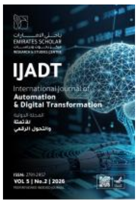

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Optimizing Artificial Intelligence for Digital Transformation: An Integrated Three-Layer Framework Linking Optimization Methods to Enterprise Value Creation

Hiroshi Tanaka, Ibrahim S. Yusuf, Julia R. Santos

JP National University - Japan, Nairobi Institute of Technology - Kenya, Canada Wave University - Canada

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ABSTRACT

Artificial intelligence (AI) has become the principal engine of contemporary digital transformation (DT), yet the value that organizations realize from AI depends less on the mere adoption of models and more on the quality of the optimization that underpins them. This paper argues that optimization is the connective tissue linking algorithmic performance, operational decision-making, and strategic investment in the digitally transforming enterprise. Drawing on the digital-transformation and AI-business-value literatures, the study develops an integrated conceptual framework—the Optimization–AI–Digital Transformation (OAD) framework—that organizes optimization into three interacting layers: learning-level optimization (model training), decision-level optimization (prescriptive and operational analytics), and strategic-level optimization (AI-portfolio and capability sequencing). Each layer is formalized mathematically and mapped to an established stage of digital transformation and to a distinct mechanism of value creation. Using illustrative scenario modeling calibrated to ranges reported in the literature, the paper demonstrates how adaptive gradient methods, constrained prescriptive optimization, and portfolio optimization jointly compound enterprise outcomes across efficiency, agility, innovation, and growth. The framework is discussed in the context of the United Arab Emirates' national AI ambitions, and implications for managers and policymakers are drawn. The paper contributes a cross-disciplinary, optimization-centered lens that reframes digital transformation as a multi-level optimization problem rather than a purely technological or organizational one.

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*Corresponding author: hiroshi.tanaka@jpinnovation.jp

1. Introduction

Digital transformation (DT) has moved from a peripheral information-technology concern to a central strategic imperative for organizations across virtually every sector. Contemporary scholarship characterizes DT not as the installation of new tools but as a process in which digital technologies trigger disruptions that compel organizations to alter their value-creation paths while managing the structural and organizational changes that condition the outcomes (Vial, 2019). Building on this view, researchers distinguish three progressive stages—digitization, digitalization, and full digital transformation—each demanding distinct capabilities, structures, and success metrics (Verhoef et al., 2021). Across these stages, artificial intelligence (AI) has emerged as the technology most closely associated with transformative rather than incremental change, precisely because it enables machines to learn from data and to act with limited human intervention (LeCun et al., 2015; Wamba-Taguimdje et al., 2020).

Despite the enthusiasm surrounding enterprise AI, a persistent gap separates AI adoption from AI value. Systematic reviews of the AI-business-value literature report that many organizations struggle to convert AI investments into measurable performance gains, and that the value-generating mechanisms of AI remain imperfectly understood (Enholm et al., 2022). This paper advances a specific and, we argue, under-appreciated explanation for that gap: the value an organization extracts from AI is governed by the quality of the optimization that operates beneath it. Optimization is not a peripheral implementation detail. Almost every machine-learning method can be expressed as the search for parameters that minimize an objective function, so the behavior, efficiency, and reliability of AI systems are direct consequences of how well the underlying optimization problems are formulated and solved (Sun et al., 2020).

We contend that optimization operates at three distinct but interdependent levels in the digitally transforming enterprise. At the learning level, optimization determines how quickly and how well predictive models converge on useful representations of data. At the decision level, optimization converts predictions into actions—schedules, routes, allocations, and prices—through prescriptive and operational models. At the strategic level, optimization guides how the organization selects and sequences its portfolio of AI initiatives under budget, risk, and capability constraints. Treating these three levels in isolation, as the literature has largely done, obscures the compounding effects that arise when they are aligned.

Accordingly, this paper addresses three research questions. First, how can optimization be conceptualized as a unifying construct that links algorithmic, operational, and strategic dimensions of AI-enabled digital transformation? Second, what mathematical structures characterize optimization at each level, and how do they map onto the recognized stages of digital transformation? Third, what managerial and policy implications follow, particularly for ambitious national contexts such as the United Arab Emirates (UAE)? To answer these questions, the paper develops the Optimization–AI–Digital Transformation (OAD) framework, formalizes each layer, and illustrates the framework through calibrated scenario modeling. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the OAD framework. Section 4 formalizes the optimization methods that populate each layer. Section 5 provides an illustrative multi-layer application. Sections 6 and 7 discuss implications and limitations, and Section 8 concludes.

