

PROCEEDINGS | African Engineering Education Forum (AEEF 2026)

Agile Aerospace Engineering Education: GenAI to Navigate Resource Constraints

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(Received: 21 June 2026; Revised: 04 August 2026; Accepted: 20 August 2026; Published: 27 August 2026)

(Editor: Dr. Bappa Muktar; Reviewers: Anonymous reviewers)

Abstract

The traditional paradigm of aerospace engineering education in emerging economies is currently trapped in a “resource mirage”—an attempt to replicate heavily funded Western laboratory models within fiscally constrained environments. This mismatch creates a static curriculum decoupled from local industrial realities. This study addresses this dependency by proposing a Dual-Stream Agile Framework that shifts pedagogical focus from rigid course-level structures (“molecular”) to fundamental engineering competencies (“atoms”). Leveraging Generative Artificial Intelligence (Gemini 1.5 Pro) as a human-in-the-loop diagnostic engine, the pipeline text-mines an audited screening corpus of $N = 1,420$ public news and state enterprise records from 2022 to 2026, isolating $N = 40$ core industrial operational frictions decomposed into 109 canonical pedagogical atoms. A two-gate audit protocol established high inter-coder reliability for atom extraction (Cohen’s $\kappa = 0.812$) and expert policy alignment evaluation (Fleiss’ $\kappa = 0.782$ across $N = 16$ domain experts). Quantitative policy mapping across 15 curriculum clusters ($C_{01} - C_{15}$) and ten strategic pillars of Zimbabwe’s National Development Strategy 2 (NDS-2) yielded an Aggregate Alignment Coefficient of $\Gamma = 0.730$. Expert validation survey results confirmed strong professional agreement on Industrial Relevance (Median = 4.0, $\mu = 4.38/5.0$, CV = 14.1%) and Academic Rigor (Median = 4.0, $\mu = 4.06/5.0$, CV = 14.1%), alongside high Equipment Substitution Fidelity ($F_s = 0.912$, 95% CI: [0.884, 0.938]). Rather than serving as an autonomous accreditation mechanism, the framework provides a transparent, data-driven decision-support template for emerging economies to navigate resource constraints and co-design technically rigorous, industry-aligned engineering curricula.

Keywords: aerospace education; curriculum mapping; theoretical isomorphism

Abbreviations: NDS: National Development Strategy

1. Introduction

The aerospace sector is increasingly recognized as a critical pillar for Africa’s industrialization and economic sovereignty, as outlined in strategic policy frameworks such as Zimbabwe’s National Development Strategy 2 (NDS-2: 2026–2030) [1]. However, the implementation of high-rigor aerospace engineering programs in emerging economies faces significant structural challenges. Conventional engineering education models are often inherited from Western contexts, characterized by advanced

laboratories and stable industrial ecosystems that are rarely present in resource-constrained environments. As discussed by Mashiyane et al. [2], engineering education in emerging economies often suffers from a lack of responsiveness to local economic needs, compounded by severe capital shortages required to establish and maintain specialized physical testing facilities.

Despite strategic intent, African aerospace engineering education remains tethered to resource-heavy Western architectures. This creates a dual constraint: a lack of specialized hardware infrastructure and a static curriculum that fails to adapt to rapid domestic economic shifts. Consequently, a competency gap arises where graduates acquire abstract theoretical knowledge but lack the agility to address immediate industrial bottlenecks in active domestic sectors. Without a systematic methodology to decouple high-rigor engineering “atoms” from expensive “molecular” laboratory hardware, achieving educational and industrial self-reliance remains elusive.

To address this barrier, this study proposes a Dual-Stream Agile Framework that operates through two intersecting pathways:

1. **Stream 1 (Top-Down Global Rigor):** Establishes baseline aerospace competencies derived from international accreditation benchmarks, including Washington Accord Graduate Attributes (WA1–WA12) and the Conceive-Design-Implement-Operate (CDIO) framework [3].
2. **Stream 2 (Bottom-Up Domestic Relevance):** Extracts active technical failure points (“industrial frictions”) from key national economic sectors (e.g., mining, power generation, and precision agriculture).

