



A STAGE-GATE ALGORITHM FOR RISK-ADJUSTED ECONOMIC ASSESSMENT OF AI INVESTMENTS IN MANUFACTURING

Nigmatjonova Nozima Ulmasjonovna

PhD, Senior Lecturer, Alfraganus University, Tashkent, Uzbekistan

ORCID: 0009-0000-3776-7545

Abstract: The paper develops a stage-gate algorithm for the risk-adjusted economic assessment of artificial-intelligence investments in manufacturing. The algorithm links problem definition, baseline measurement, technical validation, total-cost-of-ownership estimation, benefit realization, scenario analysis and post-implementation audit. It is intended to reduce the risk of scaling AI pilots that perform technically but fail to create enterprise value.

Keywords: AI investment, manufacturing, stage-gate, risk-adjusted NPV, total cost of ownership, benefit realization, industrial economics

JEL Classification: O33; L60; C44; D81; M15

Problem Statement

AI investment decisions are frequently made after a successful pilot, although technical success alone is not sufficient evidence of economic efficiency. Industrial deployment introduces costs and risks that may be absent from a laboratory or limited pilot: data engineering, integration with production systems, cybersecurity, model monitoring, retraining, user adoption and process redesign. A disciplined stage-gate procedure is therefore required.

The proposed algorithm is consistent with the broader view that AI productivity gains depend on diffusion and complementary organizational investments [4,5] and with risk-management principles requiring explicit identification and treatment of uncertainty [12].



Proposed Stage-Gate Algorithm

Gate	Required evidence	Decision criterion
G0 — Economic problem	cost driver, loss mechanism, KPI owner	problem has measurable monetary consequence
G1 — Baseline	historical KPI, variability, production boundary	credible counterfactual can be constructed
G2 — Technical validity	model quality, robustness, latency, safety	technical target met under relevant conditions
G3 — TCO-AI	CAPEX, OPEX, data, integration, MLOps, change costs	full life-cycle cost is known
G4 — Risk-adjusted economics	RA-NPV, RA-IRR, payback, scenarios	base case viable; downside tolerable
G5 — Adoption readiness	owner, workflow integration, training, controls	benefit-realization coefficient q acceptable
G6 — Scale	pilot-to-production plan and monitoring	scale only with benefit dashboard
G7 — Ex-post audit	actual vs planned cash effects	continue, redesign, or stop

Economic Core

$$RA-NPV = -I_0 + \sum_{t=1}^T [(q_t \cdot B_t - C_t - \sum_i p_{it} L_{it}) / (1+r)^t] \quad (1)$$

The formula distinguishes potential benefits B from realizable benefits $q \cdot B$ and subtracts expected monetary losses $p \times L$. The benefit-realization coefficient should be updated as evidence accumulates. During the pilot, q is an estimate; after deployment, it becomes an empirical ratio between realized and technically attainable process effects.

Scenario Analysis

Each project should be evaluated under at least three scenarios. The downside scenario should combine lower benefit realization, delayed time-to-value and higher integration or model-lifecycle costs. The purpose is not to forecast a single exact outcome but to expose the variables capable of changing the investment decision. Sensitivity analysis should therefore prioritize q , integration cost, duration of stable model performance, production volume and the monetary value of the targeted loss mechanism.

Implications for Industrial Enterprises in Uzbekistan

The stage-gate approach is relevant to the current expansion of AI projects in Uzbekistan. The national strategy provides policy support [1], while official 2026 reports demonstrate both a growing AI project pipeline and measurable industrial outcomes [2,3]. For enterprise-level scientific evaluation, however, reported operational changes must be supplemented by project costs, baseline construction and causal attribution before claims about investment efficiency are made.

Conclusion

The proposed algorithm formalizes a transition from “pilot success” to “economic proof.” Its contribution is the integration of technical validation, full life-cycle cost, risk-adjusted cash flow, organizational adoption and ex-post benefit auditing within one sequence of gates. The algorithm can be



incorporated into a corporate digital-investment policy and tested empirically in future DSc research.

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