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USING PROMPT ENGINEERING GOVERNANCE TO IMPROVE EVALUATION ACCURACY AND REDUCE DEFECTS IN GENERATIVE AI SYSTEMS

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ABSTRACT
Frontier artificial intelligence (AI) development increasingly depends on massive, heterogeneous, and continuously evolving training datasets assembled from diverse sources, modalities, languages, and annotation processes. Although expanding data scale can strengthen model capabilities, it also increases exposure to duplication, contamination, annotation errors, distributional imbalance, inconsistent formatting, uncertain provenance, and other defects capable of degrading model reliability. This study develops a scalable quality assurance framework for systematically controlling training-data quality throughout frontier AI model development. The framework integrates source provenance, automated validation, anomaly detection, deduplication, contamination screening, annotation-quality assessment, risk-based human review, dataset versioning, and continuous quality monitoring. Quantitative indicators measure defect prevalence, data-quality performance, detection effectiveness, and remediation outcomes, while comparative benchmarking evaluates alternative quality-assurance configurations across heterogeneous data environments. Downstream model evaluation further examines whether improvements in dataset quality correspond with enhanced model accuracy, robustness, and reliability. By connecting automated controls with targeted human oversight and continuous feedback, the proposed framework transforms training-data quality assurance from isolated preprocessing into a scalable lifecycle capability supporting traceable, reproducible, and reliable frontier AI development.

Keywords:
Frontier Artificial Intelligence; Training Data; Quality Assurance; Data Reliability; Defect Detection; Data Governance

1. INTRODUCTION

1.1 Generative AI Evaluation as a Quality-Control Problem

Generative artificial intelligence systems had become increasingly embedded within customer service, software engineering, healthcare administration, finance, education, legal support, research, and enterprise knowledge-management environments [1]. Their expanding operational use increased the importance of evaluation procedures capable of distinguishing genuine model deficiencies from defects introduced by the testing process itself. Model responses were elicited through prompts that varied in wording, contextual information, task definition, formatting, demonstrations, constraints, and required output structure [2]. These variations affected model interpretation and introduced uncertainty into measured performance. Evaluation was therefore treated as a quality-control problem in which both the generative model and the evaluation prompt represented potential error sources [3]. This distinction was formalized as

$$E_{\text{model}} \neq E_{\text{prompt}},$$

where E_{model} denotes an evaluation error attributable to underlying model behaviour and E_{prompt} denotes an error attributable to prompt design or specification. Without this separation, poorly constructed prompts could incorrectly attribute failure to model capability [4]. A controlled governance mechanism was consequently implemented to identify, standardize, and monitor both sources of evaluation variation.

1.2 Limitations of Ad Hoc Prompt Engineering

Initial assessment of unmanaged prompt engineering identified substantial procedural variability across evaluation activities [5]. Prompt instructions differed in specificity, revisions were inconsistently documented, few-shot examples lacked uniform verification, and task constraints were insufficiently standardized. Ambiguous success criteria further complicated determination of whether an observed response represented E_{model} or E_{prompt} [2]. Additional variation originated from prompt leakage, inconsistent evaluator instructions, and uncontrolled generation parameters, particularly temperature T, nucleus-sampling probability p_{top}, maximum output length L_{max}, random seed s, and number of generated responses n. Collectively, these conditions produced unstable

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evaluation results, reduced reproducibility, and increased false defect attribution [6]. Comparisons between model versions were particularly unreliable when prompt specifications and generation settings changed simultaneously [7]. Each evaluation prompt was consequently represented as $P_i^{(v)}$, where i identifies the evaluation prompt and v denotes its controlled version. Prompt engineering therefore constituted an evaluation risk when prompt versions, acceptance criteria, examples, and execution parameters remained unmanaged.

1.3 Research Problem, Aim, and Contribution

The investigation examined how prompt engineering governance improved the accuracy, repeatability, and defect-detection capability of generative AI evaluation [5]. A governance framework was developed and evaluated to standardize prompt construction, version control, execution conditions, defect classification, and feedback procedures. Governance requirements covered prompt ownership, documentation, approval, modification, evaluation, deployment, and retirement [1]. Controlled execution conditions were represented through the generation-parameter vector

$$\boldsymbol{\theta}_g = \left(T,\, p_{\text{top}},\, L_{\max},\, s,\, n\right),$$

where $\boldsymbol{\theta}_g$ represents the complete controlled generation configuration, T denotes temperature, p_{top} is the nucleus-sampling probability, $L_{\max}$ denotes maximum permitted output length, s represents the random seed where supported, and n denotes the number of generated responses per evaluation condition [7]. Controlling $\boldsymbol{\theta}_g$ reduced execution variability that could otherwise be incorrectly attributed to prompt or model quality.

For each evaluation condition, the generated response was represented as

$$R_{i,r} = M\left(P_i^{(v)}, \boldsymbol{\theta}_g, X_i\right),$$

where $R_{i,r}$ denotes response r for evaluation item i, M represents the generative AI model, $P_i^{(v)}$ is prompt i at governed version v, and X_i denotes the associated task input or contextual information [3]. This specification enabled the model, prompt version, task context, and execution parameters to be independently traced.

