RAAM-G: Integrating Risk Life Cycle Outputs, Readiness Gating, and Governance into Quarterly Enterprise GenAI Portfolio Optimization

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***Abstract*—Enterprise generative AI (GenAI) portfolios can include initiatives such as large language model (LLM) assistants, model fine-tuning and deployment, generative analytics, intelligent workflow automation, and synthetic data pipelines. These initiatives are subject to strict constraints on staff workload, budget, and non-fungible entitlements. In addition, it is essential to manage the delivery risk posed by emerging sociotechnical dependencies and interoperability gaps.**

This paper presents RAAM-G, a decision-support framework that integrates risk analysis, readiness assessment, prioritization, optimization, and Governance into a cohesive decision-making process. The name RAAM-G reflects the initials of its core components: Risk Analysis Life Cycle (RALC); Augmented Resilience–Systematic Level-up Interoperability Model (AR-SLIM); Alignment, Resilience, and Catalyst (ARC); Mixed-Integer Linear Programming (MILP); and Governance.

RALC has seven phases to quantify initiative risk by estimating likelihood and impact, resulting in residual-risk coefficients that inform feasibility. AR-SLIM assesses initiatives' readiness on an eight-level scale (L0–L7), enabling the deferral of immature initiatives while maintaining strategic visibility. ARC expresses strategic value owned by Governance through mission alignment, continuity protection, and innovation leverage. These outputs are combined in an MILP formulation that supports transparent and traceable initiative selection under enterprise constraints. At the same time, governance records decisions, updates policy parameters, and initiates the next review cycle.

The framework is designed as a recurring quarterly enterprise practice for reviewing proposed GenAI initiatives and as a basis for future benchmarking against existing decision-making approaches. The primary audience comprises the CIO/CTO leadership team and the PMO steering committee, while the secondary audience comprises the CISO and GRC stakeholders responsible for risk and compliance oversight.

***Keywords*—Mixed Integer Programming, Risk Analysis, Generative AI, Systems Thinking**

I. Introduction

Artificial intelligence (AI) has become a crucial aspect of organizational decision-making, particularly through generative AI (GenAI) initiatives such as Large Language Model (LLM) assistants. Haenlein and Kaplan [1] define AI as the ability to interpret and learn from data to achieve goals. Although AI has existed since the 1950s, advances in data and computing have made it essential for businesses today. GenAI heightens the challenge of evaluating emerging technologies, placing pressure on organizations to quickly assess their readiness and Governance. This ongoing decision-making process requires continual consideration of stakeholder needs, risks, and resource constraints [1], [2].

This problem is especially acute in resource-constrained enterprises. AI initiatives in resource-constrained enterprises face significant challenges, including competition for limited funding and execution risks arising from interdependencies among components. Research by Flyvbjerg et al. [3] shows that cost overruns often exceed expectations and can trigger cascading effects on schedules and costs. Classical project scheduling methods provide some insight, but are insufficient for assessing readiness or risk, necessitating a more comprehensive approach to ensure successful initiative deployment.

The literature on risk analysis helps address gaps in risk management. Haimes et al. [4] provided a structured framework for identifying and managing risks in large systems, focusing on fundamental questions about risks and management options. Their iterative approach is particularly relevant for AI portfolios, where risk is influenced by changing factors. Baker et al. [5] improve this understanding by integrating optimization with risk analysis for vehicle electrification in maritime ports. They define enterprise risk as a disruption to system order and evaluate scenarios to support decision-making, illustrating how optimization and structured risk analysis can work together in resource-constrained settings.

Readiness assessment remains a major gap in many portfolio-selection approaches. Existing project and technology assessment methods often emphasize technical maturity, while underrepresenting organizational preparedness, interoperability, assurance, and the practical conditions required for deployment. For enterprise GenAI initiatives, technical promise alone is insufficient. A portfolio decision must also account for whether an initiative is ready to be executed within the current planning window, whether its risks are tolerable, and whether the organization has the capacity, controls, and entitlements required to support delivery [6].