2. Theoretical Background and Literature Review

2.1 Digital Transformation: Stages and Value Creation

The digital-transformation literature has matured from descriptive accounts toward integrative frameworks. Vial (2019) synthesized 282 studies into an inductive framework in which digital technologies create disruptions that provoke strategic responses aimed at altering value-creation paths. Verhoef et al. (2021) complemented this process view with a phase model that separates digitization (encoding analog information), digitalization (re-engineering processes around digital data), and digital transformation proper (reconfiguring business models). A parallel stream emphasizes the organizational dynamics of transformation: Warner and Wäger (2019) show that incumbent firms succeed by continuously building dynamic capabilities, with agility functioning as the core mechanism of strategic renewal. Practitioner-facing accounts likewise stress that transformation is fundamentally about strategy and people rather than technology alone, even as they acknowledge the enabling role of advanced digital infrastructure (Ebert & Duarte, 2018).

What distinguishes digital transformation from earlier waves of information-technology-enabled change is a combination of scale, scope, and speed: the volume of data, the breadth of processes touched, and the velocity of technological change together demand that organizations treat transformation as an ongoing evolution rather than a discrete project (Vial, 2019). This continuous character is significant for the argument developed here, because it implies that the optimization problems an organization must solve are themselves non-stationary—objectives shift as markets, data distributions, and capabilities evolve—so optimization capacity, not any single optimized solution, becomes the durable source of advantage.

Crucially for the present argument, several studies observe that the benefits of transformation accrue through the optimization of processes rather than through digitization per se. Analyses of digital transformation in operations-intensive settings report that digital solutions enhance efficiency and foster continuous improvement chiefly by optimizing processes and reducing variation, while cautioning that employee resistance and technological setbacks can blunt these gains (Rihawi, 2025). Mastery of the transformation process itself—sequencing initiatives, aligning governance, and learning across projects—has been identified as a decisive determinant of outcomes (Ivančić et al., 2019). These findings foreshadow the framework developed here: optimization is the recurring mechanism through which digital capability is converted into value.

2.2 Artificial Intelligence and Business Value

AI is best understood as a broad family of technologies—machine learning, deep learning, natural-language processing, and computer vision among them—rather than a single tool. Deep learning in particular allows computational models composed of multiple processing layers to learn representations of data at successive levels of abstraction, an advance that underlies much of the recent surge in AI capability (LeCun et al., 2015). In organizational settings, Wamba-Taguimdje et al. (2020) analyzed AI-based transformation projects across numerous sectors and documented value along several dimensions, including the efficiency of operations and supply chains, the optimization of customer experience, improved forecasting and planning, and enhanced fraud detection. Their evidence highlights that AI's contribution is frequently mediated by optimization—of processes, of resource allocation, and of the matching between supply and demand.

The systematic review by Enholm et al. (2022) organizes this evidence into enablers and inhibitors of AI adoption, typologies of AI use, and first- and second-order value effects. A recurrent theme is that value is not automatic: it depends on complementary capabilities, data quality, and the alignment of AI outputs with decision processes. This conditional character of AI value motivates a framework that makes explicit the optimization mechanisms through which AI acts on the organization.

2.3 Optimization as the Mathematical Core of AI

From a computational standpoint, almost all machine-learning algorithms can be formulated as optimization problems that seek the extremum of an objective function; building models and constructing reasonable objective functions is therefore the first step of machine learning, after which numerical optimization methods search for good parameters (Sun et al., 2020). First-order gradient methods dominate large-scale learning because of their favorable trade-off between computational cost and convergence, and adaptive variants such as Adam—which maintains per-parameter estimates of the first and second moments of the gradient—have become standard for training deep models efficiently under noisy and sparse gradients (Kingma & Ba, 2015). Beyond model training, optimization also encompasses the constrained and combinatorial problems that arise in operations, as well as the derivative-free metaheuristics used when objective functions are non-convex or opaque (Sun et al., 2020). This paper treats these methods not as isolated technical devices but as the shared substrate on which AI-enabled transformation is built.

2.4 Regional Context: AI and Digital Transformation in the UAE

The framework is particularly salient in national contexts that have made AI a strategic priority. The UAE launched a national AI strategy in 2017 with the ambition of becoming a world leader in AI by 2031, investing in research infrastructure, capacity building, and cross-sector adoption (Shamout & Ali, 2021). Regional studies within the digital-transformation literature examine how AI reshapes leadership and management practice, including the evolving roles of women leaders in digitally transforming private-sector organizations (Omari, 2025). Such work situates AI-enabled transformation within specific institutional and cultural settings and underscores the need for frameworks that connect technical optimization to organizational and strategic choices—the connection this paper seeks to formalize.

2.5 Research Gap

Three observations emerge from the review. First, the digital-transformation literature convincingly frames transformation as a process of value creation but treats the underlying analytics as a black box. Second, the AI-business-value literature identifies optimization-adjacent mechanisms (efficiency, allocation, forecasting) without formalizing optimization as a unifying construct. Third, the technical optimization literature formalizes learning-level methods but rarely connects them to operational and strategic decision-making in organizations. The OAD framework addresses this gap by integrating the three perspectives into a single, multi-level account of how optimization drives AI-enabled digital transformation.

