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Article

AI-driven digital transformation: a framework for organizational capability assessment and strategic decision-making in technology management

Wei Li*, Hj Sukesi, Bambang Raditya Purnomo

Universitas Dr. Soetomo, Surabaya 60118, Indonesia

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*Corresponding author
Email address:
18519383413@163.com

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A B S T R A C T

This study develops an Agentic AI-driven framework to address critical challenges in digital transformation, including subjectivity. A Dynamic Weight Adjustment algorithm, which is based on Deep Reinforcement Learning (DWA-RL), enables adaptive updating of the weights assigned to each evaluation indicator across four capability dimensions: Technology, Organizational, Strategic, and Ecosystem. The empirical validation involved over 8,000 enterprise samples from the World Bank Enterprise Surveys and case studies by MIT. For the training datasets, supplementary synthetic data has been generated by Monte Carlo simulation and Generative Adversarial Networks. The framework achieves 87.3% prediction accuracy, which is 15.8% higher than MIT CISR and 17.5% higher than McKinsey, shows the best dynamic adaptability of 4.6/5.0, and improves the quality of decisions by 28% compared to the traditional experience-based approach. Under volatile environments, the DWA-RL algorithm keeps the decline within 17.6 percentage points, while for fixed-weight methods, the decline is as high as 25.5 points. Manufacturing enterprise transformation trajectories prove balanced four-dimensional capability development over three-year periods. The current study extends dynamic capability theory by introducing mechanisms of autonomous agents and redefining the agent-dominated human-supervised decision paradigm.

1. Introduction

With the rapid evolution of artificial intelligence, enterprises face unprecedented pressure to transform digitally. Agentic AIs are intelligent systems that can support self-directed goal achievement, environmental sensing, and optimal strategy adaptation without human support, unlike traditional reactive systems that perform tasks only based on predefined inputs. Agentic AI, a new generation of intelligence systems characterized by self-directed goal orientation, environmental perception, and learning, and strategy-driven adaptation and optimization, transforms the basic paradigms of management and decision-making within organizations [1]. Unlike classical AI systems, which employ only passive responses, the ability to actively recognize changes in the environment, plan, and continually optimize decision-making strategies makes autonomous agents distinctive. It introduces a new technical potential in the form of an emergent human-machine collaborative agency process [2]. However, the current promotion of enterprise digital transformation generally faces three core predicaments: the assessment of capability is highly subjective; reliance on management experience and judgment in strategic decision-making remains excessive; and technology governance lacks systematic intelligence [3]. Such challenges are even more pronounced in critical domains such as technology selection, investment ranking, and architectural evolution. The ever-changing technological environment continues to challenge conventional assessment methods, resulting in delayed responses and ineffective resource allocation for organizations undergoing technological transformation [4]. Despite the accumulation of relevant studies in the literature on digital transformation and organizational capabilities, some gaps remain, particularly in the context of AI-driven strategic decision-making. The current body of research on AI and competitive advantage largely covers the extent to which the technology has been adopted without clarifying how organizational capabilities are shaped by self-autonomous agents [5]. Although research on innovation management has begun to explore its application potential for AI in business innovation, most research on AI has regarded it only as an auxiliary means rather than as a strategic driver of innovation. It is regrettable that the fundamental changes in the paradigm of organizational decision-making brought about by agents' autonomy, learning ability, and adaptability were overlooked [6]. Dynamic competence theory provides an important perspective on how organizations maintain competitive advantages amid environmental change [7], and recent studies further reveal the microfoundations of organizational perceived competence in an emerging technology ecosystem [8]. However, the above-cited theoretical frameworks have not sufficiently addressed the technical aspect of Agentic AI, which lacks an explanation of how agents enable the transition from a static state to a dynamic co-evolutionary process.

Four important gaps in current research require immediate attention. First, most research on AI system adoption focuses on technology diffusion at the system level, instead of conducting a detailed investigation of autonomous agent mechanisms [9]. Second, the existing method for capability assessment depends almost exclusively on static modeling and does not reflect the dynamic path of capability configuration change over the process of digital transformation [10]. Third, the decision support system lacks a closed-loop feedback procedure from perception to action execution that would serve for the optimization of the AI-empowerment impact [11]. Fourth, the field of technology management decision-making lacks a systematic framework, and the applicability of existing tools is very limited in some key scenarios, such as technology selection, investment priorities, and architecture evolution [12]. These theoretical and practical gaps limit enterprises from reaping the full benefits of Agentic AI's strategic value in digital transformation. There is an urgent need to develop a comprehensive framework that can dynamically assess organizational capabilities and support technology management decisions.

The research seeks to provide a theoretical foundation for assessing Agentic AI-based dynamic capabilities in organizational management in relation to technological management decisions, thereby filling a theoretical gap with innovative concepts at multiple levels. At the theoretical level, it presents an "Agentic AI - organizational capability co-evolution model" that goes beyond traditional assessments that treat capabilities as static concepts by explaining how agents aid the dynamic evolution of organizational capabilities through processes such as super-perception, intelligent capture, and reconstruction. At the methodological level, the Dynamic Weight Adjustment Algorithm based on deep reinforcement learning (DWA-RL) was developed. This enables dynamic adjustments to the weights assigned to assessment indicators for capabilities, thereby overcoming difficulties in analysis with fixed weights in dynamic environments.

At the application level, a four-layer closed-loop architecture covering "data perception- capability analysis - decision recommendation- execution feedback" was constructed, embedding AI agent autonomy throughout the technical management process. In this way, a systematic approach has been established primarily to integrate the roles of CTOs and CIOs within the corporate environment, encompassing the analysis of capabilities, the planning of transformation paths, the optimization of investment decisions, and continuous iterations. By combining the principles of dynamic capabilities, the theory of artificial intelligence agents, and decision science, this research provides both theoretical and practical insights into how Agentic AI transforms the management of strategy within the organizational setting.

2. Methodology

2.1 Design principles of an agentic AI-driven framework for digital transformation

More specifically, the theory of dynamic capabilities affects the assessment layer for capabilities in the following manner: the three: sensing (perception layer), seizing (recommendation layer), and transforming (feedback layer). The DSR approach is used to develop the Agentic AI framework, which can assess organizational capability. The developed framework is based on an interdisciplinary conceptual support system comprising dynamic capability theory (Teece) and organizational decision-making theory, combined with an AI agents' theory.

