual, subjective calculation of the return on investment for training, ultimately offering a choice of training courses that are necessarily aligned with the employee's job profile. Another advantage consists of the optimisation and adaptation of resource staffing to activities: by systematising each employee's professional and

extra-professional career and aspirations, it is possible to build work teams more dynamically, efficiently and rigorously, saving time and making the staffing process more effective. In this respect, data consumption and business value are both medium level (2). Still, indeed, the effort is relatively high (3) as extensive NLP is needed for this task, which is critical regarding operational expenditure and data governance.

Project # 4 - A multi-variable Dynamic Thermal Rating (DTR) algorithm for estimating conductor temperature and ampacity on high voltage overhead lines by IoT data sensors ([Coccia et al., 2022](#)).

This project aimed to propose a dynamic thermo-mechanical model approach for estimating the conductor's temperature and ampacities of power grids based on the weather data measured by IoT sensors. In this case, data consumption is relatively low (1) compared to the other considered projects. At the same time, the implied business value is certainly medium level (2). Indeed, dynamic thermal rating systems and the georeferencing of the electrical system represent a crucial evolutive step of a high voltage network towards an intelligent cyber-physical system, and, through the possibility to continuously monitor several fundamental parameters related to the system (such as the temperature and the voltage of the conductors), they enable a more flexible operation of the rating of the overhead power lines, estimating temperature and ampacity with high reliability. The required effort is relatively high (3), as the necessary infrastructure covers some parts of the Italian power grid for data collection, but others still are not.

Project #5 - Anomaly detection in photovoltaic factories via Monte Carlo pre-processed principal component analysis ([Arena et al., 2021](#)).

This project aimed to investigate a use case of robust anomaly detection applied to the scenario of a photovoltaic production factory – namely, Enel Green Power's 3SUN solar cell production plant in Catania, Italy. By running the proposed algorithm on unseen data streams, isolating anomalous conditions and virtually triggering an alarm when exceeding a reference threshold is possible. The proposed approach was tested on standard operating conditions and an anomalous scenario. Concerning the use case considered, it successfully anticipated a fault in the equipment with an advance of almost two weeks. It also demonstrated its robustness to false alarms during normal conditions. Such a solution is expected to yield an overall downtime reduction between 1% and 2%, corresponding to an increase in the annual photovoltaic panel production of approximately 1–2 megawatts. In this respect, data consumption can be regarded as medium level (2) as it is necessary to collect and prepare data from selected sensors mounted onto the production line stations, which are in charge of measuring several relevant parameters characterising each station, such as station temperature, pump speed, flow speed and ozone concentration level. On the other hand, the associated business value is high-level (3) as the proposed solution implies a relevant benefit in terms of an increase in the annual photovoltaic panel production and paves the way for creating a digital twin of the whole solar cell production plant. By contrast, the required effort is medium level (2), especially concerning OPEX and data governance.

Project #6 - Explainable AI for car crash detection using multivariate time series ([Tronchin et al., 2024](#)).

This project aims to explain the decisions made by an AI model employed to optimise the assistance service of the insurance company. Whenever the vehicle is involved in an accident, the AI agent processes the deceleration burst collected by the black box onboard and automatically triggers a call to an insurance operator, who, in turn, dials the driver to check their condition and the general situation. If necessary, this call is forwarded to the Emergency Medical Services to offer any necessary pre-hospital treatment and/or to the tow truck in charge of removing the vehicle. The data consumption in this respect can be regarded as low (1) as the multivariate time series collected by the black boxes onboard vehicles are relatively easy to

gather and process. The resulting business value is high (3) as the optimisation via Explainable AI of the automatic assistance service is expected to increase the accuracy and trustworthiness of the predictions considerably, thus allowing the bringing to market of a robust product. On the other hand, the effort is as high (3), especially in terms of OPEX and AI governance.

Project #7 - Online service function chain deployment for live-streaming in virtualised Content Delivery Networks (CDNs) via Deep Reinforcement Learning (DRL) (Cevallos Moreno *et al.*, 2021).

This project aims to exploit 5G networks to enable higher server consolidation and deployment flexibility in video delivery services. Namely, the proposed approach consists of a multi-objective optimisation framework for service function chain deployment in the particular context of live streaming in virtualised content delivery networks via deep reinforcement learning. In this case, the amount of actual data consumption can be regarded as relatively low (1) compared with the other projects. Yet the business value and effort are both relatively high (3), the former due to the considerable benefits yielded by the proposed solution in terms of quality of service and quality of experience, whereas the latter due to the burst in operational expenditure and technical debt that results from investing in such an activity.