3. The Optimization–AI–Digital Transformation (OAD) Framework

The OAD framework conceptualizes the digitally transforming enterprise as a system of three nested optimization layers, each operating on a different unit of analysis and time horizon, and each mapped to a recognized stage of digital transformation. Figure 1 depicts the framework.

Figure 1. Three-Layer Optimization-AI-Digital Transformation (OAD) Framework

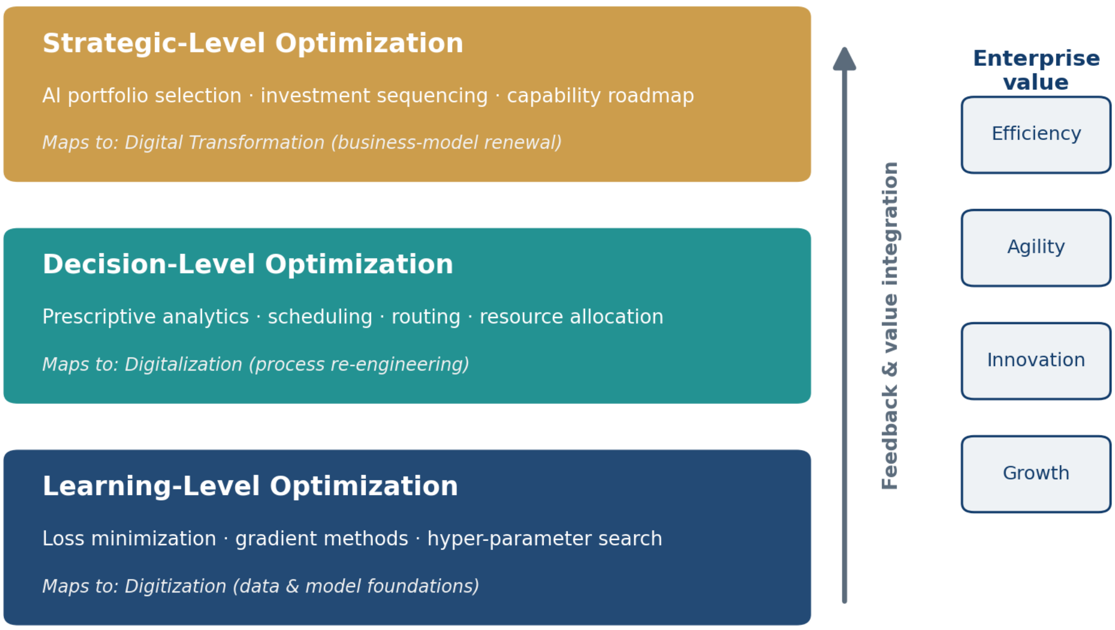

Figure 1. The three-layer Optimization–AI–Digital Transformation (OAD) framework, mapping optimization layers to digital-transformation stages and value outcomes.

Layer 1 — Learning-level optimization. At the foundation, optimization governs how AI models are trained. The unit of analysis is the model parameter vector, the time horizon is measured in training cycles, and the objective is to minimize predictive error subject to regularization. This layer corresponds to the digitization stage, in which the organization establishes the data and model foundations on which everything else depends. Its value contribution is primarily accuracy and reliability: better-optimized models produce better predictions.

Layer 2 — Decision-level optimization. Predictions become valuable only when they drive better decisions. The second layer converts model outputs into actions through prescriptive and operational optimization—scheduling, routing, inventory, pricing, and resource allocation. The unit of analysis is the operational decision, the horizon is operational (hours to weeks), and the objective is to maximize a business criterion subject to capacity and policy constraints. This layer corresponds to digitalization, in which processes are re-engineered around digital data and analytics. Its value contribution is efficiency and agility.

Layer 3 — Strategic-level optimization. At the top, optimization guides which AI initiatives the organization pursues and in what order, under budget, risk, and capability constraints. The unit of analysis is the initiative or capability, the horizon is strategic (quarters to years), and the objective is to maximize expected portfolio value while controlling risk. This layer corresponds to digital transformation proper—the reconfiguration of the business model—and its value contribution is innovation and growth. Table 1 summarizes the mapping.

Table 1. Structure of the OAD framework: layers, mathematical objects, transformation stages, and value mechanisms.

Optimization layer	Optimization object	Digital-transformation stage	Primary value mechanism
Strategic (L3)	AI-initiative portfolio; capability roadmap	Digital transformation (business-model renewal)	Innovation, growth, strategic renewal
Decision (L2)	Operational decisions (schedules, routes, allocations)	Digitalization (process re-engineering)	Efficiency, agility, responsiveness
Learning (L1)	Model parameters; hyper-parameters	Digitization (data & model foundations)	Accuracy, reliability, automation

The framework's central proposition is that value compounds across layers only when they are aligned. A superbly trained model (L1) creates little value if its predictions are not embedded in optimized decisions (L2); optimized decisions create limited strategic value if the organization invests in the wrong initiatives (L3). Conversely, gains at each layer amplify the others, producing the non-linear returns often observed in mature AI adopters (Enholm et al., 2022; Wamba-Taguimdje et al., 2020).