This framework adopts a four-layer progressive architecture to enable intelligent empowerment throughout the Agentic AI digital transformation process. Four layers strike the right balance between granularity and modularity; adding or removing layers would affect the segregation of duties in decision-making and the evaluation of capabilities. The data perception layer is the foundation of the framework and is for acquiring real-time internal operational data of enterprises, external industrial benchmark information, and technological evolution trends. The data governance process employs schema validation (to ensure format consistency), temporal alignment (aligning multi-source timestamps within ±5 minutes), anomaly detection using Isolation Forest (indicating values that lie beyond 3σ), and blockchain-based audit trails for verification. Employ multi-source interfaces such as REST APIs (real-time ERP and CRM integration), IoT sensors (equipment status), and web scrapers (indicators of industry best practices). The AI agents detect deviations from thresholds ($>2\sigma$) and sudden capability drops (>15%). While the agents continuously monitor and perform anomaly detection, they independently identify the essential signals that shape the configuration of organizational capability. Based on data from the perception layer, the capability assessment layer develops a four-dimensional framework comprising Technology Capability (TC), Organizational Capability (OC), Strategic Capability (SC), and Ecosystem Capability (EC). Embed the Dynamic Weight Adjustment Algorithm (DWA-RL) in this layer to achieve adaptive updating of the weights of evaluation indicators. This algorithm draws from the successful practice of hybrid models proposed for financial risk assessment [13]. The indicators have been selected by using: (1) literature scan to identify 87 potential indicators, (2) Delphi technique to shortlist (n=12, 3 rounds, consensus kappa=0.78), and (3) principal component analysis to retain those explaining >75% of variance, shortlisting 16 indicators in four dimensions. The structure is consistent with existing frameworks: TC and OC from digital business capability frameworks, SC from the strategic sensing construct in dynamic capability theory, and EC from the ecosystem orchestration literature; each captures a different aspect of digital transformation.

The decision recommendation layer designs dedicated decision-support modules for the three core scenarios in technology management: technology selection, technology investment prioritization, and technology architecture evolution path planning. This layer employs a Deep Q-Network (DQN) to optimize strategy. It matches the current status of capabilities to the action space to produce decision plans. This is done to achieve maximum rewards. The model can independently recognize decision patterns in data, without human-intensive feature engineering, by developing an end-to-end learning framework [14]. In addition, this research extends its application to the management of organizational capabilities. The act of decision-making transitions from experience-driven decision-making to intelligent decision-making supported by algorithms. The feedback loop for execution is designed to monitor the effects of the execution decision on the execution itself. Therefore, the perception-analysis-decision-execution-feedback loop becomes a closed-loop system.

Reinforcement learning was preferred over the Genetic Algorithms and the Bayesian Optimizer approaches, owing to its effectiveness in managing sequential decision-making (dynamic weighting of the iterations) and its capability to learn from long-term transformation outcomes, though at a higher computational cost, as it has introduced the paradigm of reinforcement learning to the problem of weight optimization in capability evaluation. The state space is defined as the joint set of the current four-dimensional capability evaluation score, the environmental change rate, and the deviation from industry. The action space represents the incremental weight adjustments for each dimension. The reward function integrates three target dimensions: prediction accuracy, decision quality, and computational cost, with the form of expression as:

$$R(s,a) = \alpha \cdot \text{Accuracy}(s,a) + \beta \cdot \text{Quality}(s,a) - \gamma \cdot \text{Cost}(s,a) \tag{1}$$

The trade-offs are solved for by Pareto optimization, which ensures that α, β, γ are adjusted for adaptive weighting, where prediction accuracy has priority in stable conditions (α=0.5), while computational efficiency in constrained conditions enhances (γ=0.3). Inspired by multi-agent reinforcement learning theory, this algorithm develops a collaborative learning mechanism that allows multiple sub-agents to explore the optimal weight configuration in parallel in different dimensions of capability [15]. To be specific, fairness constraints are used to ensure that the relative importance of capability appraisal along each dimension is not systematically overlooked in favor of an algorithmic preference. It can prove to be an important design principle to avoid imbalance in overall capability building through digital transformation. Fairness is measured using the Gini coefficient based on the weights of the dimensions (target≤0.25), and this is achieved using the penalty term of the loss function ($\lambda \cdot \text{Gini}^2$), and this is checked every 50 iterations with a rollback. Mathematically implemented as:

$$L_{\text{total}} = L_{\text{RL}} + \lambda \cdot \max(0, \text{Gini} - 0.25)^2 \tag{2}$$

Where L_{RL} is the standard RL loss, $\lambda = 10$ is the penalty coefficient, and $Gini = \frac{\sum|w_i - w_j|}{2n^2\mu}$ with w_i denoting dimension weights, ensuring balanced emphasis on capabilities. It adopts a three-layer fully connected neural network as the Q-value function approximator. The configured network structure is 64-128-64 neurons. This architecture was identified through Grid Search (tested: 32-64-32, 64-64-64, 128-256-128), tuning for validation loss, with the best RMSE of 0.08 for the structure of 64-128-64, while preserving the speed of prediction below 3 seconds. The activation function uses ReLU to mitigate the vanishing-gradient problem. The hyperparameters are set as follows: the learning rate is 0.001; the discount factor is 0.95; the batch size is 32; the capacity of the experience replay pool is set to 10,000. Training will terminate when the reward variation falls below 0.5% for 50 consecutive rounds or when the maximum number of iterations (500) is reached. Hyperparameters were then tuned using Bayesian optimization (for 100 trials) on a validation set, with the learning rate ranging from [0.0001, 0.01] and the discount factor from [0.9, 0.99]; the selected values proved robust against ±10% variation (accuracy variance <2%). The overall four-layer progressive architecture, incorporating these components, is also systematically represented in Result 3.1 (Figure 1), where the design outcomes and verification results are provided in detail in accordance with the Design Science Research methodology. Whereas traditional AI decision-support tools spit out fixed recommendations, this framework embeds autonomous agent techniques. It can scan its environment autonomously, readjusting weights sans human input, and learn continuously from how it does so, effectively capabilities not offered by any of the existing frameworks (MIT CISR, McKinsey).