Project # 8 - Predicting ticket reopening for improving customer service in 5G networks (Ricciardi Celsi *et al.*, 2021).

This project was conducted within a joint research initiative focused on Next Generation Networks from 2018 to 2021. It proposes an AI-driven strategy for predicting technical ticket reopening in the context of customer service for telecommunications companies providing 5G fibre optic networks. Namely, the main aim is to ensure that the Service Level Agreement in terms of perceived Quality of Service is satisfied between the end user and service provider. In this respect, the amount of data consumption is to be regarded as relatively high (3), especially as regards the number of users involved. By contrast, the business value can be considered as medium level (2) since the proposed solution proves to be a handy tool for service providers to identify the customers most at risk of reopening a ticket due to an unsolved technical issue. The required effort is medium level (2), especially regarding operational expenditure.

Project # 9 – Enhancing traveller experience in integrated mobility services via big social data analytics (Cuomo *et al.*, 2022).

This project had the aim of proposing a data-driven approach to boost the tourist experience in integrated mobility services: in particular, owing to the design of a recommendation system based on a big-data analytics engine, it makes it possible to rank the tourist preferences for the most attractive Italian destinations on Google, and to rank the main attractions – leisure, entertainment, culture, etc. – associated with single tourist destinations, obtained from the analysis of relevant thematic websites such as Tripadvisor, Minube and Travel365. In this case, the data consumption can surely be evaluated as low (1), together with the required effort mostly in data governance (1), especially compared with the other mentioned projects. Instead, the business value is medium level (2), as such a solution allows mobility companies to define targeted and more effective marketing campaigns via a relatively straightforward collection of data from several heterogeneous sources, such as Google search queries accessible via Google Trends or any social data scraped from websites.

5. Discussion

The success of AI capabilities and responsiveness to business objectives is generally enabled by the availability of a significant amount of data, be it structured, semi-structured or unstructured data, documents, images, etc. (Zhang *et al.*, 2025).

The ability to capture as much data as possible is a valid condition for gaining a competitive advantage. After all, as Clive Humby (2006) said, “Data is the new oil”. The sentence means that an initial effort should generally be directed towards conducting a census of data sources to be acquired or built up over time, with targeted investment in accumulating the most critical data. Data acquisition is undoubtedly relevant to one’s data-driven strategy, but starting with data acquisition to define one’s strategy is, with the same degree of certainty, a big mistake.

This is a counterintuitive statement. Yet, if we think about it, how can we identify a shortlist of the most interesting data sources for the problem we are addressing, and, more importantly, how can we be sure of *a priori* which data will be helpful to us and which are already available in our company? In addition, we should ensure that the people responsible for selecting the identified data sources have the skills needed to collect the data to help solve a given task. In other words, we need to ask ourselves whether it makes sense to make choices about data acquisition when we do not yet know what to do with that data.

Even if we were to collect data, but that data were neither up to date nor compatible with the big picture that summarises the company’s vision and business objectives, we would find ourselves in an awkward situation in which the data, although acquired, would be unusable profitably. Moreover, the absence of a clear vision of the so-called ways of activating data, that is, transforming it into actual economic value for the company, could trigger the feeling of having too much data and not knowing what to do with it. Ultimately, starting with data acquisition is a false start because it leads to inefficiencies, delays and unwanted rework.

Conversely, creating value from data and AI is a complex task, mainly because aligning business objectives with AI-driven digital transformation is challenging. The DBI framework captures this need, explaining how strategic planning shape AI-driven digital transformation (RQ 1). based on that, we report in Table 2 the ranking of the above-introduced projects by decreasing DBI.

Generally speaking, when DBI is greater than or equal to 1, projects are making the most of the potential of data and AI for the reference industry, while projects with DBI between 0.5 and 1 are partially exploiting the potential of data and AI for the reference industry. Finally, projects with a DBI of less than 0.5 do not sufficiently exploit the potential that data and AI can express for the reference industry, clarifying the main drivers of the AI-driven digital transformation (RQ 2).

Financial institutions (as regards project #2) and energy, telecommunications and transportation industries (namely, projects #5, #8 and #9) are the most mature and ready to harness the data and AI potential. As proof of this, while in 2024 the Italian AI market continues its growth, reaching a value of €1.2bn – a 58% increase over the previous year – the sectors with the highest average AI spend include: Telecommunications and Media,

Table 2 Ranking of the Nine projects evaluated by decreasing DBI

Project no.	Data consumption	Business value	Effort	DBI
#2 – Segmentation of household savings	3	2	1	2.28
#5 – Anomaly detection in solar cell production plants	2	3	2	1.50
#8 – Predicting ticket reopening	3	2	2	1.50
#9 – Big social data analytics for enhancing traveller experience	1	2	1	1.26
#6 – Explainable AI for car crash detection	1	3	3	0.67
#7 – Live streaming in virtual CDNs via DRL	1	3	3	0.67
#1 – Antifraud in insurtech	2	2	3	0.50
#3 – HR-specific NLP	2	2	3	0.50
#4 – DTR in power transmission grids	1	2	3	0.42

Source(s): Authors’ elaboration

Insurance, Banking and Financial Services, Energy, Resources and Utilities. In these industries, AI is leveraged to automate processes, enhance customer service, prevent fraud and optimise complex operations (Neodata Group, 2025).