This paper addresses this gap through RAAM-G, a systems-

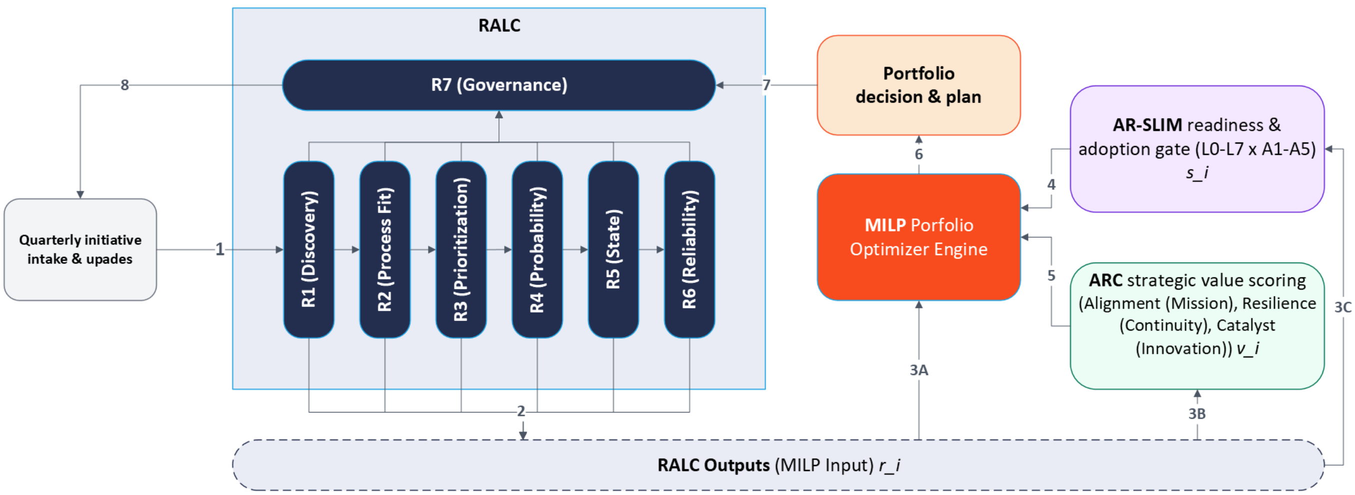

Fig. 1. RAAM-G quarterly decision cycle showing the flow from intake through RALC, AR-SLIM, ARC, MILP, and governance feedback.

engineering framework for selecting a GenAI enterprise portfolio. RAAM-G integrates five elements into a recurring quarterly decision cycle: Risk Analysis Life Cycle (RALC), which converts scenario-based evidence into decision-relevant risk parameters; Augmented Resilience–Systematic Level-up Interoperability Model (AR-SLIM), which evaluates readiness and gating eligibility; Alignment, Resilience, and Catalyst (ARC), which expresses governance-owned strategic value; Mixed-Integer Linear Programming (MILP), which selects a feasible portfolio under budget, staffing, entitlement, dependency, and risk constraints; and Governance, which records decisions, documents overrides, and updates policy parameters for the next cycle. The contribution of the paper is therefore not a new optimizer in isolation, but a governance-driven operating model that integrates risk, readiness, value, and constrained selection into a single auditable portfolio process. The present paper focuses on the definition, integration, construction, and formulation of the optimization framework; empirical validation with real organizational data and extension to broader classes of emerging technologies are reserved for future work.

II. Method

This paper proposes RAAM-G as a quarterly portfolio operating model for GenAI initiatives in enterprises with constrained budget, capacity, entitlements, and risk tolerance.