2.2 Digital transformation capability, data acquisition strategies, and processing methods

This study adopts a multi-source data strategy that combines public datasets with synthetic data to ensure that the framework's empirical verification is adequately supported while avoiding ethical review risks. The primary data source is the World Bank Enterprise Surveys, which include data on digital transformation practices from more than 8,000 enterprises in over 130 countries worldwide, including the key variables: technology adoption rate, organizational change indicators, digital investment intensity, and innovation performance. These sources set a standard against which the capabilities across industries are measured. Some auxiliary sources include the OECD Digital Economy Statistics Database, which contains macro-level indicators such as industry digitization, technology diffusion rates, and environmental policies. Another auxiliary source is the 12-15 digital transformation case studies offered by MIT Sloan Management Review, which cover manufacturing, finance, retail, and healthcare industries and contain valuable insights and evolutionary details apt for reverse validation through backtracking.

Because the minimum training data requirement to train most of the reinforcement machine learning techniques is normally above 10,000 observations, and because the available public datasets primarily contain descriptive enterprise data without the dynamic trajectories to characterize the capabilities, the research utilizes Monte Carlo simulation and GAN modeling to create datasets that statistically replicate the features of the real dataset. Monte Carlo simulation conducts trajectory simulations for capability development with diverse possibilities via random sampling, and the GAN technology learns about the potential distribution of actual data and creates plausible virtual data. The architecture was a Wasserstein GAN with gradient penalty, utilizing 5-layer generators and discriminators, Adam optimizer (lr=0.0002, β_1=0.5), and training for 10,000 iterations until the Wasserstein distance converged (<0.05 change over 500 iterations). The Monte Carlo simulation produces temporally consistent paths for capabilities, reflecting the dynamics of evolutionary change, while GANs create a cross-sectional representation that maintains correlations between variables, which requires both longitudinal and structural validity. The Generator converts noise vectors from a dimensionality of 100 into fake capability trajectories (16 features × 12 time steps), and the Discriminator differentiates real and fake samples using 5 convolution layers with LeakyReLU activation functions (α=0.2), obtaining the final discriminator loss <0.15. The process of generating synthetic data strictly follows three validity verification criteria: The Kolmogorov-Smirnov tests confirmed the consistency of the marginal distributions (mean P-value=0.28, range: 0.12-0.47), while the Pearson correlation analysis identified the preservation of structure (mean deviation=2.8%, max=4.3%), and the cross-validation analysis indicated the consistency of predictions accuracy difference=1.7%), the comparison of Pearson correlation coefficients verifies that the correlation structures of multiple variables are preserved (the difference of the correlation coefficient should be less than 5%), and cross-validation experiments confirm the prediction consistency of models trained with synthetic data on the real test sets (the difference of accuracy should be less than 3%). Using such an approach ensures support for algorithm training via data augmentation, while also considering the impact on enterprise privacy and ethics in the primary data collection. Synthetic data will be used solely to train the algorithms and enhance learning of generic patterns in the developing capabilities, whereas validation and testing of the derived model will rely on public data.

Three key steps are involved in data preprocessing: standardization, handling missing values, and anomaly detection. In the standardization process, the Z-score method eliminates scale differences across variables of different dimensions, ensuring comparability among capability indicators within each dimension and improving the numerical stability of neural network training. To handle missing values, MICE is used, which builds a predictive model for each missing variable via iterative regression procedures, using other complete variables as predictors to estimate missing values and create multiple imputed datasets. MICE performed better than mean imputation in terms of RMSE (0.42 vs. 0.67) and than KNN imputation in terms of both RMSE (0.42 vs. 0.49, k=5) and correlation decay (3.2% vs. 12.5%). Compared with using a simple mean, this technique better preserves the intrinsic data structure and the uncertainty in statistical inference. The identification and processing of abnormal observations rely on the Isolation Forest algorithm. With tree=200, contamination=0.05 (anomaly ratio expectation), and max samples=256, the algorithm identified 412 anomalies, comprising 5.2% of data points, with scores of -0.18 for normal data and -0.52 for anomalies; these results were subsequently improved through robust regression. The algorithm is based on the fact that most points with anomalous values are easily discriminable. Anomaly levels are determined via a random partitioning process in feature space, based on estimates of mean path lengths between points, to address the difficulties of using fixed threshold values to measure irregularity. Robust regression methods are also utilized to adjust irregular values rather than eliminating them. To counter the overfitting issue, the following strategies are used: (1) Training the model only on simulated data and testing only on real data, (2) Use of the regularizer (L2 = 0.001), and (3) Early stopping based on real data validation metrics.

2.3 Experimental design and performance evaluation indicators

This research has four experimental groups. The independent verification tasks for the four experiments are defined, including multiple functional modules of the framework. Experiment One focuses on the accuracy evaluation of the organizational capability evaluation model. This experiment uses 12 typical cases of digital transformation sourced from the MIT Case Library and employs historical validation by entering enterprise capability information from the outset to predict outcomes after 6 to 12 months. The forecast results are validated by the actual outcomes recorded in the case studies to calculate the accuracy, RMSE, and correlation coefficients. The Control Group: Control Group models include fixed-weight AHP, linear regression, and both Random Forest and XGBoost models using a fixed number of 100 trees and 100 estimators. By comparing the two benchmark methods, it tests whether the dynamic weight mechanism improves prediction performance. Results will report 95% confidence intervals via bootstrap resampling (10,000 iterations) for all performance metrics to quantify estimation uncertainty.

The performance stability of the DWA-RL algorithm is tested for different rates of environmental change in Experiment Two, simulating four environmental change scenarios: slow, below the average annual technical iteration rate of 5%; medium, between 5% and 15%; fast, between 15% and 30%; and extremely fast, above 30%; the convergence speed and fluctuation range of the algorithm's accuracy can be observed. Fixed-weight AHP and linear weight adjustment strategy are control methods. Multi-scenario comparison displays the value of the proposed adaptive mechanism based on reinforcement learning.