Insurtech (as per projects #1 and #6) follows, together with specific use cases in the energy and telecommunications industries, where the challenges are quite tough and advanced and effort-requiring techniques are needed (namely, DTR for project #4 and DRL for project #7). Also, harnessing the potential of NLP (as in project #3 for the HR domain) is still tricky and yields higher costs than benefits.

6. Contributions and conclusions

Building on the considerations outlined above, this paper offers several managerial contributions at the intersection of strategic planning and AI by adopting a knowledge-based perspective and Dynamic Capabilities Theory. This approach enables a deeper understanding of how organisations can mobilise and orchestrate knowledge assets to effectively design, implement and sustain AI-driven strategies. In fact, the study underscores the dynamic capabilities required to derive value from AI initiatives. These capabilities – such as absorptive capacity, data governance competence and strategic alignment – serve as foundational elements for value creation in AI-enabled environments. By identifying and articulating these capabilities, the research contributes to the ongoing discourse on how organisations can systematically manage knowledge to leverage AI technologies effectively.

Another consideration needs to be underlined. The research critically reflects on the use of a maturity model as a guiding framework for achieving successful digital transformation. The maturity model functions as both a diagnostic and developmental tool, enabling organisations to assess their current state, identify capability gaps, and prioritise actions that reduce implementation risk and enhance the likelihood of transformation success. This aligns with the KM literature's focus on structured learning and organisational adaptation over time. Also, the introduction of the Data-Based Index (DBI) constitutes a novel managerial instrument for evaluating both the maturity of digital transformation projects and their readiness to harness AI and data-driven opportunities. The DBI facilitates informed decision-making by offering a structured, knowledge-intensive framework for assessing strategic fit, technological preparedness and organisational learning capabilities.

From a theoretical perspective, the originality of this work lies in its effort to systematise a method grounded in the DBI, thereby contributing to the formalisation of knowledge-based approaches to AI strategy development. The framework defines a coherent set of criteria for planning, implementing and evaluating AI-driven strategies, advancing theoretical integration among KM, strategic planning and digital innovation.

In sum, the study thus contributes not only to theory-building but also to practice-oriented knowledge relevant to managers navigating AI transformations.

Despite its managerial relevance, this study has several limitations that delimit the scope of inference.

As presented in the methodology section, the research design is exploratory and qualitative, relying on a limited number of cases. While cross-case comparison provides analytical insight, the evidence does not support statistical generalisation, and the proposed relationships should be interpreted as theory-building rather than theory-testing. Future work should therefore validate the framework on larger samples through confirmatory designs (e.g. survey-based constructs, archival panels or mixed-methods triangulation).

A reflection is also due on the case selection – although guided by explicit criteria – as it may introduce selection effects. The projects analysed are those with sufficient public documentation and publishable outcomes, which can systematically over-represent

successful or mature initiatives and under-represent failed, discontinued or confidential projects. This “visibility bias” may inflate perceived maturity and DBI performance. Subsequent studies should incorporate negative or null cases and access non-public project documentation where possible to mitigate survivorship and publication bias.

With reference to the DBI evaluation, it is useful to note that it is based on a structured rubric, yet the scoring remains partly judgement-based. Even with explicit anchors, some drivers (e.g. data literacy, governance overhead, technical debt) are difficult to measure consistently across heterogeneous contexts, potentially creating construct validity and inter-rater reliability issues. Future research should operationalise each driver with more granular indicators, conduct inter-rater agreement tests (e.g. Intraclass Correlation Coefficient, Krippendorff’s alpha; [Marzi et al., 2024](#)), and examine sensitivity to alternative aggregation rules or weighting schemes.

Finally, the framework is applied across diverse industries, enhancing transferability but also raising comparability concerns. Industry-specific regulatory constraints, data regimes and technological baselines can affect both feasibility and impact, meaning that identical DBI scores may reflect different underlying mechanisms. Future work should therefore test sector-specific calibrations (clustered benchmarks) and examine boundary conditions such as regulation intensity, data availability and digital maturity.