A. The 10 Golden Rules of Systems Analysis

They are used in this paper as analytical guardrails rather than as a separate method step [7]. Their role is to keep RAAM-G centered on disciplined problem formulation, explicit objectives, realistic model boundaries, and separation between analysis and decision authority. In practical terms, these rules shape four choices in the framework. First, they reinforce client focus by treating the enterprise portfolio process itself as the system of interest. Second, they prevent premature solutions by requiring the problem to be framed in terms of feasibility, risk, readiness, and Governance rather than a preferred AI solution. Third, they support the explicit treatment of an index of performance through the ARC value construct. Fourth, they reinforce the distinction between the analyst's role in presenting evidence and the governance role in setting weights, thresholds, and final decisions. Used this way, the Golden Rules help position RAAM-G as a systems-analysis contribution rather than as a stand-alone optimization model.

B. Problem statement RAAM-G solves

RAAM-G addresses the enterprise problem of selecting a quarterly portfolio of GenAI initiatives under constrained resources, non-fungible entitlements, and bounded risk tolerance. Each candidate initiative competes for a limited budget and role-based delivery capacity, may depend on other initiatives or enabling capabilities, and may require entitlements that cannot be substituted by additional spending. At the same time, initiatives differ in readiness, control maturity, and residual-risk exposure. The resulting decision problem is therefore not simply "Which initiative scores highest?" but "Which combination of initiatives is both strategically valuable and feasible to execute now?" RAAM-G formulates that question as a risk- and readiness-gated portfolio optimization problem with explicit governance control.

C. MILP baseline and its role in RAAM-G

MILP provides a well-established mechanism for selecting among competing initiatives under resource limits, dependencies, and discrete decision variables, consistent with the resource-constrained project scheduling literature [8]. However, in RAAM-G, MILP is treated as the selection engine rather than the full decision method. The quality of the optimization output depends on how the value, feasibility, and risk of the initiatives are defined before optimization. Prior work has shown that optimization can be meaningfully paired with enterprise risk analysis rather than used as an isolated scheduler [5]. RAAM-G follows this logic by surrounding

MILP with explicit readiness gates, risk-derived constraints, and governance-owned value parameters, ensuring that the selected portfolio is not only optimal with respect to the model but also operationally defensible and auditable.

D. RAAM-G

This is a governance-driven decision-making pipeline for enterprise GenAI portfolio selection, integrating five components: (1) RALC: Converts scenario-based evidence into risk parameters; (2) AR-SLIM: Evaluates readiness and applies eligibility gates; (3) ARC: Translates leadership priorities into a value coefficient; (4) MILP: Selects a portfolio within budget and risk constraints; (5) Governance: Oversees policy parameters and documents decision rationales. Together, these components support feasibility assessment, clarify trade-offs, and preserve traceability across planning cycles.

*1) **RALC**:* RAAM-G's risk-evidence pipeline converts scenario-based evidence into decision-ready risk parameters. Its purpose is to transform initiative-level risk information into operational inputs for portfolio selection rather than leaving risk as a narrative side note. The life cycle contains seven phases: Discovery, Process Fit, Prioritization, Probability and Impact, Life Cycle State, Assurance, and Governance. Together, these phases structure how candidate risk scenarios are identified, filtered, evaluated, and monitored within enterprise GenAI initiatives.

Discovery identifies candidate scenarios from multiple perspectives, including technical, operational, compliance, and organizational perspectives [4], [9]. *Process Fit* maps the initiative to the business and control processes it affects [10]. *Prioritization* narrows attention to the most decision-relevant scenarios for the current planning cycle [11], [12]. *Probability and Impact* translate those scenarios into explicit risk estimates using repeatable likelihood–consequence logic [4], [9], [13]. *Life Cycle State* recognizes that risk posture changes throughout the pilot, roll-out, and scale phases [14]. *Assurance* evaluates whether current controls, evidence, and mitigations are sufficient for the initiative to proceed in the current quarter [2], [15]. *Governance* records the decision, updates assumptions, and feeds reassessment in the next cycle [12], [16]. This framework is consistent with previous work on hierarchical risk structuring, expert-informed prioritization, and iterative monitoring in complex systems [17], [18].