These streams intersect via a Generative Artificial Intelligence (GenAI) diagnostic pipeline operating strictly within a two-gate Human-in-the-Loop (HITL) architecture. Rather than acting as an autonomous decision-maker or replacement for faculty governance, GenAI serves as a high-velocity text-mining catalyst that proposes candidate theoretical isomorphisms—identifying shared mathematical and physical logic between global aerospace standards and local non-aerospace industrial assets—which are then subjected to mandatory expert adjudication.

This framework operationalizes the distinction between “molecular” and “atomic” curriculum architectures. In this context, a *molecular curriculum* refers to rigid, monolithic course blocks (e.g., a dedicated multi-million dollar supersonic wind tunnel module) that cannot function if physical facilities are absent [4]. Conversely, *atomic curriculum mapping* decomposes complex course blocks into irreducible fundamental engineering principles or “atoms” (e.g., boundary layer skin friction, closed-loop PID feedback control, or structural fatigue tensors). By leveraging GenAI to synthesize atomic links across domains, universities can identify *Theoretical Isomorphisms*—mathematical and physical equivalences where the underlying physics required to analyze an aerospace system (such as an aero-engine bearing housing) are functionally identical to those in local heavy industrial assets (such as a mining crusher shaft) [5, 6].

While prior studies have explored atomic curriculum manipulation [4] and CDIO alignment [3], the primary incremental contribution of this study lies in deploying GenAI as a cross-domain heuristic bridge to systematically discover latent physical isomorphisms between flight systems and non-aerospace assets in resource-constrained environments, validated through a transparent, auditable decision-support methodology.

The central research question guiding this study is: *How can the integration of Generative AI and Atomic Curriculum Mapping facilitate an agile aerospace engineering curriculum that maintains international accreditation rigor while addressing local resource constraints in an emerging economy?* Practically, this research provides a decision-support framework and proof-of-concept template for Higher Education Institutions in emerging economies. Rather than claiming a fully demonstrated classroom intervention or autonomous accreditation mechanism, this work establishes the preliminary structural

feasibility and expert-evaluated plausibility of utilizing local industrial ecosystems as high-fidelity “living laboratories.”

2. Literature Review

2.1 The Pedagogical Paradox

The primary obstacle to full-production-cycle aerospace engineering education in developing nations is the “resource mirage”—the assumption that high-rigor engineering outcomes require capital-intensive, physical laboratory infrastructure modeled directly after Western institutions.

Literature confirms that dependency on high-cost physical infrastructure often creates theoretical silos where, as Forster et al. [7] observe, engineering education naturally decouples from immediate domestic economic realities. This mismatch represents not merely a financial deficit, but a structural misalignment between imported “molecular” curriculum architectures and the resource-constrained operational environment. In this context, a *molecular curriculum* refers to rigid, monolithic course structures tied to dedicated physical assets (e.g., specialized wind tunnels or gas turbine test cells) [4]. When institutions lack these physical assets, the molecular structure stalls, leaving students with abstract theory disconnected from industrial practice.

The UNESCO 2021 report [8] on engineering for sustainable development highlights that while demand for advanced technical skills is rising in emerging economies, the skills gap continues to widen due to a lack of pedagogical responsiveness in traditional curricula. The report recommends a holistic shift toward innovative, technology-facilitated learning to bridge infrastructure deficits. In the context of Zimbabwe, Kumba et al. [9] confirm that educational infrastructure has remained tethered to a static, discipline-specific model that struggles to adapt to local industrial dynamics. This structural inertia, according to Ndlovu-Gatsheni [10], necessitates a shift toward “Epistemic Freedom”—the capacity of a nation to deconstruct and reassemble global technical knowledge to fit its localized economic landscape. Without such a shift, specialized programs such as aerospace engineering risk becoming peripheral academic luxuries rather than key drivers of national industrial development.