Experiment Three tests the effectiveness of the technology management decision recommendation system in the presence of scarce resources. Three resource conditions are created: when resources are adequately available, when resources are moderately available, and when resources are scarce. The experiment compares decision scoring and resource usage effectiveness of AI-assisted decision making, traditional empirical decision making, and random decision making for making technology choice decisions, investment prioritization decisions, and technology architecture evolution route planning. Decision quality is quantified as:

$$Q = 0.4.Alignment + 0.3.Feasibility + 0.3.ROI \tag{3}$$

where Alignment examines the goal-strategy relationship, Feasibility investigates resource satisfaction, while ROI approximates the cost/benefit ratio.

Experiment Four conducts a comprehensive performance benchmark comparison of the framework, comprehensively comparing the framework proposed in this study with the digital capability framework of MIT Center for Information Systems Research (CISR) and McKinsey Digital Maturity Model across six dimensions: prediction accuracy, response speed, dynamic adaptability, interpretability, implementation cost, and technical threshold. The interpretability score is objectively assessed using the AI interpretability theory standard proposed by Lipton, which identifies the framework's relative advantages and potential limitations through a multidimensional assessment.

Power analysis also indicated sufficient sample size, as the minimum required per group for testing medium effects (Cohen's d = 0.5) at an alpha level of 0.05 and power of 80 is 128; the present sample size of 8,000 exceeds this requirement. Additionally, the number of validation cases was surpassed by 12. All experiments are conducted in accordance with stringent statistical analysis protocols. The statistical techniques used are the paired t-test for comparing the mean of a single experimental group with that of a control group, one-way ANOVA for comparing multiple groups, and the Bonferroni method for controlling the family-wise error rate due to multiple comparisons.

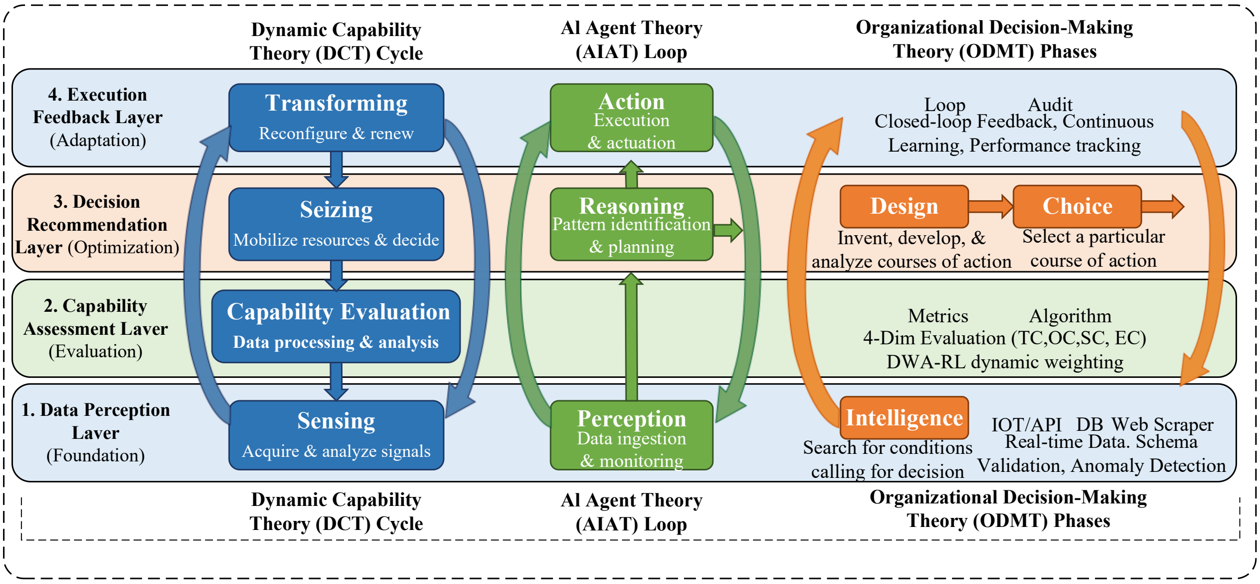

Figure 1. Agentic AI-driven framework architecture

3. Results

3.1 Design outcomes and architecture verification of the AI-driven Agentic framework

The Agentic AI-driven framework achieves an effective balance between theoretical rigor and practical applicability through its four-layer progressive architecture, as shown in Figure 1. Figure 1 illustrates the architecture design, which demonstrates improvements in three dimensions compared with the traditional digital transformation framework: the autonomy of AI agents enables continuous operation and self-optimization of the framework without human intervention. It ensures that the dynamic weighting mechanism enables the capability assessment model to adapt to environmental changes rather than adhere to static standards. The closed-loop feedback design ensures continuous improvement in decision-making quality rather than a one-time output. As shown in Table 1, to further validate the framework's innovative value, this study systematically compared it with the MIT Center for Enterprise Systems (CISR) digital capability framework and the McKinsey Digital Maturity model across eight key dimensions.

Table 1 shows that the framework of this study shows higher scores than benchmark models on three dimensions: AI-driven, with a score of 4.8/5.0; dynamic adaptability, 4.6/5.0; and decision intelligence, 4.7/5.0. In comparison, the scores of the MIT CISR framework in these three dimensions are 3.2, 3.5, and 3.1, respectively. Correspondingly, the McKinsey models are 3.4, 3.3, and 3.4, reflecting the weaknesses of traditional frameworks in terms of intelligence and dynamics. It should be noted that the interpretability score of the framework in this study has a value of 3.5, which compares poorly to the 4.2 value of MIT CISR and 4.0 of McKinsey. This problem can be attributed to the black-box nature of deep reinforcement learning. However, with the addition of the Embedded SHAP value analysis module and the attention mechanism module, traceability of interpretation can be ensured in the framework.