To make the RALC handoff explicit, the life cycle produces three optimizer-relevant outputs for each initiative i: a normalized residual-risk coefficient r_i, an assurance gate g_i, and a life cycle state marker m_i,

$$\mathrm{RALC}(i) \rightarrow (r_i, g_i, m_i) \tag{1}$$

where

$$r_i = \mathcal{N}[P_i I_i (1-\kappa_i)], \tag{2}$$

$$g_i = \mathbf{1}[A_i \geq A_{\min}], \tag{3}$$

and $m_i = L_i$ denotes the current classification of the life cycle state for monitoring and reassessment.

In this formulation, Discovery, Process Fit, and Prioritization determine the relevant risk evidence for initiative i; Probability and Impact produce the initiative-level likelihood and consequence estimates P_i and I_i; controls are summarized through the control-effectiveness term κ_i; Assurance produces the assurance score A_i and gate g_i; and Life Cycle State produces the monitoring marker m_i. Governance does not directly compute initiative risk, but sets the minimum assurance threshold $A_{\min}$ and the portfolio-level risk tolerance $R_{\max}$, which is later enforced in the MILP risk-budget constraint. Thus, RALC converts risk analysis into operational parameters for portfolio selection, while Governance defines the decision boundaries within which optimization occurs.

*2) **AR-SLIM**:* RAAM-G's readiness-gating construct. It prevents the optimizer from selecting initiatives that are strategically attractive but not operationally ready for the current quarter. Prior work suggests that readiness assessment should extend beyond narrow technology-maturity measures to broader system-readiness considerations and support explicit gate decisions on advancement [6], [19]. For enterprise GenAI initiatives, this is essential because feasibility depends not only on technical promise, but also on interoperability, operational readiness, evidence quality, and delivery discipline within a governed life-cycle process [2]. Since AR-SLIM is introduced here, its level definitions are stated explicitly within the framework.

AR-SLIM evaluates each initiative along two dimensions: readiness level L_i, which captures the initiative's system and evidence state, and adoption maturity M_i, which captures the degree to which its delivery and operational practices are institutionalized. Readiness indicates whether the initiative is mature enough to be considered for current-cycle selection, whereas adoption maturity indicates whether the surrounding execution practices are stable enough to support delivery and operations.

AR-SLIM Readiness Level (L0–L7):

- L0 — Void (Blind/Analog): No instrumentation, usable data, stable ownership, or defined operating context; discovery only and not eligible for portfolio selection.
- L1 — Ad-Hoc (Fragile/Descriptive-ready): Siloed data, unreliable metrics, and individual-dependent execution; suitable only for exploratory analysis.
- L2 — Mature (Stable/Diagnostic-ready): Core inputs, interfaces, and metrics are sufficiently stable for controlled pilots, but execution remains constrained.
- L3 — Interoperable (Coherent/Predictive-ready): Data, interfaces, and meanings are aligned enough for coherent scenario analysis and predictive use, but operational deployment remains gated.
- L4 — Level-Up (Optimized/Prescriptive-ready): Validated structure, evidence, and controls are sufficient for optimization, prescriptive analysis, or bounded deployment planning.

- L5 — Systematic (Reflective/GenAI-ready): Controlled GenAI-enabled assistance is in place, with formal monitoring, review, and human oversight.
- L6 — Resilient (Collaborative/Agentic-ready): Human–AI collaboration remains stable under stress, adaptive policies are defined, and recovery performance is measurable and improving.
- L7 — Augmented (Antifragile/Evolutionary): The initiative improves through operational stress and feeds learning back into Governance, controls, and execution.