4. Optimization Methods Across the Three Layers

4.1 General Problem Formulation

The learning layer is grounded in the principle of regularized empirical risk minimization. Given a dataset of input–output pairs, the goal is to find a parameter vector that minimizes the average loss over the data plus a regularization term that discourages overfitting:

$$\theta^* = \arg\min_{\theta} \frac{1}{n}\sum_{i=1}^{n}\mathcal{L}(f(x_i\,;\theta),\, y_i) + \lambda\,\Omega(\theta)$$

Here the loss function measures the discrepancy between the model prediction and the target, the regularization term penalizes model complexity, and the hyper-parameter controls the trade-off between fit and generalization. The tractability and quality of the solution depend on the geometry of the objective and on the optimization method employed (Sun et al., 2020).

4.2 First-Order Gradient Methods (Learning Level)

The canonical solution method is gradient descent, which iteratively updates parameters in the direction of steepest descent scaled by a learning rate:

$$\theta_{t+1} = \theta_t - \eta\,\nabla_{\theta} J(\theta_t)$$

For large datasets, computing the full gradient at each step is prohibitively expensive, so stochastic (mini-batch) gradient descent estimates the gradient from a random subset of the data:

$$\theta_{t+1} = \theta_t - \eta\frac{1}{|B_t|}\sum_{i \in B_t}\nabla_{\theta}\mathcal{L}_i(\theta_t)$$

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Momentum accelerates convergence and dampens oscillation by accumulating an exponentially weighted history of past gradients:

$$v_{t+1} = \mu v_t - \eta \nabla J(\theta_t), \qquad \theta_{t+1} = \theta_t + v_{t+1}$$

Adaptive methods refine this idea by scaling the update separately for each parameter using estimates of the first and second moments of the gradient. The Adam optimizer, now a de-facto standard for deep learning, applies bias-corrected moment estimates as follows (Kingma & Ba, 2015):

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t}, \quad \theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

These methods differ markedly in convergence speed, robustness to noisy gradients, and sensitivity to hyper-parameters—differences that translate directly into training cost and model quality at Layer 1. The learning rate embodies a fundamental trade-off: values that are too large cause the optimizer to overshoot and diverge, while values that are too small stall progress in flat regions of the loss surface. Practical training therefore relies on learning-rate schedules and adaptive scaling, and on careful selection among optimizers, decisions that are frequently automated through the metaheuristic search procedures discussed below. From a managerial standpoint, these seemingly low-level choices are consequential: they govern how rapidly an organization can retrain models as data evolves, and thus how responsive the entire transformation program can be (Sun et al., 2020).

4.3 Constrained and Prescriptive Optimization (Decision Level)

At the decision layer, the objective is no longer to fit a model but to choose actions that maximize a business criterion subject to operational constraints. Many such problems take the form of a linear or mixed-integer program:

$$\max_x c^\top x \quad \text{s.t.} \quad Ax \le b, \quad x \in \mathcal{X}$$

where the decision vector represents quantities such as production levels, vehicle assignments, or staff allocations, and the constraints encode capacity, budget, and policy limits. Duality provides both computational leverage and managerial insight: the Lagrangian relaxes the constraints into the objective through multipliers that carry an economic interpretation as shadow prices:

$$\mathcal{L}(x, \mu) = c^\top x - \mu^\top (Ax - b), \qquad \mu \ge 0$$

In AI-enabled settings, the coefficients of these programs are increasingly supplied by predictive models from Layer 1—forecast demand, predicted travel times, or estimated failure probabilities—so the quality of the decision depends jointly on prediction accuracy and on the fidelity of the optimization model. This coupling is the operational expression of the OAD framework's alignment proposition.

4.4 Metaheuristics for Non-Convex and Black-Box Problems

Many practical problems are non-convex, combinatorial, or lack usable gradients. In such cases, derivative-free metaheuristics provide robust, if approximate, solutions (Sun et al., 2020). Population-based methods such as genetic algorithms evolve a set of candidate solutions through selection, crossover, and mutation, while particle-swarm optimization moves candidate solutions through the search space by combining individual and collective best-known positions. These methods are

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widely used for hyper-parameter search at Layer 1, for complex scheduling and network-design problems at Layer 2, and for initiative-selection problems at Layer 3, making them a connective mechanism across the framework.