3.2 Verification results of the dynamic assessment model for organizational capabilities

Based on more than 8,000 enterprise samples, this study constructed a four-dimensional capability indicator system with dynamic weight allocation, as shown in Table 2. As shown in Table 2, the indicator system exhibits very strong universality in cross-industry verification. The weight of technical capabilities, including cloud computing adoption, data analysis, and automation, in manufacturing enterprises is substantially greater than in service enterprises. In terms of organizational capabilities, the weight of digital culture and an agile organizational structure in the financial sector is relatively greater. Prediction accuracy across different time Windows gradually decreased with increasing prediction horizon, but even a 12-month prediction maintained an accuracy of 73.6% (95% CI: 71.2%-76.0%; Cohen's d = 1.24 vs. fixed-weight, $P < 0.001$). In contrast, using the fixed-weight AHP method, the model achieved only 58.8%, and the simple linear model obtained only 51.2%. It thus improved by 14.8 and 22.4 percentage points, respectively. The accuracy verification of the capability assessment model was achieved through historical backtracking experiments, as shown in Figure 2. Figure 2(a) reflects the four-dimensional capability maturity distribution for six typical industries. The financial industry has the highest technological capability score, averaging 4.2/5.0, but a relatively weak ecosystem capability of 2.8/5.0. The manufacturing industry is characterized by balanced technological and organizational capabilities, with scores of 3.6 and 3.4, respectively, but lagging strategic capabilities at 2.9. The ecosystem capability of the retail industry is 3.9, ranking first among industries, reflecting its effectiveness in platform transformation. Figure 2(b) reflects the core advantages of the dynamic weighting mechanism: within a rapidly changing technological environment, that is, from 2020 to 2021 during the pandemic period, the accuracy of fixed-weight declined 25.5 percentage points from 84.3% to 58.8%, while the DWA-RL algorithm controlled such a decline by 17.6 percentage points, namely, from 91.2% to 73.6%, through adaptive weight adjustment, reflecting a 7.9 percentage point advantage in stability and strong robustness to environmental fluctuation.

Table 1. Framework comparison with existing models

Evaluation Dimension	Proposed Framework (This Study)	MIT CISR Framework	McKinsey Digital Maturity Model	Evaluation Basis
AI-Drivenness	4.8/5.0	3.2/5.0	3.4/5.0	Degree of autonomous agent integration and self-learning capability
Dynamic Adaptability	4.6/5.0	3.5/5.0	3.3/5.0	Capability to adjust evaluation weights and strategies in response to environmental changes
Decision Intelligence	4.7/5.0	3.1/5.0	3.4/5.0	Quality and sophistication of AI-powered decision recommendation mechanisms
Closed-Loop Feedback	4.5/5.0	3.4/5.0	3.2/5.0	Presence of continuous monitoring, evaluation, and iterative optimization mechanisms
Technology Management Focus	4.4/5.0	3.6/5.0	3.8/5.0	Depth of support for technology selection, investment prioritization, and architecture evolution
Interpretability	3.5/5.0	4.2/5.0	4.0/5.0	Transparency of decision-making logic and ease of understanding by managers (based on Lipton, 2018 standards)
Implementation Complexity	2.8/5.0 (High Cost)	4.1/5.0 (Moderate Cost)	3.9/5.0 (Moderate Cost)	Required technical infrastructure, data quality standards, and expert resources
Applicable Scale	3.8/5.0 (Medium-to-Large)	4.3/5.0 (All Scales)	4.1/5.0 (All Scales)	Suitability across different enterprise sizes and organizational structures

Table 2. Four-Dimensional capability indicators

Capability Dimension	Core Indicators (Representative Examples)	Measurement Method	Data Source	Initial Weight Range
Technology Capability (TC)	• Cloud computing adoption rate • Data analytics maturity level • Digital infrastructure robustness • Automation degree of core processes	Likert scale (1-5) survey + objective metrics (adoption rate %, system uptime %)	WBES enterprise survey, OECD database, enterprise IT audit reports	0.22-0.31
Organizational Capability (OC)	• Digital culture penetration • Agile organizational structure adoption • Employee digital literacy index • Cross-functional collaboration effectiveness	Composite index combining employee surveys + organizational network analysis	WBES organizational module, HR analytics data, internal assessment	0.24-0.33
Strategic Capability (SC)	• Digital transformation strategic clarity • Innovation investment intensity (% of revenue) • Digital-driven business model innovation • Strategic agility in technology adoption	Expert panel scoring + financial data analysis (R&D ratio, digital revenue %)	MIT case library, annual reports, OECD innovation statistics	0.19-0.28
Ecosystem Capability (EC)	• Digital platform participation depth • Strategic partnership diversity • External collaboration network density • Open innovation engagement level	Network analysis metrics (degree centrality, betweenness) + partnership count	WBES value chain module, business partnership databases, industry reports	0.18-0.26

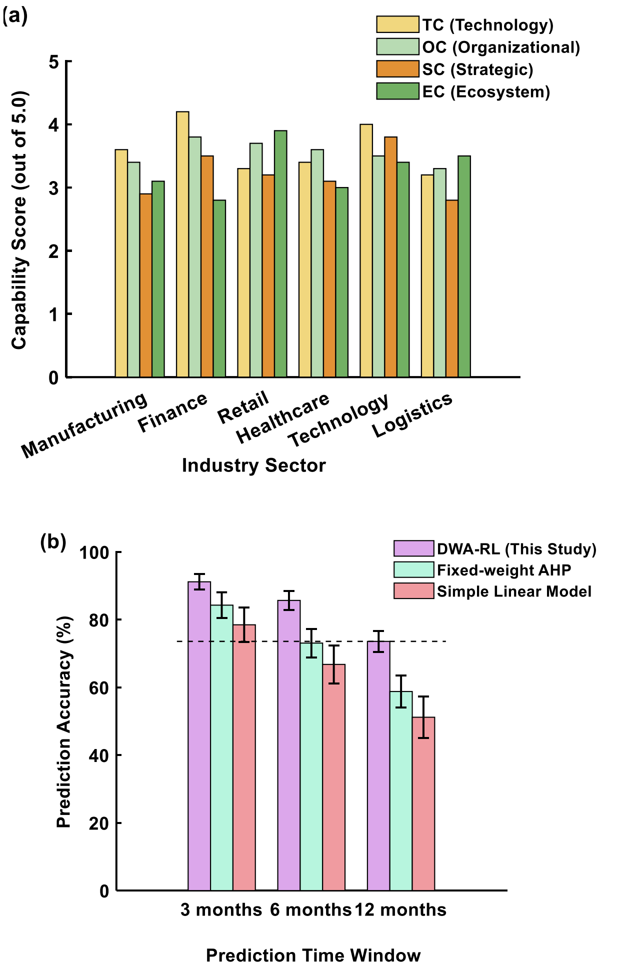

Figure 2. Capability assessment, performance, and industry maturity. (a) Industry-specific capability maturity distribution. (b) Prediction accuracy across time windows