AR-SLIM Adoption Maturity (M1–M5):

- M1 — Initial: Execution is ad hoc, and outcomes depend on individuals.
- M2 — Repeatable: A repeatable delivery pattern exists, and basic tracking is in place.
- M3 — Defined: Processes, roles, and artifacts are documented and consistently used.
- M4 — Capable: Execution is stable across teams and measured with meaningful performance data.
- M5 — Efficient: Continuous improvement, automation, and leading indicators are in active use.

To operationalize readiness in the portfolio model, AR-SLIM is implemented as either a value-scaling soft gate or a threshold-based hard gate. This follows the general logic of readiness frameworks that use explicit indicators and gate decisions to determine whether an initiative should proceed under current conditions [6]. In (4), the soft-gate formulation scales effective initiative value by

$$s_i = \frac{L_i}{7} \cdot \frac{M_i}{5} \tag{4}$$

where L_i and M_i denote the readiness level and adoption maturity of initiative i, respectively. In (5), x_i is a binary selection variable, $\mathbf{1}[\cdot]$ is an indicator function, $L_{\min}$ is the minimum required readiness level, and $M_{\min}$ is the minimum required adoption maturity. The hard-gate constraint, therefore, permits selection only when both governance-defined thresholds are satisfied:

$$x_i \leq \mathbf{1}[L_i \geq L_{\min} \ \wedge \ M_i \geq M_{\min}] \tag{5}$$

The soft gate preserves strategic visibility for less mature initiatives by reducing their effective contribution to the objective, whereas the hard gate excludes initiatives that are not sufficiently ready for execution in the current planning cycle. In both forms, the intent is the same: to prevent the optimizer from favoring strategically attractive but operationally immature initiatives.

*3) **ARC**:* RAAM-G's governance-owned value model. Its purpose is to translate leadership priorities into a clear, reproducible initiative score for the current planning cycle. ARC does not aim to measure intrinsic or universal value; rather, it provides a policy-driven mechanism to express the organization's intended priorities during the current portfolio review.

The inclusion of ARC is important because enterprise portfolio decisions are rarely based on a single objective. This model provides a structured way to clarify leadership trade-offs when mission contribution, continuity protection, and innovation pacing do not align with the same portfolio choice.

ARC has three dimensions: Alignment, Resilience, and Catalyst. *Alignment* captures mission and strategic fit; *Resilience* captures business continuity, compliance, reliability, and the value of risk reduction; and *Catalyst* captures innovation leverage, reuse potential, and learning speed. Each initiative is scored on an anchored 0–5 rubric for the three dimensions and normalized to $A'_i, R'_i, C'_i \in [0,1]$. A weighted additive value function is then used to compute the initiative value coefficient v_i, with weights set by governance policy parameters rather than analyst-defined constants. This structure is intentionally simple: its purpose is not to hide the judgment, but to make the judgment explicit and auditable [20], [21].

Each initiative i is scored on a 0–5 anchored rubric for the three ARC pillars and then normalized to $A'_i, R'_i, C'_i \in [0,1]$ by dividing by 5. The ARC coefficient is computed as

$$v_i = w_A A'_i + w_R R'_i + w_C C'_i, \tag{6}$$

subject to

$$w_A + w_R + w_C = 1. \tag{7}$$

In (6), v_i is the value coefficient for initiative i, A'_i, R'_i, and C'_i are the normalized scores for Alignment, Resilience, and Catalyst, and w_A, w_R, and w_C are the corresponding governance-defined weights. Higher values of v_i indicate that an initiative better matches the organization's priorities for the quarter. This additive value-function form is consistent with prior work that normalizes criterion weights, aggregates scores across multiple objectives, and supports reprioritization when stakeholder preferences or operating conditions change [21]–[24]. Recommended default weights may be used for illustration, but in application they should be treated as governance-owned policy parameters rather than universal constants.