4.5 Strategic Portfolio Optimization (Strategic Level)

At the strategic layer, the organization selects a portfolio of AI initiatives to maximize expected value while controlling risk and respecting a budget, in direct analogy to financial portfolio theory:

$$\max_{w} \sum_{j} w_j r_j - \gamma \sum_{j} \sum_{k} w_j w_k \sigma_{jk} \quad \text{s.t.} \quad \sum_{j} w_j c_j \leq B$$

Here the decision weights indicate the level of investment in each initiative, the first term captures expected value contribution, the second penalizes portfolio risk through the covariance of initiative outcomes, and the constraint enforces the budget. The risk-aversion parameter encodes the organization's tolerance for implementation and adoption uncertainty—a tolerance that is itself shaped by dynamic capabilities and organizational agility (Warner & Wäger, 2019). Table 2 compares the principal optimization methods across the three layers.

Table 2. Comparison of optimization methods used across the OAD layers.

Method	Typical layer	Problem type	Strengths	Limitations
Gradient / SGD	Learning (L1)	Smooth, high-dimensional	Scalable; low memory	Learning-rate sensitive; local minima
Adam (adaptive)	Learning (L1)	Noisy, sparse gradients	Fast; little tuning	Possible generalization gap
Linear / MILP	Decision (L2)	Constrained, combinatorial	Optimal; interpretable duals	Scales poorly if fully integer
Metaheuristics	L1–L3	Non-convex, black-box	Flexible; gradient-free	No optimality guarantee
Portfolio optimization	Strategic (L3)	Risk-constrained selection	Aligns risk and value	Needs covariance estimates

5. Illustrative Multi-Layer Application

To demonstrate how the OAD framework operates in practice, this section presents an illustrative application to a stylized enterprise digital-transformation program. The quantitative results reported here are illustrative simulations, not empirical observations. Parameters are calibrated to ranges reported in the reviewed literature and are intended to make the framework's logic concrete rather than to estimate effect sizes for any specific organization. This modeling strategy is consistent with the conceptual aims of the paper.

5.1 Learning-Level Illustration: Optimizer Convergence

Figure 2. contrasts the illustrative convergence behavior of stochastic gradient descent, momentum, and Adam on a representative model-training task. The adaptive optimizer reaches a low training loss in substantially fewer epochs, translating—at Layer 1—into lower computational cost and faster model iteration. In a transformation program, faster and more reliable training shortens the cycle between data availability and deployable predictions, an advantage repeatedly emphasized in the deep-learning literature (Kingma & Ba, 2015; LeCun et al., 2015).

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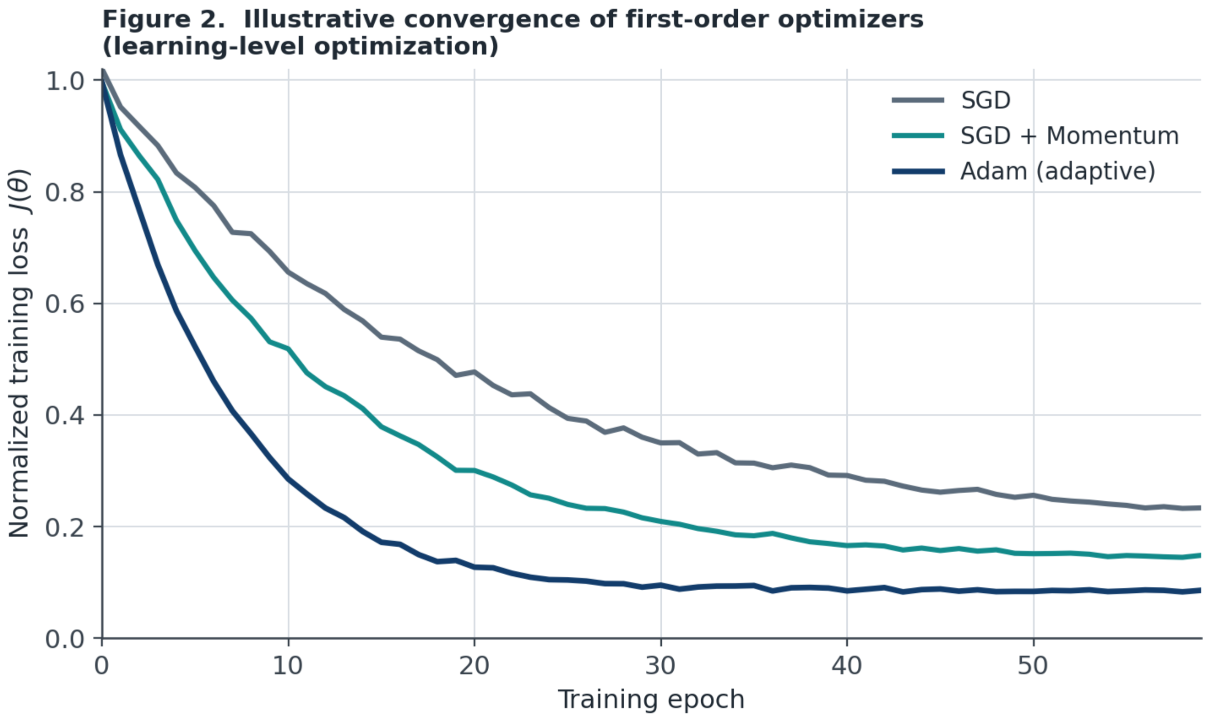

Figure 2. Illustrative training-loss convergence of three first-order optimizers. Adaptive methods converge faster and more smoothly (simulated).