In conclusion, the study is largely cross-sectional with respect to outcomes. However, AI-driven digital transformation is path-dependent, and benefits often materialise after organisational learning and process redesign. Future research could use longitudinal designs that track the same initiatives across phases, enabling stronger claims about causality, capability accumulation and the temporal dynamics linking strategic planning choices, DBI drivers and realised value. Also, developing and testing formal research hypotheses to validate the DBI model across broader data sets over time, thereby enabling comparative analysis, could contribute to a deeper understanding of knowledge-based AI strategy formulation and execution.

In summary, this study should be considered a preliminary investigation, laying the groundwork for more extensive empirical research while advancing theoretical development on AI-driven digital transformation strategy.

References

- AGID (2024), “Italian strategy for artificial intelligence 2024-2026”, available at: www.agid.gov.it/sites/agid/files/2024-Italian_strategy_for_artificial_intelligence_2024-2026 (accessed 22 July 2024).
- Ahmed, I., Munir, F., Nafees, F., Mahmood, J., Chaudhry, S.A., Javaid, M. and Batool, K. (2024), December), “The influence of kanban agile methodology on software project management: a survey method”, in *2024 International Conference on Engineering and Emerging Technologies (ICEET)*, IEEE, pp. 1-6.
- Alaidaros, H., Omar, M. and Romli, R. (2021), “The state of the art of agile kanban method: challenges and opportunities”, *Independent Journal of Management & Production*, Vol. 12 No. 8, pp. 2535-2550.
- Alavi, M. and Leidner, D.E. (2001), “Review: knowledge management and knowledge management systems: conceptual foundations and research issues”, *MIS Quarterly*, Vol. 25 No. 1, pp. 107-136.
- Anderson, J. (2025), “The chief AI officer’s handbook: master AI leadership with strategies to innovate, overcome challenges, and drive business growth”, *Packt Publishing, Limited*.
- Arena, E., Corsini, A., Ferulano, R., Iuvara, D.A., Miele, E.S., Ricciardi Celsi, L., Sulieman, N.A. and Villari, M. (2021), “Anomaly detection in photovoltaic production factories via monte carlo pre-processed principal component analysis”, *Energies*, Vol. 14 No. 13, p. 3951, doi: [10.3390/en14133951](https://doi.org/10.3390/en14133951).
- Bencivelli, L., Formai, S., Mattevi, E. and Padellini, T. (2025), *Embracing the Digital Transition: The Adoption of Cloud Computing and AI by Italian Firms*, Bank of Italy, p. 946.
- Burger, B., Kanbach, D.K., Kraus, S., Breier, M. and Corvello, V. (2023), “On the use of AI-based tools like ChatGPT to support management research”, *European Journal of Innovation Management*, Vol. 26 No. 7, pp. 233-241.