Evaluation accuracy was measured before and after governance implementation, while identified failures were classified as prompt-induced, model-induced, evaluator-related, or execution-related defects [8]. Governed evaluation was subsequently benchmarked against unguided prompting using defect-detection accuracy, false attribution, repeatability, consistency, and evaluation variance [6]. The implemented governance cycle was represented as

$$M \rightarrow P_g^{(v)} \rightarrow E \rightarrow D_c \rightarrow F \rightarrow P_g^{(v+1)},$$

where M denotes the model, $P_g^{(v)}$ the governed prompt at version v, E the controlled evaluation process, D_c defect classification, F evaluation feedback, and $P_g^{(v+1)}$ the revised prompt version. This closed-loop architecture established prompt governance as a measurable quality-control layer between model execution and evaluation.

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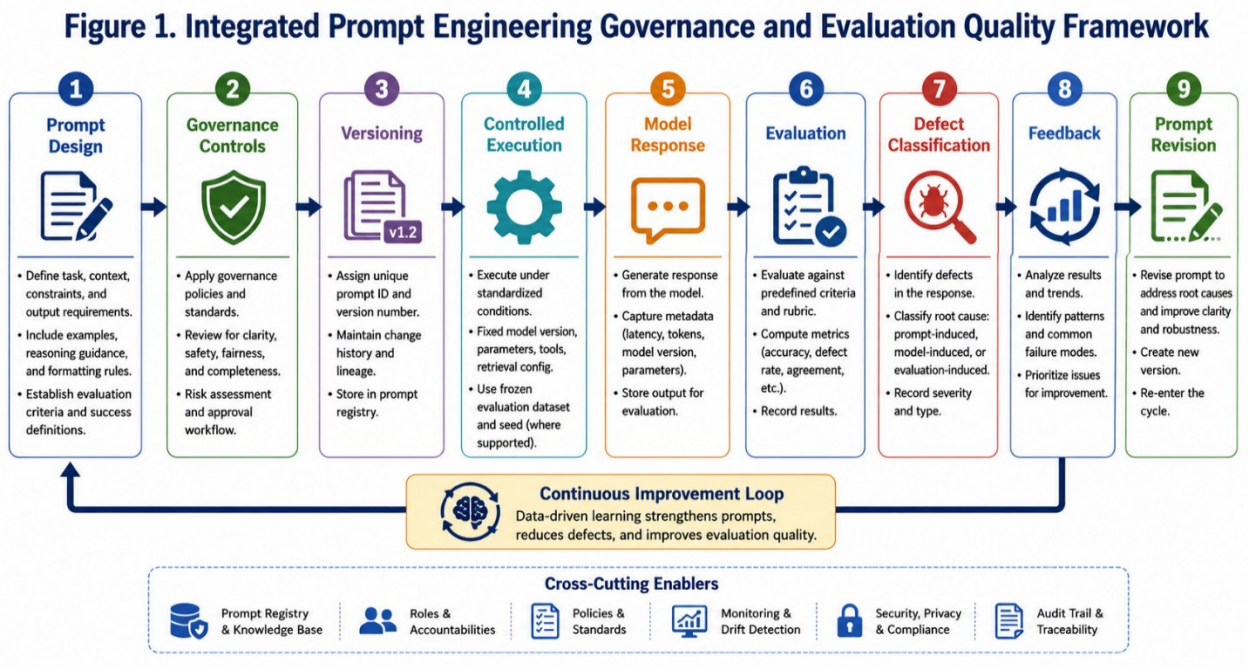

2. PROMPT ENGINEERING GOVERNANCE FOUNDATIONS

2.1 From Prompt Engineering to Prompt Governance

Prompt engineering and prompt governance were treated as related but operationally distinct activities [11]. Prompt engineering concentrated on constructing and refining instructions that elicited responses consistent with specified tasks, whereas prompt governance controlled how those instructions were created, authorized, modified, deployed, and audited. The implemented governance architecture therefore incorporated ownership, approval, documentation, version control, testing, auditability, access control, and change management [7]. Each evaluation prompt passed through a controlled lifecycle represented as

$$P_{\text{draft}} \rightarrow P_{\text{review}} \rightarrow P_{\text{test}} \rightarrow P_{\text{approved}} \rightarrow P_{\text{deployed}} \rightarrow P_{\text{monitored}} \rightarrow P_{\text{revised}},$$

where P_{draft} denotes the initial prompt, P_{review} the reviewed specification, P_{test} the experimentally tested version, P_{approved} the authorized artifact, P_{deployed} the operational evaluation prompt, $P_{\text{monitored}}$ the version under performance monitoring, and P_{revised} the modified prompt following documented feedback [13]. This lifecycle prevented informal prompt alterations from entering formal evaluations. Evaluation prompts were consequently managed as controlled test artifacts whose integrity affected the reliability and comparability of measured model performance [9].

2.2 Components of a Governed Evaluation Prompt

Governed prompts were decomposed into controlled components so evaluation conditions could be reconstructed across repeated experiments [12]. Each prompt contained a system instruction, task instruction, contextual information, examples, output constraints, evaluation criteria, prohibited behaviours, and required response format. These components were supplemented by metadata recording prompt identifier, version, owner, creation date, target model, evaluation purpose, and approved generation configuration [8]. The governed prompt was represented as

$$P_i^{(v)} = \{S_i, T_i, C_i, E_i, O_i, A_i, B_i, F_i\},$$

where $P_i^{(v)}$ denotes prompt i at version v, S_i is the system instruction, T_i the task instruction, C_i context, E_i examples, O_i output constraints, A_i evaluation or acceptance criteria, B_i prohibited behaviours, and F_i required output format [14]. Changes to any component generated a traceable prompt revision because apparently minor modifications could alter model interpretation and measured evaluation outcomes. Standardizing this specification preserved prompt integrity across repeated testing [10].