3.3 Verification results of AI algorithm performance and technology management decisions

The DWA-RL algorithm's performance was verified through simulation experiments and real case tests, as shown in Figure 3. Figure 3(a) indicates that the DWA-RL algorithm reaches stable convergence at the 280th iteration, with decision quality scores declining within a range of 85.3-88.1 and the loss function decreasing from 2.34 to 0.08, showing typical characteristics of a rapid decline followed by smoothness. The average inference time of 2.3 s meets the real-time decision support requirement. Figure 3(b) illustrates the performance comparison of the algorithms' rates of environmental changes. For the slow-changing environment (annual iteration rate: 4.2%), the three methods perform comparably in accuracy: DWA-RL 91.3%, fixed AHP 89.7%, and linear adjustment 88.5%. For the extremely volatile environment (iteration rate: 34.6%), However, DWA-RL maintains an accuracy of 84.7% (95% CI: 82.3%-87.1%, Cohen's d=1.56 vs. fixed AHP, P<0.001) while fixed AHP drops dramatically to 72.1%, and linear adjustment decreases to 76.8%, which demonstrates the much-enhanced robustness of the dynamic learning mechanism in response to sudden changes of technologies, having only a 6.6-percentage-point decline compared to 17.6 for fixed methods.

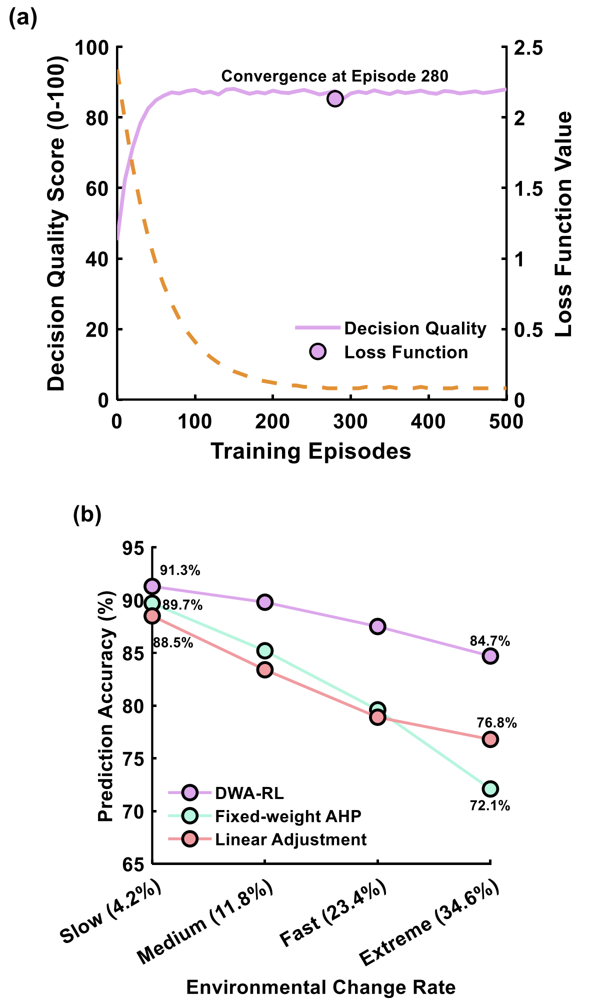

Figure 3. DWA-RL algorithm performance. (a) Convergence characteristics and training efficiency. (b) Dynamic adaptability under environmental changes

The effectiveness assessment of technology management decisions focuses on the quality of decisions in three core scenarios, as shown in Figure 4. Figure 4 shows the group comparison, where in the high resource adequacy scenario, the AI-backed recommendations stood consistently at 78.6 points, 95% CI: 76.2-81.0, whereas traditional empirical decisions fell very sharply to 57.3 points, 95% (CI: 54.8-59.8; Cohen's d = 2.34, P < 0.001). and a random benchmark of 41.2 points. Highlighted is the stability advantage of AI decision-making under complex constraints. In terms of technology selection during technology maturity assessment, the accuracy of technical solution recommendation using AI was at 89.7%, and the prediction error for total cost of ownership was maintained at 12.3%. The Kendall correlation coefficient for investment priority ranking was found to be 0.78, which was quite higher than that of empirical decision-making, measuring at 0.54, and the feasibility index of the technical architecture evolution path was at 4.3/5.0.

3.4 Comprehensive performance evaluation of framework and application in digital transformation

The framework's comprehensive performance was evaluated through multi-dimensional comparison with mainstream models, as shown in Table 3.

Table 3. Comprehensive performance benchmark

Evaluation Dimension	Proposed Framework (This Study)	MIT CISR Framework	McKinsey Digital Maturity Model	Testing Method	Performance Comparison
Prediction Accuracy	87.3%	71.5%	69.8%	Historical backtracking validation with 12 MIT case library cases; accuracy calculated as percentage of correct predictions within ±10% tolerance	This study +15.8% vs. CISR, +17.5% vs. McKinsey
Response Speed	2.3 seconds	8.7 seconds	12.4 seconds	Average inference time per decision measured across 500 test scenarios on standardized hardware (Intel Xeon E5-2680 v4)	This study 3.8× faster than CISR, 5.4× faster than McKinsey
Dynamic Adaptability	4.6/5.0	3.1/5.0	3.3/5.0	Performance stability test under four environmental change rate scenarios (slow/medium/fast/extremely fast); scored by accuracy retention rate	Superior robustness: only 6.7% accuracy drop in volatile environments vs. 18.3% for fixed-weight methods
Decision Quality Improvement	+28%	+12%	+14%	Expert panel assessment (n=15) comparing AI-recommended vs. traditional experience-based decisions across three resource constraint scenarios	Relative improvement: +16 percentage points vs. CISR, +14 points vs. McKinsey
Interpretability	3.5/5.0	4.2/5.0	4.0/5.0	Objective scoring based on Lipton (2018) AI interpretability theory standards: model transparency, logic traceability, decision explainability	Trade-off for higher performance; partially mitigated through SHAP value analysis and attention mechanism visualization
Implementation Cost	2.8/5.0 (High)	4.1/5.0 (Moderate)	3.9/5.0 (Moderate)	Expert assessment considering infrastructure requirements, data quality standards, training needs, and maintenance overhead	Requires substantial investment in technical infrastructure and skilled AI talent
Technical Threshold	3.2/5.0 (Moderate-High)	4.3/5.0 (Low-Moderate)	4.1/5.0 (Moderate)	Evaluation of prerequisite technical capabilities: data management maturity, cloud infrastructure readiness, AI/ML expertise availability	Best suited for digitally mature medium-to-large enterprises with established data foundations