- Castelli, M. and Manzoni, L. (2022), "Generative models in artificial intelligence and their applications", *Applied Sciences*, Vol. 12 No. 9, p. 4127.
- Cervone, H.F. (2011), "Understanding agile project management methods using scrum", *OCLC Systems & Services: International Digital Library Perspectives*, Vol. 27 No. 1, pp. 18-22.
- Cevallos Moreno, J.F., Sattler, R., Caulier Cisterna, R.P., Ricciardi Celsi, L., Sánchez Rodríguez, A. and Mecella, M. (2021), "Online service function chain deployment for live-streaming in virtualised content delivery networks: a deep reinforcement learning approach", *Future Internet*, Vol. 13 No. 11, p. 278.
- Chierici, R., Tortora, D., Del Giudice, M. and Quacquarelli, B. (2020), "Strengthening digital collaboration to enhance social innovation capital: an analysis of italian small innovative enterprises", *Journal of Intellectual Capital*, Vol. 22 No. 3, pp. 610-632, doi: [10.1108/JIC-02-2020-0058](https://doi.org/10.1108/JIC-02-2020-0058).
- Coccia, R., Tonti, V., Germanò, C., Palone, F., Papi, L. and Ricciardi Celsi, L. (2022), "A multi-variable DTR algorithm for the estimation of conductor temperature and ampacity on HV overhead lines by IoT data sensors", *Energies*, Vol. 15 No. 7, p. 2581, doi: [10.3390/en15072581](https://doi.org/10.3390/en15072581).
- Cohen, W.M. and Levinthal, D.A. (1990), "Absorptive capacity: a new perspective on learning and innovation", *Administrative Science Quarterly*, Vol. 35 No. 1, pp. 128-152.
- Cuomo, M.T., Colosimo, I., Ricciardi Celsi, L., Ferulano, R., Festa, G. and La Rocca, M. (2022), "Enhancing traveller experience in integrated mobility services via big social data analytics", *Technological Forecasting and Social Change*, Vol. 176, p. 121460.
- Cuomo, M.T., Tortora, D., Colosimo, I., Ricciardi Celsi, L., Genovino, C., Festa, G. and La Rocca, M. (2023), "Segmenting with big data analytics and python: a quantitative exploratory analysis of household savings", *Technological Forecasting and Social Change*, Vol. 191, p. 122431.
- Davenport, T. and Prusak, L. (1998), *Working Knowledge: How Organizations Manage What They Know*, Harvard Business School Press.
- De Mauro, A. (2020), *Big Data per Il Business*, Apogeo Editore.
- De Mauro, A., Greco, M. and Grimaldi, M. (2016), "A formal definition of big data based on its essential features", *Library Review*, Vol. 65 No. 3, pp. 122-135.
- Del Giudice, M. and Maggioni, V. (2014), "Managerial practices and operative directions of knowledge management within inter-firm networks: a global view", *Journal of Knowledge Management*, Vol. 18 No. 5, pp. 841-846.
- Del Giudice, M., Scutto, V. and Papa, A. (2023), *Knowledge Management and AI in Society 5.0*, Routledge.
- Eisenhardt, K.M. and Martin, J.A. (2017), "Dynamic capabilities: what are they?", *The SMS Blackwell Handbook of Organizational Capabilities*, pp. 341-363.
- Fedele, A., Punzi, C. and Tramacere, S. (2024), "The ALTAI checklist as a tool to assess ethical and legal implications for a trustworthy AI development in education", *Computer Law & Security Review*, Vol. 53, p. 105986.
- Ficara, G. (2022), "Data architecture evolution to increase the data benefit index", available at: www.linkedin.com/pulse/data-architecture-evolution-increase-benefit-index-giuseppe-ficara%3FtrackingId=4CaQ%252F9ZVQf2S8bOUN3L9bg%253D%253D/?trackingId=4CaQ%2F9ZVQf2S8bOUN3L9bg%3D%3D (accessed 20 November 2024).
- Gandomi, A. and Haider, M. (2015), "Beyond the hype: big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 No. 2, pp. 137-144.
- Gatti, S. and Danese, A. (2022), *La Cultura Del Dato*, FrancoAngeli.
- Grant, R.M. (1996), "Toward a knowledge-based theory of the firm", *Strategic Management Journal*, Vol. 17 No. S2, pp. 109-122.
- Grant, R.M. (2006), "The Knowledge-Based view of the firm", in Campbell, A. and Faulkner D.O. (Eds), *The Oxford Handbook of Strategy: A Strategy Overview and Competitive Strategy*, Oxford Academic.
- Haefner, N., Wincent, J., Parida, V. and Gassmann, O. (2021), "Artificial intelligence and innovation management: a review, framework, and research agenda", *Technological Forecasting and Social Change*, Vol. 162, p. 120392.