5.2 Decision-Level Illustration: Process and Resource Optimization

Figure 3. traces illustrative operational key-performance indicators as the enterprise progresses through the three layers.

Moving from a pre-AI baseline through digitization (L1) and digitalization (L2) to full transformation (L3), the process cycle-time index falls while resource utilization rises. The largest single improvement occurs at the transition into decision-level optimization, where predictive outputs are embedded in prescriptive scheduling and allocation models—consistent with evidence that digital transformation delivers its efficiency gains chiefly through process optimization rather than digitization alone (Rihawi, 2025; Wamba-Taguimdje et al., 2020).

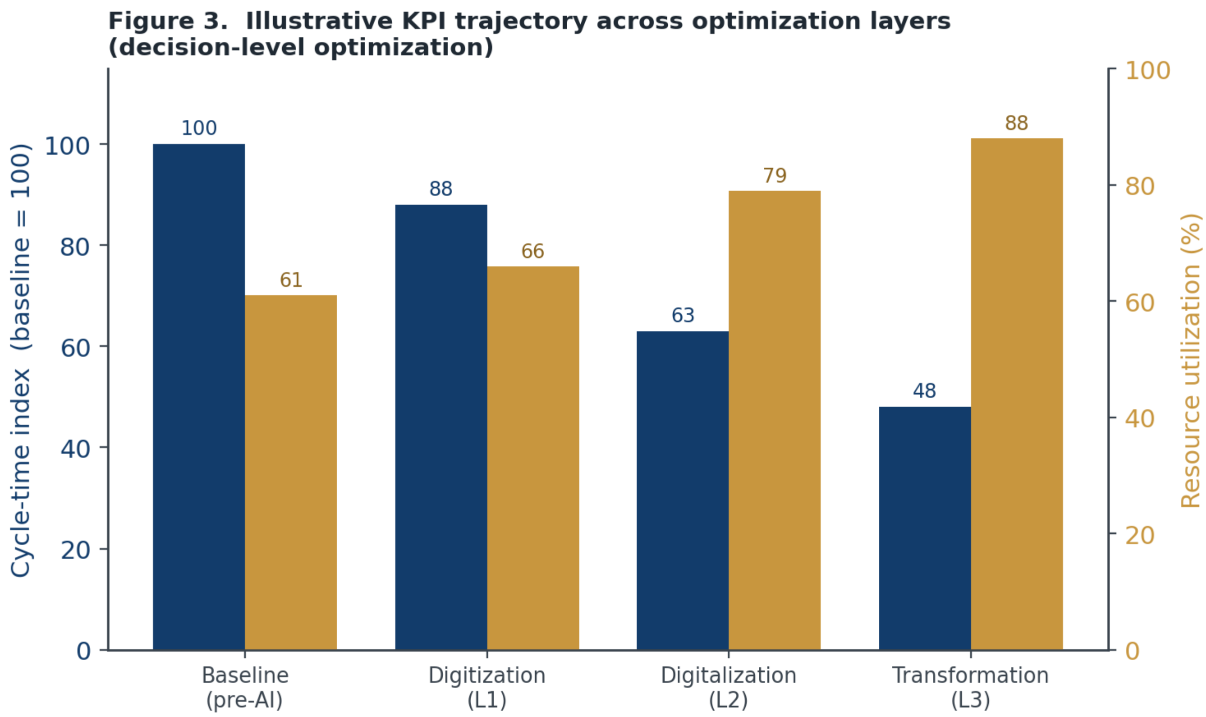

Figure 3. Illustrative trajectory of process cycle-time and resource utilization across the OAD layers (simulated indices).

Table 3. Illustrative decision-level scenario: outcomes of embedding optimized decisions on a stylized service operation.

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Performance indicator	Baseline	L2 optimized	Change
Process cycle-time index	100	63	-37%
Resource utilization (%)	61	79	+18 pts
On-time completion (%)	82	94	+12 pts
Rework / exception rate (%)	14	6	-8 pts

The pattern in Table 3 illustrates the alignment proposition numerically: predictive accuracy from Layer 1 is necessary but not sufficient; the visible operational gains materialize only once predictions are consumed by optimized decisions at Layer 2.