2.3 Versioning, Traceability, and Change Control

Prompt versioning linked every evaluation result to the exact artifact and execution configuration responsible for generating it [15]. Each approved prompt received a persistent identifier and version number, while modifications

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generated change logs recording the altered component, rationale, author, reviewer, approval status, and implementation date. The complete lineage record was represented as

$$P_i^{(v)} = \left\{I_i^{(v)}, C_i^{(v)}, E_i^{(v)}, F_i^{(v)}, G_i^{(v)}, M_i^{(v)}\right\},$$

where $I_i^{(v)}$ represents instructions, $C_i^{(v)}$ context, $E_i^{(v)}$ examples, $F_i^{(v)}$ formatting requirements, $G_i^{(v)}$ generation configuration, and $M_i^{(v)}$ governance metadata for version v [11]. This expression provided formal specification rather than statistical estimation. Test results were linked simultaneously to $P_i^{(v)}$ and the evaluated model version $M^{(k)}$, enabling differences caused by prompt revisions to be distinguished from those associated with model changes [8]. Historical versions remained recoverable, supporting rollback, reproducibility, and retrospective defect investigation.

2.4 Roles, Review, and Approval Controls

Governance responsibilities were distributed across prompt authors, subject-matter reviewers, QA reviewers, model evaluators, and governance owners [13]. Prompt authors constructed evaluation artifacts, while domain reviewers assessed factual and task-specific adequacy. QA reviewers verified testability, formatting, acceptance criteria, and reproducibility, and model evaluators executed approved test configurations. Governance owners-maintained authorization, version integrity, and change records [9]. Where operationally feasible, prompt creation and final approval were separated to reduce uncontrolled self-validation. Formal approval gates were applied to substantial prompt modifications, new evaluation domains, model-version changes, and high-risk applications [15]. Only an approved version $P_i^{(v)}$ progressed into controlled evaluation; rejected revisions returned to review with documented findings. This role-based architecture connected prompt integrity with evaluation reliability by ensuring that consequential changes were independently examined, authorized, traceable, and reproducible.

3. EVALUATION ARCHITECTURE AND EXPERIMENTAL DESIGN

3.1 Building a Controlled Evaluation Dataset

The evaluation dataset was constructed independently of prompt development to prevent prompt-design decisions from influencing benchmark composition [17]. The dataset incorporated representative tasks, multiple difficulty levels, boundary conditions, adversarial cases, known-answer tasks where objective verification was possible, and domain-specific examples reflecting intended deployment contexts. Evaluation item represented the -th controlled test instance, while the complete benchmark dataset at version was defined as

$$\mathcal{D}^{(k)} = \{D_1, D_2, \ldots, D_N\},$$

where $\mathcal{D}^{(k)}$ denotes evaluation-dataset version k, D_i denotes evaluation item i, and N represents the total number of benchmark items. Prompt examples were screened against $\mathcal{D}^{(k)}$ to prevent duplicated or substantially overlapping examples from contaminating evaluation results [14]. Each benchmark cycle used a frozen dataset version, ensuring that comparisons between prompt conditions were based on identical tasks [19]. Dataset modifications consequently generated a new version $\mathcal{D}^{(k+1)}$ rather than silently altering the existing benchmark. This separation preserved experimental comparability and prevented benchmark changes from being misinterpreted as improvements in prompt or model performance.

3.2 Standardizing Model and Generation Conditions

Model execution conditions were standardized after the evaluation dataset had been frozen [16]. Controlled parameters included model version $M^{(k)}$, temperature T, nucleus-sampling probability p_{top}, maximum output length L_{max}, random seed s where supported, tool availability A_{tool}, retrieval configuration R_{cfg}, and system-message specification S_{sys}. These parameters were incorporated into the generation vector $\boldsymbol{\theta}_g$ because prompt governance alone could not establish reproducibility while execution conditions varied [20]. Each controlled evaluation unit was therefore defined as

$$E_i = \left(P_i^{(v)}, D_i, M^{(k)}, \boldsymbol{\theta}_g\right),$$

where E_i denotes controlled evaluation instance i, $P_i^{(v)}$ is governed prompt version v, D_i is the corresponding evaluation item, $M^{(k)}$ denotes model version k, and $\boldsymbol{\theta}_g$ represents the approved generation configuration [15]. This specification allowed observed performance differences to be traced to controlled experimental changes rather than undocumented configuration variation.

3.3 Ground-Truth and Evaluation Criteria Construction

Reference criteria were established before model responses were scored, reducing the possibility that acceptance requirements were retrospectively modified to accommodate generated outputs [18]. Evaluation item D_i was

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associated with reference criterion Y_i^*, representing the expected answer, acceptable semantic content, validated factual state, or rubric-defined target applicable to that task. Scoring was expressed as

$$S_{i,r} = f(R_{i,r}, Y_i^*, \mathcal{R}_i),$$

where $S_{i,r}$ denotes the evaluation score assigned to response r for item i, $R_{i,r}$ is the generated response, Y_i^* represents the reference criterion, and $\mathcal{R}_i$ denotes the predefined scoring rubric [13]. Exact-match scoring was applied where one objectively correct response existed, while semantic equivalence, factual verification, structured-output validation, and rubric-based assessment were used for less deterministic tasks [17]. Acceptance thresholds were established before execution, with responses satisfying $S_{i,r} \geq \tau_i$ classified as acceptable. Evaluator guidelines documented how borderline, partially correct, and structurally defective outputs were adjudicated.