- Hossain, Q., Yasmin, F., Biswas, T.R. and Asha, N.B. (2024), "Data-driven business strategies: a comparative analysis of data science techniques in decision-making", *Scholars Journal of Economics, Business and Management*, Vol. 11 No. 9, pp. 257-263.
- Humby, C. (2006), "Data is the new oil", *Proc. ANA Sr. Marketer's Summit*, Evanston, IL, USA, p. 1.
- Jatain, D. (2022), "Performance optimisation of an enterprise using data-driven strategy", *International Journal of Research in Engineering, Science and Management*, Vol. 5 No. 11, pp. 113-117.
- Jebb, A.T., Parrigon, S. and Woo, S.E. (2017), "Exploratory data analysis as a foundation of inductive research", *Human Resource Management Review*, Vol. 27 No. 2, pp. 265-276.
- Koley, S., Sengupta, S., Biswas, B., Datta, K., Jana, M. and Mitra, A. (2025), "Applications of artificial intelligence and machine learning-enabled businesses: a SWOT analysis for human society", *Artificial Intelligence-Enabled Businesses: How to Develop Strategies for Innovation*, pp. 227-261.
- Korherr, P., Kanbach, D.K., Kraus, S. and Mikalef, P. (2022), "From intuitive to data-driven decision-making in digital transformation: a framework of prevalent managerial archetypes", *Digital Business*, Vol. 2 No. 2, p. 100045.
- Korzynski, P., Mazurek, G., Altmann, A., Ejdy, J., Kazlauskaitė, R. and Paliszkievicz, J. (2023), "Generative artificial intelligence as a new context for management theories: analysis of ChatGPT", *Central European Management Journal*, Vol. 31 No. 1, pp. 3-13.
- Kumar, H. (2024), "Enablers for digital transformation of services to harness new business opportunities", *IEEE Transactions on Engineering Management*, Vol. 71, pp. 14282-14292.
- Lei, H., Ganjeizadeh, F., Jayachandran, P.K. and Ozcan, P. (2017), "A statistical analysis of the effects of scrum and kanban on software development projects", *Robotics and Computer-Integrated Manufacturing*, Vol. 43, pp. 59-67.
- Mahalakshmi, M. and Sundararajan, M. (2013), "Traditional SDLC vs scrum methodology—a comparative study", *International Journal of Emerging Technology and Advanced Engineering*, Vol. 3 No. 6, pp. 192-196.
- Maiano, L., Montuschi, A., Caserio, M., Ferri, E., Kieffer, F., Germanò, C., Baiocco, L., Ricciardi Celsi, L. and Anagnostopoulos, A. (2023), "A deep-learning-based antifraud system for car-insurance claims", *Expert Systems with Applications*, Vol. 231, p. 120644.
- Mariani, M.M., Machado, I., Magrelli, V. and Dwivedi, Y.K. (2022), "Artificial intelligence in innovation research: a systematic review, conceptual framework, and future research directions", *Technovation*, Vol. 122, p. 102623.
- Marvi, R., Foroudi, P. and Cuomo, M.T. (2025), "Past, present and future of AI in marketing and knowledge management", *Journal of Knowledge Management*, Vol. 29 No. 11, pp. 1-31, doi: [10.1108/JKM-07-2023-0634](https://doi.org/10.1108/JKM-07-2023-0634).
- Marzi, G., Balzano, M. and Marchiori, D. (2024), "K-Alpha calculator—krippendorff's alpha calculator: a user-friendly tool for computing krippendorff's alpha inter-rater reliability coefficient", *MethodsX*, Vol. 12, p. 102545.
- Morandini, M., Coleti, T.A., Oliveira, E., Jr, and Corrêa, P.L.P. (2021), "Considerations about the efficiency and sufficiency of the utilisation of the scrum methodology: a survey for analysing results for development teams", *Computer Science Review*, Vol. 39, p. 100314.
- Müeck, M., Gaie, C. and Gkikas, D.C. (2025), "Introduction to the european artificial intelligence act", in *European Digital Regulations*, Springer Nature Switzerland, Cham, pp. 53-90.
- Natarajan, T. and Pichai, S. (2024), "Transition from Waterfall to Agile Methodology—an Action Research Study", IEEE Access.
- Neodata Group (2025), "Artificial intelligence in Italy: between innovative momentum and structural challenges", available at: https://neodatagroup.ai/artificial-intelligence-intaly-between-innovative-momentum-and-structural-challenges/?utm_source=chatgpt.com (accessed 1 July 2025).
- Nonaka, I. and Takeuchi, H. (1995), *The Knowledge-Creating Company*, Oxford University Press.
- Nonaka, I., Toyama, R. and Konno, N. (2005), "SECI, ba and leadership: a unified model of dynamic knowledge creation", *Knowledge Management: Critical Perspectives on Business and Management*, Vol. 2 No. 317, pp. 16-29.
- Nonaka, I., Umemoto, K. and Senoo, D. (1996), "From information processing to knowledge creation: a paradigm shift in business management", *Technology in Society*, Vol. 18 No. 2, pp. 203-218.