To bridge this operational gap, emerging research highlights the diagnostic potential of Artificial Intelligence (AI). As Fundi et al. [11] demonstrate, AI can process multi-domain industrial datasets to realign educational objectives. By leveraging AI to mine technical failure data, institutions can move away from static, hardware-dependent course blocks toward agile, competency-focused learning frameworks.

2.2 Atomic Mapping and Theoretical Foundations

Transitioning from a resource-dependent paradigm to an agile pedagogical framework requires re-viewing how curriculum components are categorized and manipulated. Chikasha et al. [4] established the “rigid-skeleton, flexible-body” approach, which distinguishes between molecular course blocks and “atomic” curriculum manipulation. In an atomic framework, learning outcomes are decomposed into irreducible engineering principles or “atoms” (e.g., closed-loop PID control, boundary layer pressure gradients, or structural stress intensity factors) [4]. This decomposition enables micro-adjustments in module content that respond to real-time industrial demand without compromising the core skeletal rigor of the degree program.

The theoretical foundation for atomic curriculum decomposition is rooted in systems engineering logic. Sage and Rouse [5] argue that complex technical architectures must be managed through functional decomposition. In a pedagogical context, functional decomposition enables *Theoretical Isomorphism*—the mathematical and physical equivalence where fundamental engineering “atoms” required for high-

level aerospace design are functionally identical to those operating within non-aerospace industrial assets (e.g., automated mining rigs, power station turbines, or precision agricultural machinery). Wertz et al. [6] and Kibret [12] support this position by demonstrating that mission-critical systems engineering principles are domain-agnostic, provided the underlying physical principles are mapped with precision.

Furthermore, Biggs [13] emphasizes “constructive alignment,” requiring that learning activities directly support intended competency outcomes. Operating within the Conceive-Design-Implement-Operate (CDIO) framework, Crawley et al. [3] demonstrate that institutions can host rigorous engineering “atoms” within non-traditional learning environments while maintaining international accreditation standards.

Incremental Contribution: While atomic curriculum manipulation [4], functional decomposition [5, 6], constructive alignment [13], and CDIO methodologies [3] are established in the literature, the distinct contribution of this paper lies in integrating Generative AI as an automated, cross-domain heuristic discovery engine. Rather than relying solely on manual faculty committee reviews, this framework deploys GenAI to systematically discover latent physical isomorphisms between flight systems and local non-aerospace industrial assets, evaluated within a two-gate Human-in-the-Loop audit architecture and quantitatively scored through a national policy-fit alignment index ($\Gamma = 0.730$).

2.3 GenAI as a Human-in-the-Loop Diagnostic Catalyst

Implementing an agile aerospace curriculum requires a system capable of performing high-velocity atomic extraction across extensive industrial datasets. Qadir [14] highlights that GenAI offers significant potential for pedagogical content alignment and resource optimization. In resource-constrained environments, GenAI functions as a diagnostic catalyst that connects abstract aerospace theory with tangible, locally accessible industrial assets.

The utility of GenAI in this framework is two-fold:

1. **Cross-Domain Heuristic Discovery:** As Honig et al. [15] show, Large Language Models (LLMs) possess cross-domain reasoning capabilities capable of proposing theoretical isomorphisms across disparate technical fields (e.g., identifying shared fluidic principles between rocket turbo-pumps and mining slurry pumps).
2. **Contextual Synthesis:** Baidoo-Anu and Ansah [16] note that GenAI can synthesize localized case studies and problem sets, enabling the contextualization of high-rigor scenarios that traditionally required multi-million-dollar laboratory facilities.