*4) **MILP**:* RAAM-G's portfolio-selection engine. Its role is to identify the set of initiatives that maximizes readiness-adjusted strategic value while satisfying the enterprise constraints of the current quarter. These constraints include budget, role-based delivery capacity, non-fungible entitlements, initiative dependencies, readiness eligibility, assurance requirements, and portfolio-level risk tolerance. This formulation extends the logic of resource-constrained project selection by embedding risk- and readiness-derived feasibility conditions directly into the optimization model [5], [8].

Let I denote the set of candidate initiatives and let $x_i \in \{0,1\}$ indicate whether initiative i is selected. The objective is to maximize the total readiness-adjusted ARC value of the selected portfolio subject to enterprise constraints.

Objective Function:

$$\max \sum_{i \in I} x_i s_i v_i \tag{8}$$

TABLE I

RAAM-G DATA DICTIONARY: SETS, VARIABLES, AND PARAMETERS

Variable	Type	Values	Definition	Produced by
i	index	$i \in I$	Candidate initiative index	Governance/ Intake
s	index	scenario identifier	Risk-scenario index for initiative i	RALC Discovery
r_i	scalar	typically $[0,1]$	Normalized residual-risk coefficient for initiative i	RALC
g_i	binary	$\{0,1\}$	Assurance gate; 1 if initiative satisfies the minimum assurance threshold for the current cycle	RALC Assurance
m_i	categorical / ordinal	e.g., pilot, roll-out, scale	Life Cycle State marker used for monitoring and reassessment	RALC Life Cycle State
P_i	scalar	typically $[0,1]$	Initiative-level likelihood estimate after scenario review and aggregation	RALC Prob.
I_i	scalar	anchored score or normalized value	Initiative-level impact / consequence estimate	RALC Impact
κ_i	scalar	$[0,1]$	Control-effectiveness term; higher values indicate stronger mitigation	RALC controls / assurance review
A_i	scalar	e.g., $[0,1]$ or $[0,100]$	Assurance score summarizing evidence, controls, and current-cycle readiness to proceed	RALC Assurance
$A_{\min}$	scalar threshold	same scale as A_i	Minimum assurance threshold required for selection eligibility	Governance
$R_{\max}$	scalar budget	governance def.	Portfolio-level residual-risk budget / tolerance for the quarter	Governance
L_i	ordinal	$\{0,\ldots,7\}$	AR-SLIM readiness level for initiative i	AR-SLIM
M_i	ordinal	$\{1,\ldots,5\}$	AR-SLIM adoption-maturity for initiative i at L_i	AR-SLIM
s_i	scalar	$[0,1]$	AR-SLIM soft-gate multiplier that scales effective initiative value	AR-SLIM
h_i	binary	$\{0,1\}$	AR-SLIM hard-gate eligibility indicator	AR-SLIM
$L_{\min}$	ordinal threshold	$\{0,\ldots,7\}$	Minimum readiness level required for hard-gate eligibility	Governance
$M_{\min}$	ordinal threshold	$\{1,\ldots,5\}$	Minimum adoption-maturity level required for hard-gate eligibility	Governance
A'_i	scalar	$[0,1]$	Normalized ARC Alignment score	ARC
R'_i	scalar	$[0,1]$	Normalized ARC Resilience score	ARC
C'_i	scalar	$[0,1]$	Normalized ARC Catalyst score	ARC
w_A	scalar weight	$[0,1]$	Governance-owned weight on Alignment in ARC	Governance
w_R	scalar weight	$[0,1]$	Governance-owned weight on Resilience in ARC	Governance
w_C	scalar weight	$[0,1]$	Governance-owned weight on Catalyst in ARC	Governance
v_i	scalar	typically $[0,1]$	ARC value coefficient for initiative i	ARC
I	set	finite set	Candidate initiative set for the quarter	Governance/ Intake
x_i	decision variable	$\{0,1\}$	Selection variable; 1 if initiative i is selected	MILP
c_i	scalar	nonnegative	Cost of initiative i in the quarter	Governance
B	scalar budget	nonnegative	Total budget available for the quarter	Governance
K	set	finite set	Resource-class index set	Governance
a_{ik}	scalar	nonnegative	Demand of initiative i for resource class k	Governance
C_k	scalar capacity	nonnegative	Available capacity for resource class k	Governance
L	set	finite set	Entitlement-class index set	Governance
$e_{i\ell}$	scalar	nonnegative	Demand of initiative i for entitlement class ℓ	Governance
E_ℓ	scalar capacity	nonnegative	Available capacity for entitlement class ℓ	Governance
D_i	set	subset of I	Dependency set; initiatives that must be selected if i is selected	Governance