3.4 Repeated Trials and Evaluation Stability

Repeated executions were conducted to quantify stochastic variability rather than treating a single generated response as definitive evidence of model quality [19]. For each controlled evaluation instance E_i, the model generated R_i repeated responses under unchanged prompt, model, dataset, and generation conditions. Stability was assessed through response variation, score variance, evaluator agreement, and defect recurrence [16]. Outcome consistency was quantified as

$$C_i = \frac{N_{i,\text{eq}}}{R_i}, \qquad 0 \leq C_i \leq 1,$$

where C_i denotes consistency for evaluation item i, $N_{i,\text{eq}}$ represents the number of repeated executions producing equivalent evaluation outcomes, and R_i is the total number of repeated runs. Values of C_i approaching indicated greater repeatability, whereas lower values identified unstable evaluation behaviour [14]. Defect recurrence was examined separately to determine whether failures represented persistent deficiencies or isolated stochastic responses. Governed prompts were expected to improve C_i without simplifying tasks or weakening validity criteria.

3.5 Baseline and Governance Comparison Design

Two experimental conditions were constructed to isolate the effect of prompt governance [20]. The baseline condition, G_0, contained prompts developed without formalized review, versioning, approval, or standardized change controls. The intervention condition, G_1, contained prompts constructed, reviewed, approved, versioned, and executed through the governance framework. Their comparative effect was represented as

$$\Delta Q = Q(G_1) - Q(G_0),$$

where $Q(G_1)$ denotes an evaluation-quality metric under governed prompting, $Q(G_0)$ denotes the corresponding metric under ungoverned prompting, and ΔQ represents the observed governance-associated difference. Both conditions used identical $\mathcal{D}^{(k)}$, $M^{(k)}$, $\boldsymbol{\theta}_g$, repeated-run requirements, and scoring procedures [18]. Comparisons therefore isolated prompt-governance differences while holding major evaluation conditions constant. Outcomes included accuracy, consistency, defect attribution, reproducibility, and evaluation variance.

Table 1. Prompt Governance Variables and Experimental Control Parameters

Control Dimension	Ungoverned Condition G_0	Governed Condition G_1	Measurement Variable	Expected Effect
Prompt specification	Inconsistent or informal instructions	Standardized prompt components	Prompt completeness PC	Increased specification consistency
Version control	Revisions may overwrite prior prompts	Unique version $P_i^{(v)}$ retained	Version traceability VT	Improved reproducibility
Review and approval	No formal approval process	Defined review and approval gates	Approval compliance AC	Reduced uncontrolled prompt changes
Evaluation dataset	Potentially variable test items	Frozen dataset $\mathcal{D}^{(k)}$	Dataset consistency DC	Reduced benchmark variation
Model configuration	Settings may vary between tests	Fixed model version $M^{(k)}$	Configuration consistency MC	Improved comparability

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Control Dimension	Ungoverned Condition G_0	Governed Condition G_1	Measurement Variable	Expected Effect
Generation settings	Uncontrolled or undocumented	Fixed \(\boldsymbol{\theta}_g\)	Generation consistency GC	Reduced execution variability
Evaluation criteria	Informal or post hoc criteria	Predefined Y_i^*, $\mathcal{R}_i$, and τ_i	Evaluation accuracy A	More reliable scoring
Repeated evaluation	Single or inconsistent runs	Controlled repeated runs R_i	Consistency C_i	Increased repeatability
Defect attribution	Failures primarily assigned to model	Separated into D_P, D_M, and D_E	Defect rate DR	Improved root-cause attribution
Evaluator control	Reviewer interpretation may vary	Standardized evaluator guidance	Agreement κ	Increased evaluator agreement
Change documentation	Limited change history	Formal change logs and lineage	Change traceability CT	Improved auditability
Overall evaluation quality	Uncontrolled evaluation variability	Controlled governance architecture	Evaluation Quality Index EQI	Higher evaluation reliability

4. ACCURACY, DEFECT TAXONOMY, AND EVALUATION METRICS

4.1 Evaluation Accuracy Measurement

Evaluation accuracy measured the extent to which the implemented evaluation process correctly determined whether generated responses satisfied predefined acceptance criteria [23]. Each evaluated output was compared with its applicable reference criterion Y_i^*, scoring rubric $\mathcal{R}_i$, and acceptance threshold τ_i. For binary evaluation, accuracy was calculated as

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN},$$

where TP denotes acceptable outputs correctly identified as acceptable, TN represents defective outputs correctly identified as defective, FP denotes defective outputs incorrectly accepted, and FN represents acceptable outputs incorrectly rejected [20]. Both error types were consequential in generative AI quality assurance. A high FP count indicated that genuine model or response defects escaped detection, potentially overstating system capability [26]. Conversely, a high FN count indicated that valid outputs were incorrectly classified as defective, thereby understating performance and potentially generating unnecessary remediation. Accuracy was therefore interpreted alongside false-acceptance and false-rejection behaviour rather than as an isolated measure of evaluation quality [24].