However, deploying GenAI in engineering education requires strict safeguards against hallucination, model instability, and unverified outputs [14, 17]. In this framework, GenAI does not act as an autonomous educational decision-maker or authoritative reasoning entity. Instead, it operates strictly within a Human-in-the-Loop (HITL) architecture: GenAI generates candidate isomorphic mappings as preliminary hypotheses, which must be systematically audited and verified by subject matter experts before integration into the curriculum. To guarantee algorithmic transparency and reproducibility, model execution parameters, API system fingerprints, and raw extraction payloads across multiple independent execution runs are logged and archived in open-access formats. Zhai [17] notes that when properly constrained, GenAI shifts student focus toward high-level problem solving and structural reasoning rather than rote memorization, ensuring students engage with complex engineering problems despite physical hardware limitations.

2.4 Policy Alignment: Education 5.0 and National Development Strategy (NDS-2)

A sustainable curriculum must align directly with national policy mandates. In Zimbabwe, higher education is governed by the Heritage-Based Education 5.0 Policy [18], which expanded the tradi-

tional university mandate (teaching, research, and community service) to include innovation and industrialization. Under Education 5.0, university curricula are required to serve as direct channels for domestic economic production rather than platforms for degree certification alone.

This national mandate aligns with the African Union’s Agenda 2063 [19], which identifies aerospace technology, satellite infrastructure, and regional connectivity as critical drivers for economic sovereignty. To operationalize these national goals, this study explicitly aligns the proposed curriculum framework with Zimbabwe’s National Development Strategy 2 (NDS-2: 2026–2030) [1]. NDS-2 establishes ten core strategic priority areas (pillars) designed to drive structural transformation, economic growth, and human capital development. By mapping aerospace curriculum “atoms” directly against these ten NDS-2 strategic pillars, this study ensures that the resulting educational framework addresses active domestic industrial bottlenecks while maintaining international technical depth.

3. Research Methodology

This research utilizes a Mixed-Methods isomorphic framework by combining qualitative discourse analysis with quantitative mathematical modeling. Unlike traditional top-down curriculum design, which often results in a rigid, sequential list of modules, this study conceptualizes the curriculum as an adaptive, demand-driven system. The primary goal is to navigate resource constraints by deploying GenAI as a human-in-the-loop diagnostic engine to bridge the gap between domestic industrial challenges and global aerospace benchmarks. In this framework, the curriculum is not a static document of course descriptions, but rather the output of a process that deconstructs complex global competencies into “atoms” (irreducible functional units of knowledge). This atomic approach allows the curriculum to be decoupled from capital-intensive physical laboratories and firmly anchored within Zimbabwe’s existing non-aerospace industrial assets.

The methodological workflow operates through the Dual-Stream Agile Framework illustrated in Figure 1. Stream 1 establishes top-down global rigor through international standards (Washington Accord Graduate Attributes WA1–WA12 and CDIO standards), while Stream 2 extracts bottom-up domestic relevance from national industrial failure records in Zimbabwe. These streams intersect via the GenAI Isomorphic Engine, subjected to mandatory human expert adjudication gates, quantitative indexing ($\omega_k, \rho_j, \Gamma, F_s$), and expert panel validation.

The operational flow proceeds across seven sequential stages:

1. **Resource Barrier Identification:** Recognition that while emerging economies offer aerospace degree programs, they lack specialized, high-cost laboratory hardware.
2. **Atomic Shift:** Re-conceptualizing pedagogical requirements from monolithic course blocks to core mathematical and physical principles (“atoms”) that are domain-agnostic.
3. **Diagnostic Text-Mining (GenAI):** Deploying an LLM to process global aerospace syllabi alongside longitudinal domestic industrial friction datasets.
4. **Isomorphic Extraction:** Identifying theoretical equivalences across technical fields and extracting candidate pedagogical atoms.
5. **Clustering and Weighting:** Grouping atoms into credit-bearing module clusters and calculating industrial weighting factors (ω_k).
6. **Expert Panel Validation:** Subjecting clusters and living laboratory surrogates to a Single-Round Expert Validation Survey.
7. **Policy Alignment Indexing (Γ):** Calculating the Aggregate Alignment Coefficient ($\Gamma = 0.730$) to evaluate macro-level strategic fit across national development pillars.