5.3 Strategic-Level Illustration: AI-Portfolio Optimization

Figure 4. depicts an illustrative AI-initiative portfolio problem. A cloud of candidate initiatives is characterized by expected value contribution and implementation-and-adoption risk; the optimized efficient frontier identifies, for each level of risk, the portfolio delivering the greatest expected value. Three representative selections—conservative, balanced, and aggressive—correspond to different risk-aversion settings. This strategic layer connects optimization to the dynamic-capability perspective: an organization's position on the frontier reflects its agility and its capacity for strategic renewal (Warner & Wäger, 2019), while its ability to execute the chosen portfolio reflects its mastery of the transformation process (Ivančić et al., 2019).

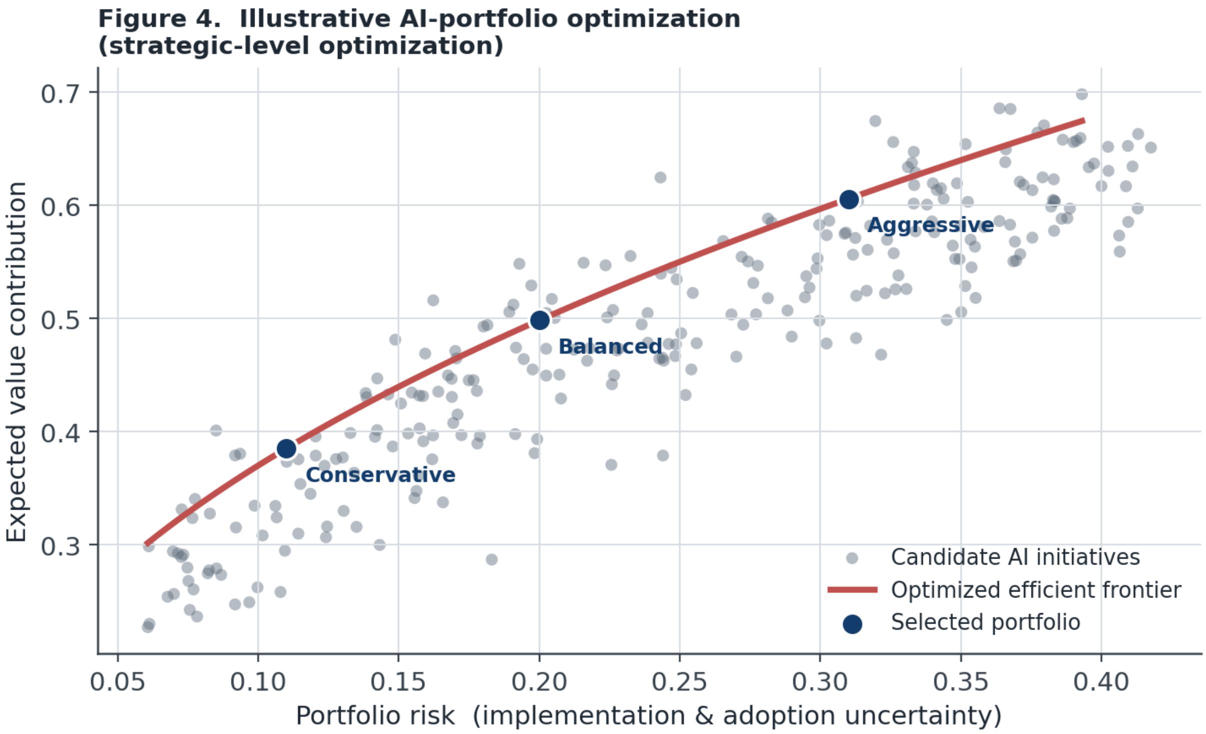

Figure 4. Illustrative AI-portfolio optimization. The efficient frontier identifies value-maximizing portfolios at each risk level (simulated).

5.4 Synthesis: Reading the Three Layers Together

Read in isolation, each illustration tells a familiar story—faster optimizers, leaner processes, better-chosen investments. Read together, they reveal the framework's core insight. The learning layer determines the accuracy of the predictive inputs; the decision layer determines whether those inputs are converted into optimized actions; and the strategic layer determines whether the organization is solving the right problems at all. A weakness at any layer caps the value obtainable from the others, which is why organizations that invest heavily in model development while neglecting decision integration frequently report disappointing returns (Enholm et al., 2022). Table 4 recasts the three illustrations as a diagnostic instrument: for each layer it identifies the governing optimization question, a representative metric, and the value at risk when the layer is neglected.

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Layer	Governing optimization question	Representative metric	Value at risk if neglected
Learning (L1)	Are models trained and refreshed efficiently and accurately?	Convergence speed; validation error	Stale or inaccurate predictions
Decision (L2)	Are predictions embedded in optimized operational decisions?	Cycle-time; utilization; on-time rate	Insight without action; low efficiency
Strategic (L3)	Are the right initiatives selected and sequenced under risk?	Portfolio value; risk-adjusted return	Misallocated investment; weak renewal

Table 4. OAD diagnostic: governing question, representative metric, and value at risk by layer.