4.2 Prompt-Induced versus Model-Induced Defects

Observed evaluation failures were classified according to their most plausible source rather than being automatically attributed to the generative model [21]. Prompt-induced defects, denoted D_P, included ambiguous instructions, conflicting constraints, missing contextual information, weak output specifications, and misleading examples. Model-induced defects, denoted D_M, included hallucinations, factual errors, reasoning failures, instruction noncompliance, formatting errors, and incomplete responses [27]. A third category, evaluation-induced defects D_E, captured failures originating from ambiguous rubrics, evaluator inconsistency, or incorrect reference answers.

The complete defect set $\mathcal{D}_{\text{def}}$ was therefore represented as

$$\mathcal{D}_{\text{def}} = D_P \cup D_M \cup D_E,$$

where D_P represents prompt-induced defects, D_M represents model-induced defects, and D_E represents evaluation-induced defects. Attribution was based on documented evidence from governed prompt version $P_i^{(v)}$, repeated responses $R_{i,r}$, evaluator records, and reference criterion Y_i^* [22]. This three-way separation prevented deficiencies originating from prompt design or evaluation procedures from artificially increasing the measured model-defect rate.

4.3 Defect Rate and Defect Density

Defect frequency was quantified using complementary rate and density measures [25]. Defect rate DR measured the proportion of evaluated outputs containing at least one identified defect and was calculated as

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$$DR = \frac{N_{\text{defective}}}{N_{\text{evaluated}}},$$

where $N_{\text{defective}}$ represents the number of outputs containing one or more identified defects and $N_{\text{evaluated}}$ denotes the total number of evaluated outputs. Because an individual response $R_{i,r}$ could contain multiple independent failures, defect density DD was additionally calculated as

$$DD = \frac{N_{\text{defects}}}{N_{\text{evaluated}}},$$

where N_{defects} denotes the total number of individually identified defects [28]. Defects contributing to N_{defects} were further classified as critical, major, or minor according to predefined severity criteria. Critical defects included severe factual failures in high-risk tasks or violations of essential output constraints [21]. Major defects materially reduced response correctness or usefulness, whereas minor defects affected presentation or limited aspects of completeness without invalidating the principal response.

4.4 Inter-Evaluator Agreement and Repeatability

Human-scored evaluations were examined for agreement and repeatability because inconsistent judgments introduced measurement error independently of prompt or model performance [24]. Percentage agreement provided a descriptive measure, while Cohen's kappa κ was applied to two-evaluator conditions and Fleiss' kappa κ_F to evaluations involving multiple reviewers [19]. For two evaluators, chance-adjusted agreement was calculated as

$$\kappa = \frac{P_o - P_e}{1 - P_e},$$

where P_o denotes observed evaluator agreement and P_e represents agreement expected by chance. Higher values of κ indicated stronger evaluator consistency after accounting for P_e [26]. Repeatability was additionally compared across the same governed prompt $P_i^{(v)}$ and model $M^{(k)}$ over repeated executions, revised prompt $P_i^{(v+1)}$ with unchanged $M^{(k)}$, and unchanged $P_i^{(v)}$ evaluated against a subsequent model version $M^{(k+1)}$. These comparisons separated stochastic response variation, prompt-revision effects, and model-version effects [23].

4.5 Composite Evaluation Quality Index

A composite Evaluation Quality Index EQI integrated complementary dimensions of evaluation performance rather than relying on accuracy alone [27]. The index was specified as

$$EQI = w_1 A + w_2 R + w_3 I + w_4 D - w_5 F, \qquad \sum_{j=1}^{5} w_j = 1,$$

where A represents evaluation accuracy, R denotes repeatability, I represents inter-evaluator agreement, D denotes defect-detection performance, F represents the false-acceptance rate, and w_1, w_2, w_3, w_4, w_5 are normalized component weights [22]. The negative term $-w_5 F$ penalized evaluation procedures that permitted defective outputs to pass. Each component was normalized to a comparable scale before aggregation. The constraint $\sum_{j=1}^{5} w_j = 1$ ensured that the assigned component weights summed to unity. Alternative w_j specifications were sensitivity-tested to determine whether differences between governed condition G_1 and ungoverned condition G_0depended materially on the selected weighting structure [25].

5. PROMPT OPTIMIZATION, BENCHMARKING, AND DEFECT REDUCTION

5.1 Controlled Prompt Revision Cycle

Prompt improvement was conducted through controlled revision experiments rather than informal rewriting. The approved prompt version $P_i^{(v)}$ served as the baseline artifact, and each subsequent version $P_i^{(v+1)}$ introduced changes to one or a limited number of controlled components [28]. Revised variables included instruction specificity I_s, example count N_E, context length L_C, formatting constraints F_c, reasoning guidance R_g, and output-schema specification O_s. The revision process was represented as

$$P_i^{(v+1)} = P_i^{(v)} + \Delta X_i, \qquad \Delta X_i \in \{I_s, N_E, L_C, F_c, R_g, O_s\},$$

where ΔX_i denotes the controlled modification introduced between prompt versions v and $v+1$. Limiting ΔX_i reduced ambiguity regarding which modification produced an observed performance change [30]. Each revised prompt was assigned a new version identifier rather than replacing $P_i^{(v)}$, thereby preserving historical results, rollback capability, and experimental traceability. Controlled revisions consequently allowed prompt improvements to be associated with specific design changes [29].