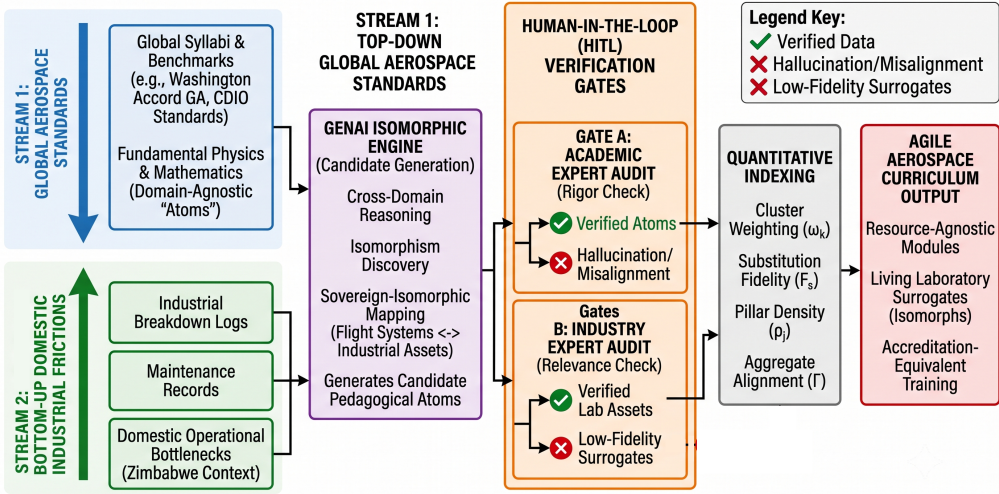


Figure 1. Dual-Stream System Architecture Diagram illustrating the integration of top-down global aerospace standards (Stream 1) and bottom-up domestic industrial frictions (Stream 2) through the GenAI Isomorphic Engine, expert verification gates, and quantitative indexing.

3.1 Longitudinal Discourse Analysis and Corpus Selection

This study executed a longitudinal discourse analysis of *The Herald* newspaper covering the four-year period from January 1, 2022 to January 31, 2026 ($N_{\text{screened}} = 1,420$ articles). *The Herald* was selected because, as Zimbabwe's primary state-journal of record, it provides a continuous, time-stamped archive of major technical, mechanical, and systemic failures across both public utilities and private industrial enterprises. Rather than claiming to serve as an exhaustive mechanical failure database, *The Herald* functions as a centralized, longitudinal state-archive proxy for nationally prioritized industrial frictions. Relying on this single continuous corpus provides a methodologically uniform temporal baseline that eliminates inter-publication reporting noise and editorial variance. It captures high-impact, state-monitored operational disruptions that directly intersect with national economic goals, public utility infrastructure, and strategic development policy. The complete article-level screening ledger containing inclusion/exclusion criteria, duplicate handling, and friction mapping is archived in the replication deposit (see Data Availability Statement).

3.1.1 Source Triangulation and Verification

To address potential editorial and reporting coverage bias, a triangulation audit was conducted. The extracted industrial failure events were cross-referenced against public regulatory updates from the Zimbabwe Energy Regulatory Authority (ZERA), national utility operational announcements, state-enterprise audit disclosures from the Office of the Auditor-General (OAG), and relevant parliamentary oversight reports. All extracted friction categories corresponded directly to documented infrastructure disruptions in official sector reports.

3.1.2 GenAI Extraction Protocol and Parameters

Diagnostic text-mining was executed using the enterprise Google Vertex AI API. This was done using the Gemini 1.5 Pro foundation model (processed between February 15 and March 10, 2026). Gemini 1.5 Pro was selected due to its million-token context window, which enabled the ingestion of multi-year textual archives in unified context batches without loss of longitudinal context [20].