Constraints:

$$\sum_{i\in I} c_i x_i \le B \tag{9}$$

$$\sum_{i\in I} a_{ik} x_i \le C_k \qquad \forall k \in K \tag{10}$$

$$\sum_{i\in I} e_{i\ell} x_i \le E_\ell \qquad \forall \ell \in L \tag{11}$$

$$x_i \le x_j \qquad \forall j \in D_i \tag{12}$$

$$x_i \le h_i \qquad \forall i \in I \tag{13}$$

$$x_i \le g_i \qquad \forall i \in I \tag{14}$$

$$\sum_{i\in I} r_i x_i \le R_{\max}. \tag{15}$$

In (8), v_i is the ARC value coefficient, s_i is the AR-SLIM soft-gate multiplier. In (9), c_i is initiative cost. In (10), a_{ik} is the demand for resource class k (e.g., data engineering hours, security review effort, product ownership time). In (11), $e_{i\ell}$ is demand for entitlement class ℓ. In (12), D_i is the dependency set. In (13), h_i is the AR-SLIM hard-gate eligibility term, and in (14), g_i is the RALC assurance gate. Finally, in (15), r_i is the residual-risk coefficient of RALC. The governance-owned parameter $R_{\max}$ represents the portfolio-level risk budget for the quarter. The result is not merely a highest-scoring list of initiatives, but a constrained-feasible portfolio whose selection logic is explicit, reviewable, and repeatable.

*5) **Governance:*** RAAM-G's control plane. It owns the decision rights and policy parameters that shape each quarterly portfolio cycle, including ARC weights, AR-SLIM thresholds, assurance requirements, and the portfolio risk budget $R_{\max}$. Its role extends beyond final approval: it records assumptions, overrides, and deferrals, and updates policy settings for the next cycle. This makes the portfolio process traceable over time and prevents value weights, readiness thresholds, and risk tolerances from remaining implicit or ad hoc. In RAAM-G, Governance functions as an active design component of the decision-making process rather than as an after-the-fact review body.

III. Conclusion

Enterprise GenAI portfolio selection is a constrained portfolio-optimization and governance problem. Candidate initiatives compete for limited budget, role-based delivery capacity, and non-fungible entitlements, while differing in readiness, control maturity, and residual-risk exposure. This paper introduces RAAM-G as a systems-engineering framework that integrates RALC, AR-SLIM, ARC, MILP, and Governance into a recurring quarterly portfolio-selection cycle. The contribution of RAAM-G is the integration itself.

RALC converts risk evidence into decision-ready parameters; *AR-SLIM* gates execution readiness; *ARC* expresses strategic values owned by Governance; and *MILP* selects a feasible, constrained portfolio subject to budget, capacity, entitlement, dependency, assurance, and risk-budget constraints. *Governance* closes the loop by setting thresholds and weights, recording decisions, and updating the next planning cycle. In this way, portfolio selection becomes a repeatable and auditable system problem rather than a one-time scoring exercise.

RAAM-G is a framework contribution rather than a completed empirical validation study. Future work should evaluate it using real organizational portfolio data, benchmark it against simpler baseline methods, test the reliability of its risk and readiness constructs, and extend it to multi-period planning. Even in its current form, RAAM-G provides a practical structure that makes enterprise GenAI portfolio decisions more transparent, defensible, and operationally credible.

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