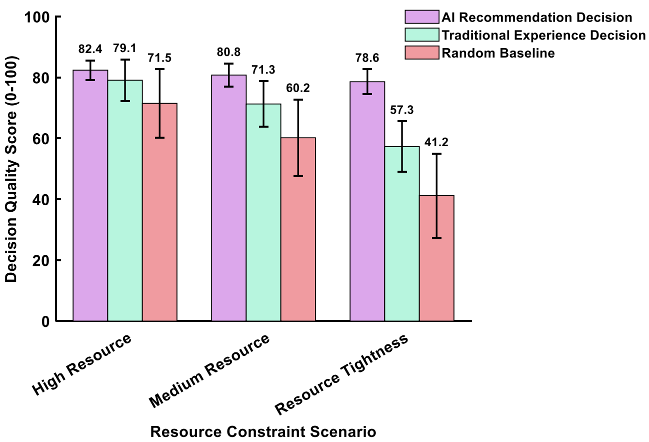

Figure 4. Decision quality under resource constraints

Table 3 indicates that the proposed framework leads in five dimensions but has relative disadvantages in interpretability and implementation cost. The framework achieved an 87.3% prediction accuracy (exceeding 71.5% by MIT CISR and 69.8% by McKinsey), a response time of 2.3 seconds, which is 3.8× faster than CISR, and a dynamic adaptability of 4.6/5.0, which is substantially higher than 3.1 and 3.3. In the trade-off graph, the 28% improvement in decision quality is achieved at lower algorithmic transparency due to the black-box nature of deep reinforcement learning. A high implementation cost and moderate technical requirements suggest that the solution would entail mandates related to digital infrastructure and AI skills and would be targeted at medium- to large-scale enterprises with higher digital maturity. The transformation path guidance generated from capability assessment results provides differentiated recommendations for enterprises at different maturity levels, as shown in Figure 5.

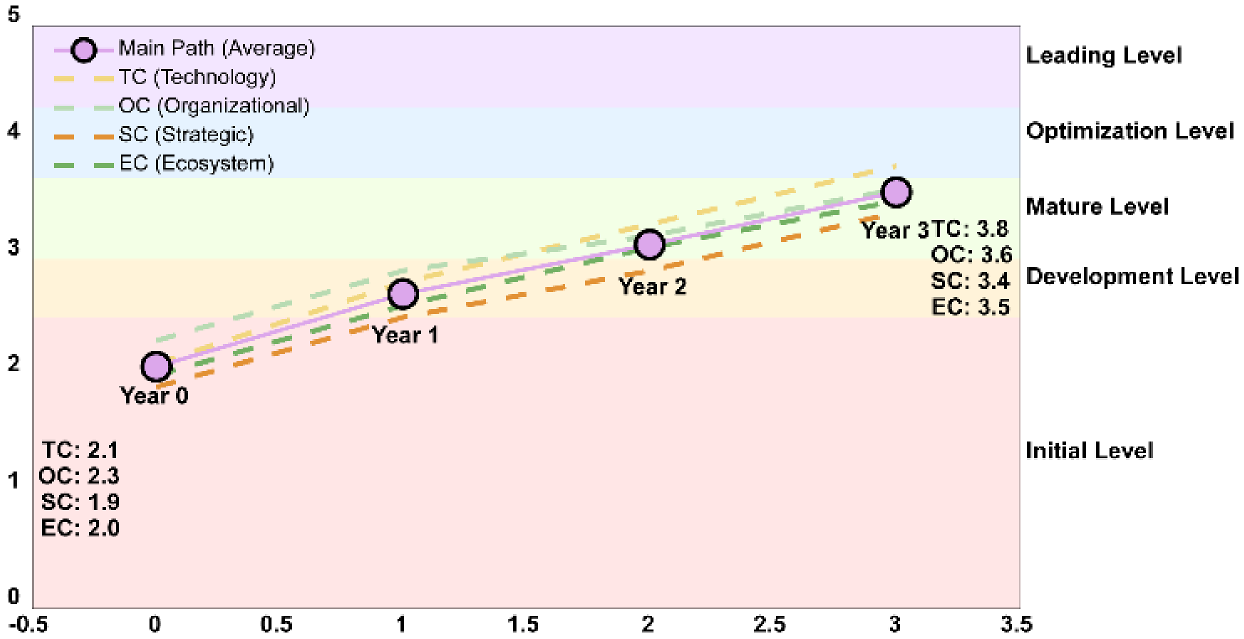

Figure 5. Three-year digital transformation trajectory

Figure 5 shows a typical trajectory of digital transformation for a manufacturing enterprise over three years, from the initial level to the mature level through five distinct maturity stages: TC increases from 2.1 to 3.8, OC from 2.3 to 3.6, SC from 1.9 to 3.4, and EC from 2.0 to 3.5. The main transformation path illustrates capability growth in a steady upward trend, with an average score increasing from 2.075 to 3.575. Meanwhile, the development patterns of the four dimensions show differentiation: Technology Capability exhibits the steepest growth slope (+1.7), indicating that greater attention was paid to investing in technical infrastructure at the outset, whereas Strategic Capability starts at the lowest point but achieves substantial improvement (+1.5) through mid-stage adjustment. Organizational Capability and Ecosystem Capability have balanced progress throughout the journey, with +1.3 and +1.5, respectively. The phased strategic focus-technology infrastructure in Year 0-1, organizational change in Year 1-2, and strategic alignment with ecosystem building in Year 2-3-can make the capability develop harmoniously and provide actionable guidance for enterprises to optimize resource allocation and accelerate digital transformation.