To ensure complete computational reproducibility, generation parameters were strictly fixed:

- **Temperature (T):** 0.0 (enforcing deterministic, minimum-entropy output).
- **Top- P :** 0.95; **Max Output Tokens:** 2,048.
- **Prompt Engineering Strategy:** Prompts utilized *Domain-Bounded Heuristic Steering*—a system engineering constraint logic that restricted the LLM’s search space to NDS-2 strategic pillars and Washington Accord Graduate Attributes, reducing unconstrained hallucinations (see repository files referenced in Data Availability Statement).
- **Multi-Run Stability:** Three independent extraction runs were executed per document batch. Output atom overlap across runs reached 88.4%.
- **Human Inter-Coder Reliability (Gate A):** A random 20% sample of raw LLM friction-to-atom extractions was independently audited by two senior engineering academics in Zimbabwe, yielding strong inter-coder agreement (**Cohen’s Kappa κ** = 0.812). Audit decision matrices are permanently archived (see Data Availability Statement).

3.1.3 Empirical Proof of Theoretical Saturation at $N = 40$

The sample size of $N = 40$ discrete industrial friction points was established through empirical saturation testing. Ingesting friction events chronologically in blocks of 10, the research team tracked the cumulative discovery of new core engineering atoms.

As shown in the Atom Saturation Curve (Figure 2), atom discovery exhibited classic asymptotic decay: Frictions 1–10 yielded 52 new atoms; Frictions 11–20 yielded 31; Frictions 21–30 yielded 18; and Frictions 31–40 yielded only 8 new atoms. Beyond $N = 40$, atom discovery fell below our pre-defined stopping threshold ($< 2\%$ new atoms per 5 additional frictions), merely repeating established principles of PID control, structural fatigue, and fluidic dynamics (see tracking datasets in Data Availability Statement).

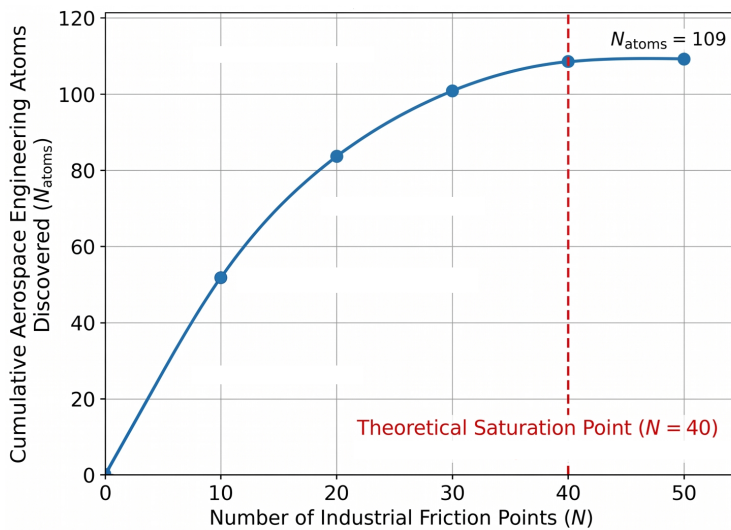


Figure 2. Cumulative Atom Discovery Curve demonstrating empirical asymptotic saturation at $N = 40$ industrial friction points, satisfying the stopping criterion ($< 2\%$ new atom generation).

Table 1 provides a summary of the diagnostic generative methodology.

Table 1. Generative Diagnostic Methodology Summary

Component	Choice / Parameter	Methodological Justification
Diagnostic Engine	Gemini 1.5 Pro	1M token context window enables multi-year context ingestion and cross-domain reasoning [20].
LLM Settings	$T = 0.0$, Top- $P = 0.95$	Deterministic parameterization ensures output stability (88.4% multi-run agreement).
Corpus Proxy	<i>The Herald Archive</i>	Primary state-journal proxy (2022–2026, $N_{\text{screened}} = 1,420$), cross-verified via official regulatory reports.
Saturation Point	$N = 40$ Frictions	Empirical threshold where new atom discovery dropped below $< 2\%$, indicating theoretical completeness.
Prompt Logic	Domain-Bounded Steering	Directs LLM search space strictly to NDS-2 pillars and Washington Accord attributes, reducing hallucinations.