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5.2 Prompt Component Ablation Testing

Ablation testing isolated the contribution of individual prompt components by removing or modifying one element while holding the remaining evaluation conditions constant. The full governed prompt P_{full} was compared with an ablated prompt P_{-j}, where component $j$represented a few-shot example, formatting rule, role specification, contextual element, or explicit evaluation criterion 31]. The contribution of component j to evaluation quality was calculated as

$$\Delta Q_j = Q(P_{\text{full}}) - Q(P_{-j}),$$

where $Q(P_{\text{full}})$ denotes evaluation quality under the complete prompt and $Q(P_{-j})$ denotes performance after component j was removed or altered. Positive ΔQ_j indicated that the component contributed useful evaluation information, whereas values approaching zero suggested limited incremental value [32]. Component effects were assessed across accuracy, defect rate DR, and consistency C_i. This procedure identified prompt elements that improved evaluation reliability and those that increased complexity without measurable benefit.

5.3 Benchmarking Governed and Ungoverned Prompting

The ungoverned condition G_0 and governed condition G_1 were benchmarked under identical evaluation dataset $\mathcal{D}^{(k)}$, model version $M^{(k)}$, generation configuration $\boldsymbol{\theta}_g$, and scoring criteria. Comparative metrics included evaluation accuracy A, false-acceptance rate FAR, false-rejection rate FRR, defect rate DR, repeatability R, inter-evaluator agreement I, response latency L, and token consumption T_c [33]. For any benchmark metric Q, absolute change was calculated as

$$\Delta Q = Q_{G_1} - Q_{G_0},$$

while relative change was calculated as

$$\Delta Q_{\%} = \frac{Q_{G_1} - Q_{G_0}}{Q_{G_0}} \times 100.$$

Here, Q_{G_0} and Q_{G_1} represent the metric values under ungoverned and governed prompting, respectively [34]. Improvements were interpreted according to metric direction: increases were desirable for A, R, and I, whereas reductions were preferable for FAR, FRR, DR, L, and T_c when evaluation quality remained unchanged.

Table 2. Comparative Evaluation Performance Before and After Prompt Governance

Metric	Ungoverned Prompting G_0	Governed Prompting G_1	Absolute Change ΔQ	Relative Change $\Delta Q_{\%}$	Interpretation
Evaluation accuracy A	78.4%	91.6%	+13.2 pp	+16.8%	Substantial improvement in correct evaluation decisions
False-acceptance rate FAR	14.8%	6.1%	−8.7 pp	−58.8%	Fewer defective outputs were incorrectly accepted
False-rejection rate FRR	11.6%	5.3%	−6.3 pp	−54.3%	Fewer acceptable outputs were incorrectly rejected
Defect rate DR	21.7%	12.4%	−9.3 pp	−42.9%	Governance reduced observed evaluation defects
Repeatability R	76.2%	90.5%	+14.3 pp	+18.8%	Greater consistency across repeated evaluations
Inter-evaluator agreement κ	0.68	0.86	+0.18	+26.5%	Stronger agreement between independent evaluators
Response latency L	2.84 s	2.97 s	+0.13 s	+4.6%	Governance produced a small latency overhead
Token consumption T_c	486	532	+46	+9.5%	More structured prompts moderately increased token usage
Evaluation Quality Index EQI	0.71	0.88	+0.17	+23.9%	Overall evaluation quality improved substantially

5.4 Defect Trend and Stability Analysis

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Defect behaviour was tracked longitudinally across approved prompt versions $P_i^{(1)}, P_i^{(2)}, P_i^{(3)}, \ldots, P_i^{(n)}$ rather than evaluating only the final prompt [32]. For each version v, the corresponding defect rate $DR^{(v)}$ was calculated under unchanged benchmark conditions. The version sequence was represented as

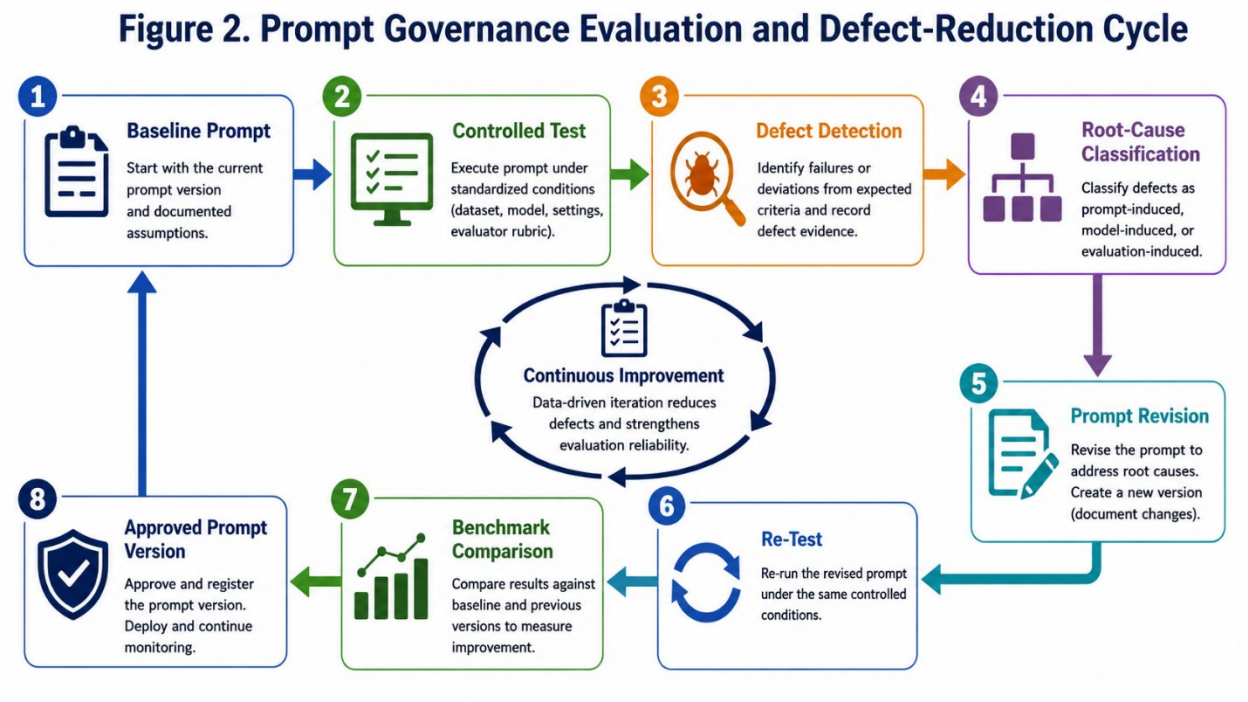
$$P_i^{(1)} \rightarrow P_i^{(2)} \rightarrow P_i^{(3)} \rightarrow \cdots \rightarrow P_i^{(n)},$$