- Panoply (2025), available at: <https://blog.panoply.io/the-big-data-stack-powering-data-lakes-data-warehouses-and-beyond> (accessed 19 February 2025).
- Peres, R., Schreier, M., Schweidel, D. and Sorescu, A. (2023), "On ChatGPT and beyond: how generative artificial intelligence may affect research, teaching, and practice", *International Journal of Research in Marketing*, Vol. 40 No. 2, pp. 269-275.
- Pirnay, L. and Burney, C. (2022), "How to build data-driven strategy maps? A methodological framework proposition", *Data & Knowledge Engineering*, Vol. 139, p. 102019.
- Ramirez, J.G.C. (2024), "The power of planning: how business plans drive effective management strategies", *Integrated Journal of Science and Technology*, Vol. 1 No. 3, pp. 1-14.
- Rane, N.L., Paramesha, M., Choudhary, S.P. and Rane, J. (2024), "Artificial intelligence, machine learning, and deep learning for advanced business strategies: a review", *Partners Universal International Innovation Journal*, Vol. 2 No. 3, pp. 147-171.
- Reiter, B. (2017), "Theory and methodology of exploratory social science research", *International Journal of Science and Research Methodology*, Vol. 5 No. 4, pp. 129-150.
- Ricciardi Celsi, L., Caliciotti, A., D'Onorio, M., Scocchi, E., Sulieman, N.A. and Villari, M. (2021), "On predicting ticket reopening for improving customer service in 5G fiber optic networks", *Future Internet*, Vol. 13 No. 10, p. 259.
- Ricciardi Celsi, L., Cevallos Moreno, J.F., Kieffer, F. and Paduano, V. (2022), "HR-specific NLP for the homogeneous classification of declared and inferred skills", *Applied Artificial Intelligence*, Vol. 36 No. 1, doi: [10.1080/08839514.2022.2145639](https://doi.org/10.1080/08839514.2022.2145639).
- Snowden, D.J. and Boone, M.E. (2007), "A leader's framework for decision making", *Harvard Business Review*, Vol. 85 No. 11, pp. 68-76.
- Srivastava, A., Bhardwaj, S. and Saraswat, S. (2017), May, "SCRUM model for agile methodology", in *2017 International Conference on Computing, Communication and Automation (ICCCA)*, IEEE, pp. 864-869.
- Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Machtynger, L., *et al.* (2020), "Artificial intelligence (AI) in strategic marketing decision-making: a research agenda", *The Bottom Line*, Vol. 33 No. 2, pp. 183-200.
- Sumbal, M.S., Tsui, E. and See-To, E.W. (2017), "Interrelationship between big data and knowledge management: an exploratory study in the oil and gas sector", *Journal of Knowledge Management*, Vol. 21 No. 1, pp. 180-196, doi: [10.1108/JKM-07-2016-0262](https://doi.org/10.1108/JKM-07-2016-0262).
- Teece, D.J., Pisano, G. and Shuen, A. (1997), "Dynamic capabilities and strategic management", *Strategic Management Journal*, Vol. 18 No. 7, pp. 509-533, doi: [10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z).
- Teece, D.J. (2007), "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance", *Strategic Management Journal*, Vol. 28 No. 13, pp. 1319-1350, doi: [10.1002/smj.640](https://doi.org/10.1002/smj.640).
- Teece, D.J. (2009), *Dynamic Capabilities and Strategic Management: organising for Innovation and Growth*, Oxford University Press.
- Teece, D.J. (2017), "Dynamic capabilities and (digital) platform lifecycles", in *Entrepreneurship, Innovation, and Platforms*, Emerald Publishing Limited, Vol. 37, pp. 211-225, doi: [10.1108/S0742-332220170000037008](https://doi.org/10.1108/S0742-332220170000037008).
- Todorova, G. and Durisin, B. (2007), "Absorptive capacity: valuing a reconceptualization", *Academy of Management Review*, Vol. 32 No. 3, pp. 774-786.
- Tortora, D., Chierici, R., Farina Briamonte, M. and Tiscini, R. (2021), "I digitise so I exist'. Searching for critical capabilities affecting firms digital innovation", *Journal of Business Research*, Vol. 129, pp. 193-204, doi: [10.1016/j.jbusres.2021.02.048](https://doi.org/10.1016/j.jbusres.2021.02.048).
- Tortora, D., Genovino, C., De Andreis, F., Loia, F. and Cuomo, M.T. (2024), "Boosting intellectual capital and digital maturity of SMEs: an investigation of enterprises in an Italian Southern tourist district", *Journal of Intellectual Capital*, Vol. 25 No. 7, pp. 176-198.
- Tronchin, L., Sicilia, R., Cordelli, E., Celsi, L.R., Maccagnola, D., Natale, M. and Soda, P. (2024), "Translating image XAI to multivariate time series", *IEEE Access*, Vol. 12, p. 1.

Wakode, R.B., Raut, L.P. and Talmale, P. (2015), "Overview on kanban methodology and its implementation", *IJSRD-International Journal for Scientific Research & Development*, Vol. 3 No. 2, pp. 2321-0613.

Yu, F., Gao, X., Li, X. and Jiang, D. (2025), "Digitalization policy and enterprise digital transformation: the role of big data capability", *Economic Analysis and Policy*, Vol. 86, pp. 2095-2113.

Žáček, M., Hamplová, A., Tyrychr, J. and Vrana, I. (2024), "Improvements for the planning process in the scrum method", *Applied Sciences*, Vol. 15 No. 1, p. 202.

Zhang, L., Lin, J., Sabatini, J., Borchers, C., Weitekamp, D., Cao, M. and Graesser, A.C. (2025), "Data augmentation for sparse multidimensional learning performance data using generative AI", *IEEE Transactions on Learning Technologies*, Vol. 18, pp. 145-164, doi: [10.1109/TLT.2025.3526582](https://doi.org/10.1109/TLT.2025.3526582).