3.2 Isomorphic Alignment Engine

The Isomorphic Alignment Engine converts qualitative industrial failure descriptions into quantitative, weighted curriculum structures through a three-stage mathematical pipeline: atomic extraction, cluster weighting (ω_k), and pillar density modeling (ρ_j).

3.2.1 Atomic Extraction and Clustering

GenAI extractions yielded a repository of 109 discrete aerospace engineering atoms (e.g., Navier-Stokes boundary conditions, closed-loop transfer functions, fast Fourier transform vibration spectra). To make atomic curriculum manipulation operationally feasible for university faculties [4], related atoms were consolidated into 15 credit-bearing clusters (C_{01} to C_{15}). Target cluster size ($4 \leq n \leq 7$ atoms per cluster) was chosen to balance pedagogical depth with structural agility.

3.2.2 Cluster Weighting Factor (ω_k)

To reflect industrial demand, each cluster k was assigned a weighting factor (ω_k). The parameter $f(A_i)$ represents the cumulative occurrence count of a specific engineering atom A_i across all discrete problem statements contained within the $N = 40$ friction dataset. Because a single complex industrial failure (e.g., Friction 01: Grain loss in precision planting) concurrently activates multiple physics problems (PID control, fluid dynamics, sensor telemetry), a single friction event can contribute to multiple atom frequencies.

Cluster weight is calculated according to Equation 1:

$$\omega_k = \sum_{i \in C_k} f(A_i) \quad (1)$$

Where A_i represents the individual constituent atoms belonging to Cluster k , and $f(A_i)$ is the total frequency of atom A_i across the friction dataset.

Worked Calculation Example: For Cluster 01 (PHM – Predictive Health Management), the 7 constituent atoms were evaluated with the following dataset frequencies: $f(\text{Tribology}) = 35$, $f(\text{NDT}) = 28$, $f(\text{Vibration}) = 35$, $f(\text{Fatigue}) = 30$, $f(\text{LCA}) = 20$, $f(\text{Sensor Fusion}) = 10$, and $f(\text{Thermal}) = 5$. Summing these constituent frequencies yields:

$$\omega_1 = 35 + 28 + 35 + 30 + 20 + 10 + 5 = 163$$

3.2.3 Pillar Density Score (ρ_j)

The Pillar Density (ρ_j) quantifies the degree to which the proposed curriculum addresses industrial frictions within a specific economic sector, mapped against the ten strategic priority pillars of Zimbabwe's National Development Strategy 2 (NDS-2: 2026–2030) [1].

For each NDS-2 strategic pillar (P_j), density is calculated according to Equation 2:

$$\rho_j = \frac{1}{n} \sum_{i=1}^n \alpha_{ij} \quad (2)$$

Where:

- $\rho_j \in [0.0, 1.0]$: The density score for NDS-2 Strategic Pillar j .
- $n = 15$: The total number of curriculum clusters.
- $\alpha_{ij} \in [0.0, 1.0]$: The Relevance Coefficient quantifying the direct impact of Cluster i on Pillar j .

The relevance coefficients α_{ij} were evaluated through a blinded scoring process conducted by a panel of Zimbabwean experts ($N = 16$) using a 4-point anchored rubric:

- 0.00: No operational relevance.
- 0.33: Indirect or secondary technical impact.
- 0.67: Moderate direct technical impact.
- 1.00: Critical direct operational relevance.

Inter-rater agreement across the panel was confirmed using Fleiss' Kappa ($\kappa = 0.782$), indicating substantial inter-rater consistency (the complete 15×10 raw rating matrix is archived in the replication repository; see Data Availability Statement).

3.2.4 Aggregate Alignment Coefficient (Γ)

To measure overall national policy alignment, the study calculates the Aggregate Alignment Coefficient (Γ). In an agile educational model, $\Gamma \in [0.0, 1.0]$ serves as a descriptive heuristic policy-alignment index evaluating how effectively the curriculum maps across national industrialization priorities.