with the associated defect trajectory

$$DR^{(1)}, DR^{(2)}, DR^{(3)}, \ldots, DR^{(n)}.$$

Declining and subsequently stable values of $DR^{(v)}$ provided stronger evidence of sustained improvement than a single reduction between two prompt versions. Trends were examined by task type T_j and model version $M^{(k)}$ to determine whether gains generalized across evaluation conditions [30]. Control-chart logic was additionally applied where repeated observations were sufficient to distinguish systematic improvement from stochastic variation.

Figure 2. Prompt Governance Evaluation and Defect-Reduction Cycle



5.5 Robustness and Stress Testing

Governed prompts were stress-tested under controlled perturbations to determine whether evaluation performance remained stable beyond the original benchmark formulation. Perturbation conditions included paraphrased requests V_p, extended context V_c, incomplete inputs V_i, adversarial wording V_a, multilingual inputs V_m, edge cases V_e, and model-version changes V_M [31]. The stress-test set was represented as

$$\mathcal{V} = \{V_p, V_c, V_i, V_a, V_m, V_e, V_M\}.$$

For each perturbation $V_j \in \mathcal{V}$, governed-prompt performance Q_{V_j} was compared with baseline performance Q_0. Robustness was supported when deviations $\left|Q_{V_j} - Q_0\right|$ remained within predefined tolerance ϵ [36]. This criterion was expressed as

$$\left|Q_{V_j} - Q_0\right| \leq \epsilon.$$

The analysis therefore assessed whether prompt governance produced evaluation procedures that remained reliable under realistic variation rather than performing well only under narrowly controlled benchmark conditions.

6. OPERATIONAL GOVERNANCE, MONITORING, AND STANDARDS ALIGNMENT

6.1 Prompt Registry and Governance Repository

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A centralized prompt registry was established as the organizational source of truth for evaluation artifacts and their governance histories [31]. Each registered prompt was assigned a unique prompt identifier PID_i and linked to its approved version $P_i^{(v)}$, owner O_i, approval status A_i, use case U_i, compatible model set $\mathcal{M}_i$, evaluation history H_i^E, defect history H_i^D, and retirement status R_i. The registry record was formally represented as

$$\mathcal{R}_i = \left\{PID_i,\ P_i^{(v)},\ O_i,\ A_i,\ U_i,\ \mathcal{M}_i,\ H_i^E,\ H_i^D,\ R_i\right\}.$$

Here, $\mathcal{R}_i$ denotes the complete governance record for prompt i. Evaluation results and identified defects were linked directly to the corresponding PID_i and $P_i^{(v)}$, preventing findings from being separated from the exact prompt configuration that generated them [33]. Superseded versions remained archived rather than overwritten, preserving rollback, auditability, and historical comparison. The repository therefore provided traceability across prompt creation, approval, deployment, revision, and retirement.

6.2 Continuous Monitoring and Drift Detection

Post-deployment monitoring assessed whether the performance of approved prompt version $P_i^{(v)}$ changed following model updates, retrieval modifications, new evaluation domains, policy changes, or shifts in user behaviour [34]. Monitored indicators included evaluation accuracy A_t, defect rate DR_t, mean output length L_t, evaluator disagreement ED_t, and token cost TC_t at monitoring period t. Drift for metric X was measured relative to its approved baseline X_0 as

$$\Delta X_t = X_t - X_{0.}$$

Where ΔX_t represents the observed change in monitored metric X_t relative to baseline X_0. A revalidation trigger was activated when the absolute deviation exceeded a predefined tolerance δ_X:

$$|\Delta X_t| > \delta_X.$$

This mechanism prevented previously approved prompts from remaining operational indefinitely when their measured behaviour no longer corresponded with validated baseline conditions.

6.3 Human Oversight and Escalation

Human oversight was concentrated on uncertain and operationally consequential cases rather than being applied uniformly to every generated response [32]. Escalation conditions included repeated critical defects N_{crit}, evaluator disagreement ED, unexplained accuracy degradation ΔA, and entry into a new high-risk domain H_{risk}. The escalation decision was represented as

$$E_{\text{human}} = \mathbb{1}(N_{\text{crit}} \geq \tau_c \ \vee\ ED \geq \tau_e \ \vee\ |\Delta A| \geq \tau_a \ \vee\ H_{\text{risk}} = 1),$$

where $E_{\text{human}} = 1$ indicates mandatory human review, while τ_c, τ_e, and τ_a denote predefined escalation thresholds. This risk-based structure directed specialist attention toward ambiguous, recurrent, or high-impact evaluation failures.