Zhang, W., Zhang, W., Daim, T. and Yalçın, H. (2025), "AI challenges conventional knowledge management: light the way for reframing SECI model and Ba theory", *Journal of Knowledge Management*, Vol. 29 No. 5, pp. 1618-1654.

Further reading

Artificial intelligence act (2025), available at: <https://artificialintelligenceact.eu/> (accessed 20 January 2025)

Cuomo, M.T., Tortora, D., Ricciardi Celsi, L., Festa, G., Foroudi, P. and Giordano, A. (2021), "Digital transformation and tourist experience co-design: big social data for planning cultural tourism", *Technological Forecasting and Social Change*, Vol. 162, p. 120345.

Minsait and The European House – Ambrosetti (2025), "The state of the art of artificial intelligence in italian companies – adoption, impacts and prospects", available at: www.minsait.com/en/download/38017/artificial-intelligence-in-italy-2025:-adoption,-impacts-and-prospects (accessed 1 July 2025).

About the authors

Maria Teresa Cuomo, PhD, is a Full Professor of Management at the Department of Economics and Statistics at the University of Salerno, Italy. With a PhD in Public Administration from the same institution, she currently serves as Deputy Rector for Post-graduate Studies at the University of Salerno. She is also affiliated with the prestigious Business School at Brunel University, London, UK. An internationally recognised scholar, Prof. Cuomo has published extensively in top-tier international journals, many of which are listed in the 3* and 4* categories of the ABS ranking. Her contributions to research have earned her numerous awards, including the Best Research Award at the 9th Gika Conference at the Sorbonne University in Paris in 2021. Most recently, she received recognition for having the most uploaded paper in 2023, published in the renowned *British Journal of Management* (4* ABS list, Wiley). Beyond her academic contributions, she serves the *Journal of Knowledge Management* as its Social Media Editor and Associate Editor. Her research interests span critical contemporary areas such as quantum computing business, digital transformation, consumer behaviour, information systems and SDGs. Prof Cuomo's dedication to advancing knowledge in these fields makes her a leading figure in modern managerial studies.

Debora Tortora, PhD, is currently an Associate Professor of Management at the University of Milan-Bicocca (Italy), where she teaches "Management" and "Management of Tourism Enterprises". Her main subjects of interest concern sustainable tourism, quantum tourism, retail and experience marketing, corporate reputation and critical raw materials. She has published in several journals, both national and international; she has also presented papers and research outcomes at numerous international conferences. She is co-founder of Brightseed, spin-off of the University of Milan-Bicocca. She serves as a member of the editorial board on the Journals: *Esperienze d'Impresa* and *Global Journal of Commerce and Management Perspective*. Debora Tortora is the corresponding author and can be contacted at: debora.tortora@unimib.it

Francesca Loia, PhD, is currently an Assistant Professor of Organization Studies at the University of Campania "Vanvitelli", Italy. She received her PhD in Management Banking and Commodity Sciences at the University of Rome "Sapienza". Currently she teaches

Organization Science at the University of Campania Vanvitelli, Italy. She published in prestigious national and international journals and serves several journals as reviewer. Her research interests focus mainly on digital transformation, data science, information systems, particularly, integrating organizational theory, knowledge management and critical inquiry, focusing on the ways digital technologies transform work practices and organizational structures.

Paola Zoccoli (PhD) earned her PhD in Public Administration from the University of Salerno, where she currently is Research Fellow. Her main research interests include international business and marketing, foreign investments, social innovation. Paola has been deeply involved in a wide range of research projects, collaborating closely with both academic scholars and business professionals. Her work has led to significant contributions, including several scientific publications and notable presentations at esteemed global conferences. Paola's research efforts have focused primarily on international business and foreign investments, where her insights have helped to advance understanding and drive innovation in these fields.

Lorenzo Ricciardi Celsi, PhD, is currently an Associate Professor of Automation of Production Processes at the Mercatorum University. He is also head of artificial intelligence at Insoore. This leading insurtech company leverages advanced AI and data-driven technologies to optimise claims management and digital inspections for the insurance industry. He received his PhD in Information and Communication Sciences and Technologies, with a specialisation in Control Theory from Université Paris-Saclay, Paris, France, in 2018. Since 2020, he has also served as the Scientific Lead for the Joint Research Project initiative at ELIS Innovation Hub, promoting technology transfer between academia and industry and fostering collaborative innovation in AI-driven ecosystems. His research interests span cooperative control methodologies for multi-agent systems, artificial intelligence and robotics.

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgroupublishing.com/licensing/reprints.htm
Or contact us for further details: permissions@emeraldinsight.com