6. Discussion and Implications

6.1 Cross-Layer Synergies

The illustrative application makes visible a claim that is easy to state but hard to operationalize: the returns to AI in digital transformation are multiplicative across layers, not additive. Investment concentrated in a single layer yields bounded returns—faster training that no decision consumes, or an ambitious portfolio the organization cannot execute. The managerial task, therefore, is less about maximizing any one layer than about maintaining alignment among them. This reframing helps explain the well-documented gap between AI adoption and AI value (Enholm et al., 2022): organizations that report disappointing returns are frequently optimizing at one layer while leaving the others untouched.

6.2 Managerial Implications

For managers, the OAD framework offers a diagnostic. It prompts three questions that map to the three layers: Are our models trained and updated efficiently enough to keep pace with the business (L1)? Are model outputs embedded in optimized operational decisions rather than presented as dashboards to be interpreted manually (L2)? And are we selecting and sequencing AI initiatives with an explicit view of value and risk rather than by enthusiasm or imitation (L3)? Framing transformation as a multi-level optimization problem also clarifies where scarce analytical talent should be deployed and where the binding constraint on value currently lies. Consistent with practitioner accounts, the framework reinforces that transformation is ultimately a strategic and organizational undertaking; optimization supplies the mechanism, but leadership, culture, and capability determine whether it is realized (Ebert & Duarte, 2018; Warner & Wäger, 2019).

6.3 Policy and Regional Implications

At the national level, the framework speaks directly to jurisdictions pursuing AI-led development. The UAE's strategy of investing simultaneously in research infrastructure, human capital, and cross-sector adoption can be read as an attempt to raise optimization capacity at all three layers at once—building the talent to train models, the institutions to embed them in public and private decision-making, and the strategic coordination to allocate national investment (Shamout & Ali, 2021). The framework suggests that such simultaneity is not merely efficient but necessary, given the multiplicative nature of cross-layer returns. It also implies that measurement and management of AI-enabled transformation—in the private sector and in government—should track optimization outcomes at each layer rather than adoption counts alone (Omari, 2025; Rihawi, 2025).

6.4 Toward a Layered Measurement Model

A practical corollary of the framework is that organizations should measure AI-enabled transformation at each layer rather than relying on aggregate adoption statistics. Adoption counts—the number of models deployed or use cases launched—are weakly related to value because they say nothing about alignment across layers. A layered measurement model instead pairs each layer with leading and lagging indicators: at the learning layer, model-refresh cadence and validation accuracy; at the decision layer, the share of decisions executed through optimized rather than manual policies, together with the operational KPIs those decisions move; and at the strategic layer, the risk-adjusted value of the initiative portfolio and the rate of business-model renewal it enables. Such a model gives leaders an early warning when value is being lost to misalignment, and it directs remediation to the specific layer where the binding constraint lies. It also complements existing dynamic-capability accounts of transformation by supplying the

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operational instrumentation those accounts often leave implicit (Warner & Wäger, 2019; Ivančić et al., 2019).

7. Limitations and Future Research

Several limitations bound the contribution and motivate future work. First, the paper is conceptual: the quantitative results are illustrative simulations calibrated to literature ranges, not empirical estimates, and should not be interpreted as effect sizes. Empirical validation—through case studies, panel data, or controlled field experiments—is a priority for establishing the magnitude and boundary conditions of cross-layer synergies. Second, the framework treats the three layers as cleanly separable, whereas in practice they overlap and interact through feedback loops that merit richer, possibly systems-dynamic, modeling. Third, the framework foregrounds optimization while holding constant important complements—data governance, ethics, workforce adaptation, and change management—that condition whether optimization translates into value. Future research could integrate these complements, extend the framework to specific sectors, and examine how organizational and national capabilities co-evolve with optimization capacity over time.

8. Conclusion

This paper has argued that optimization is the connective tissue of AI-enabled digital transformation, and that the persistent gap between AI adoption and AI value is, in large part, an optimization-alignment problem. By developing the three-layer Optimization–AI–Digital Transformation framework, formalizing the mathematical structures at each layer, and illustrating their interaction through calibrated scenario modeling, the paper reframes digital transformation as a multi-level optimization challenge that spans model training, operational decision-making, and strategic investment. The central proposition—that value compounds across layers only when they are aligned—offers both an explanation for uneven AI returns and a practical diagnostic for managers and policymakers. As organizations and nations, including the UAE, deepen their commitment to AI, treating optimization as a strategic, multi-level capability rather than a technical afterthought may prove decisive in converting digital ambition into durable value.

Declarations

Conflicts of interest: The author declares no conflict of interest. Funding: This research received no external funding. Note: All quantitative figures are illustrative simulations used to demonstrate the conceptual framework and do not represent empirical data from any specific organization.

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