6.4 Standards and Governance Alignment

The implemented prompt-governance framework was conceptually benchmarked against established AI and software-governance approaches [35]. The NIST AI Risk Management Framework provided relevant functions across Govern, Map, Measure, and Manage, particularly for documenting evaluation risks, measuring performance, and establishing corrective controls. ISO/IEC 42001 provided complementary principles for AI management systems, accountability, lifecycle controls, documented responsibilities, and continuous monitoring. ISO/IEC 23894 informed the identification, analysis, evaluation, treatment, and monitoring of AI-related risks, while ISO/IEC 25010 provided software-quality characteristics relevant to reliability, maintainability, and functional suitability [36].

Prompt governance operated at a more specific implementation layer than these broader frameworks. Version control V_c, traceability T_r, monitoring M_o, human oversight H_o, defect management D_m, and change control C_c translated general governance principles into controls applicable to evaluation prompts. The framework therefore complemented rather than replaced organizational AI governance by operationalizing governance requirements within day-to-day generative AI evaluation.

6.5 Responsible Use and Governance Risks

Prompt governance also introduced operational risks that required explicit management [37]. Excessive standardization could reduce adaptability, while overly complex prompt specifications could increase brittleness and maintenance requirements. Hidden evaluator bias could persist despite formalized review, and extensive documentation could increase governance workload and delay legitimate experimentation. These trade-offs were addressed through proportional governance in which control intensity G_i was aligned with evaluation risk R_i:

$$G_i \propto R_i.$$

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Higher-risk evaluations therefore received stronger approval, monitoring, documentation, and escalation controls, whereas lower-risk experimental tasks used lighter governance requirements. This proportional approach prevented governance from becoming an unnecessary operational constraint while preserving rigorous controls where evaluation errors could produce significant organizational, safety, compliance, or decision-making consequences.

7. DISCUSSION, IMPLICATIONS, AND CONCLUSION

7.1 Interpretation of the Evaluation Improvements

The comparative evaluation indicated that prompt governance improved the reliability of generative AI assessment across evaluation accuracy A, repeatability R, defect-identification performance D, and inter-evaluator agreement I. Improvements observed between the ungoverned condition G_0 and governed condition G_1 were interpreted as improvements in the evaluation process, rather than direct evidence that the underlying model had improved [38]. This distinction was represented as

$$\text{Prompt Improvement} \neq \text{Model Improvement}.$$

When model version $M^{(k)}$ remained unchanged, an increase in evaluation quality $\Delta Q = Q(G_1) - Q(G_0)$ primarily demonstrated that governance reduced uncontrolled prompt variation and improved measurement consistency. Consequently, higher A, R, D, or I did not independently establish improved model capability. Instead, governed prompting produced more dependable evidence about the capabilities and defects already present in the evaluated model.

7.2 Implications for Generative AI Quality Engineering

The framework demonstrated that evaluation prompts could function as controlled quality-assurance artifacts within generative AI engineering [39]. Approved prompt version $P_i^{(v)}$ could be linked to model version $M^{(k)}$, evaluation dataset $\mathcal{D}^{(k)}$, generation configuration $\boldsymbol{\theta}_g$, and evaluation results, creating reproducible test records. This architecture supported model-release testing, regression testing, benchmark management, safety testing, red-team evaluation, and enterprise quality assurance. When a model changed from $M^{(k)}$ to $M^{(k+1)}$, retaining the same controlled prompt and benchmark conditions enabled performance changes to be attributed more reliably to the model revision. Evaluation prompts were therefore treated as version-controlled testing assets rather than disposable natural-language instructions.

7.3 Methodological Contribution

The principal methodological contribution was the integration of prompt governance with controlled experimentation, systematic defect attribution, comparative benchmarking, version management, and continuous monitoring. The architecture was summarized as

$$\text{Prompt Governance} \rightarrow \text{Controlled Evaluation} \rightarrow \text{Defect Taxonomy} \rightarrow \text{Benchmarking} \rightarrow \text{Versioning} \rightarrow \text{Continuous Monitoring}.$$

This integration transformed prompt engineering from an informal optimization activity into a measurable and auditable quality-engineering process. By linking $P_i^{(v)}$, $M^{(k)}$, $\mathcal{D}^{(k)}$, and $\boldsymbol{\theta}_g$, the framework strengthened experimental traceability and repeatability [40].

7.4 Limitations, Future Research, and Conclusion

The framework remained subject to model-specific prompt effects, subjective scoring, domain dependence, rapid model updates, and evaluator bias. Prompt behaviour validated for model version $M^{(k)}$ could not automatically be assumed to remain stable under $M^{(k+1)}$ or across substantially different domains. Future research should investigate automated prompt governance, constrained prompt optimization, multi-model prompt portability, multilingual governance, and adaptive evaluation prompts.

Overall, prompt engineering governance improved generative AI evaluation by reducing uncontrolled variation in testing conditions, strengthening defect attribution, and increasing the reproducibility of model-quality evidence. Its central value was therefore not the assumption of better model behaviour, but the establishment of a more controlled, traceable, repeatable, and defensible mechanism for determining how well generative AI systems actually perform.

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