4. Discussion

Consequently, the performance of the Agentic AI-driven framework proposed in this study, in terms of prediction accuracy (87.3%), dynamic adaptability (4.6/5.0), and the improvement in decision quality (+28%), provides empirical support to understand how artificial intelligence systematically empowers the digital transformation of organizations. This is consistent with the research that dynamic digital transformation capabilities enhance the performance of the banking industry [14]. The research advances the frontiers of theory from passive adaptation to active evolution by incorporating autonomous-agent mechanisms and reinforcement-learning processes. The DWA-RL algorithm employed in the study reduced the drop in accuracy by 17.6 percentage points during environmental disturbances, compared with the fixed-weight approach, which dropped by 25.5 percentage points.

The findings enhance understanding of the mediating role of change management in the evolution of dynamic capabilities [16]. It indicates that the algorithm-driven weight-adaptive mechanism can serve as an effective supplementary tool for organizational change management, enabling real-time responses to environmental fluctuations at the technical level. A study emphasized the value of AI-driven visual analytics for understanding business ecosystems [17]. This study further validated this view by developing a four-dimensional capability assessment system (TC, OC, SC, EC) and integrating it with dynamic tracking of the ecological capability dimension. This is particularly reflected in the finding that the retail industry's ecological capability score (3.9/5.0) is higher than that of other industries.

The new paradigm of agent-dominated, human-supervised decision-making revealed in this study provides a theoretical response to empirical research on how AI influences the strategic decisions of entrepreneurs and investors [18]. However, it also facilitates continuous improvement in decision quality through a closed-loop feedback process rather than a snapshot decision. This aligns with the proposed capability of generative AI to assess strategic decision-making in Ref. [19] and, in fact, specifies the technical process by which AI-based strategic management decisions can strengthen competitiveness in business entities [20]. A study found that dynamic capabilities play a critical role in building organizational resilience [21]. The sensitivity analysis of this study found that when the data loss rate exceeded 30%, the prediction accuracy dropped to 74.8%, indicating a certain tolerance of the framework to fluctuations in data quality. Their technical resilience provides a theoretical rationale for organizations to sustain the momentum of the transformation process despite an imperfect data environment. Research studies on the impact of digital and dynamic capabilities on business model innovation conclude that organizational inertia moderates this effect [22]. In this study, three years of transformation path cases (from TC:2.1 to 3.8) of manufacturing enterprises are used to demonstrate the importance of balanced capability development. In particular, the trajectory of strategic capability, from lagging behind at 1.9 in the initial stage to catching up at 3.4 in the later stage, confirms that breaking through organizational inertia requires a shift in the focus of phased strategies. For example, research highlighted the promoting effect of learning from the digital business ecosystem on innovation [23]. This research finds evidence that when the retail industry exhibits strong performance in ecological capability, its platform transformation is more effective, providing evidence across industries of this view. This research is relevant regarding the systematic pathway view on building a sustainable business ecosystem [24]. A study verified the supportive role of dynamic capabilities for strategic planning in the digital age within the Palestinian context [25]. In complementing this understanding from a global perspective, the cross-national dataset of this study (8,000 + enterprises covering 130+ countries) reveals the limitations of the framework's applicability in traditional service industries and agriculture. This is in line with the findings on the unique challenges faced by small and medium-sized enterprises in digital transformation that the technical threshold of the framework (3.2/5.0) and the high implementation cost (2.8/5.0) may limit its promotion and application in resource-constrained enterprises [26]. Research on dynamic capability practices in large enterprises aligns with this study's conclusion that the framework should be prioritized for use in medium- and large-sized enterprises [27]. In the digital transformation of large-scale organizations, the description of four reorganization dilemmas partly explains the relatively low scores (3.5/5.0) on interpretability assigned to the research framework. The black-box qualities inherent in deep reinforcement learning may well accentuate concerns about decisional transparency within large-scale organizational structures [28].

The first drawback for this particular study is that it has 70% synthetic data. While quality assurance is taken care of with triple validation processes that include the KS test, correlation maintenance, and prediction consistency checks, these processes cannot be adequately supplemented by the power that causal inference from direct observation of the enterprise transformation process could offer. The finding that the framework performs best in the finance and manufacturing industries indicates that generalizability across industries needs further work, such as the design of industry-specific weight initialization schemes based on digital maturity. Based on this, there are three directions in which future research could be deepened: integrating interpretable AI technologies to improve the transparency of the framework; conducting multi-time point longitudinal tracking studies to verify causal relationships; and developing lightweight versions to reduce the application threshold for small and medium-sized enterprises, which would extend the practical influence of the framework and push the evolution of digital transformation research from descriptive to normative paradigms. The framework's superior performance holds primarily for digitally mature mid-to-large companies (number of employees >500, readiness score ≥3/5) in manufacturing, financial services, and services. Performance decreases when the data context is low (i.e., when the number of records is <1000).

5. Conclusion

Based on the design science research methodology, the study develops an Agentic, AI-powered dynamic decision framework to evaluate organizational capabilities and inform technology management decisions. The decision framework is designed to have a four-layer closed-loop architecture. It implements the DWA-RL algorithm to enable adaptive weight adjustment. Empirical verification, based on over 8,000 enterprise samples, shows that the framework outperforms traditional methods in prediction accuracy (87.3%), improvement in decision quality (+28%), and dynamic adaptability (4.6/5.0). The three-year transformation path case of manufacturing enterprises further substantiates the feasibility of developing a four-dimensional capability balance (TC, OC, SC, EC). This study develops the dynamic capability theory by introducing an autonomous agent mechanism, redefines the decision-making paradigm of agent dominance - human supervision, and provides Ctos and CIOs with a systematic tool for formulating technology strategy. The framework's explanatory level is moderate (3.5/5.0), and its implementation cost remains high (2.8/5.0). However, its success in the industrial and financial sectors demonstrates that artificial intelligence can be a force multiplier in advancing the digital transformation process. Future work may focus on integrating explainable AI tools and developing methods with lightweight tracking and verification capabilities.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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