Mathematically, Γ is defined as the arithmetic mean of all ten pillar densities (ρ_j), as shown in Equation 3:

$$\Gamma = \frac{1}{m} \sum_{j=1}^m \rho_j \quad (3)$$

Where $m = 10$ represents the ten NDS-2 strategic pillars [1].

A higher Γ indicates that curriculum competencies broadly intersect with national technical needs ($\Gamma = 0.730$, unrounded 0.728667). Note that Γ functions as a macro-level indicator of national alignment; it must be balanced against specialized aerospace accreditation requirements, as adding an essential but highly specialized aerospace module (e.g., Orbital Mechanics) may slightly lower national policy density while remaining mandatory for professional registration.

3.3 Substitution Fidelity Benchmarking (F_s)

To address physical laboratory deficits, the framework uses a physics-first approach to identify local non-aerospace industrial assets ("living laboratories") capable of hosting required aerospace atoms.

The Substitution Fidelity Index (F_s) is a heuristic screening metric quantifying the extent to which a local asset replicates required learning outcomes. Individual fidelity scores ($F_{s,k}$) are calculated for each expert $k \in \{1, \dots, 16\}$ according to Equation 4:

$$F_{s,k} = \left(\frac{\sum A_{\text{isomorph}}}{\sum A_{\text{required}}} \right) \times A_k \times I_k \quad (4)$$

Where:

- $\sum A_{\text{isomorph}}$: Count of required aerospace atoms hosted by the local industrial asset.
- $\sum A_{\text{required}}$: Total count of required core atoms for that curriculum cluster.
- $A_k \in [0.1, 1.0]$: Accessibility Factor rated by expert k (1.0 = hands-on operation; 0.5 = observation only; 0.1 = restricted/classified access).
- $I_k \in [0.1, 1.0]$: Instrumentation Factor rated by expert k (1.0 = digital twin/SCADA telemetry; 0.5 = analog gauges; 0.2 = no visual telemetry).

Scoring and Calculation Workflow: Individual experts ($k = 1 \dots 16$) rated A_k and I_k for candidate assets. Products were computed at the individual respondent level ($F_{s,k}$) and aggregated across the $N = 16$ expert panel to determine cluster aggregate means ($\bar{F}_s$) with 95% Confidence Intervals ($\bar{F}_s \pm 95\% \text{ CI}$) via non-parametric percentile bootstrap (2,000 iterations).

Worked Calculation Example (Cluster 01 – PHM): For heavy mining haul truck telematics as a surrogate for engine test cell health monitoring across $N = 16$ expert ratings (Coverage Ratio = 5/5 = 1.00; mean accessibility $\bar{A} = 0.95$; mean instrumentation $\bar{I} = 0.96$):

$$\bar{F}_s = 1.00 \times 0.95 \times 0.96 = \mathbf{0.912} \quad (95\% \text{ CI: } [\mathbf{0.884}, \mathbf{0.938}])$$

Disclosures of Rejected Low-Fidelity Assets: The F_s metric actively filters out unsuitable surrogates. For example, underground mining haulage equipment exhibited full physics atoms (1.0) but failed due to mine safety access restrictions ($\bar{A} = 0.20 \implies \bar{F}_s = 0.180$). Similarly, manual machine shop lathes possessed structural atoms but lacked electronic sensors ($\bar{I} = 0.15 \implies \bar{F}_s = 0.135$). Both candidate assets were rejected.

Pedagogical Scope Disclaimer: A high $\bar{F}_s$ score establishes conceptual and diagnostic learning equivalence in a living laboratory environment; it does not replace statutory flight-safety or regulatory flight-test certification.

3.4 Single-Round Expert Validation Survey

To evaluate the operational viability of the living laboratory framework, a Single-Round Expert Validation Survey was conducted. A Coefficient of Variation ($CV \leq 20\%$) served as the diagnostic metric for professional agreement [21, 22].

3.4.1 Panel Composition and Demographics

The survey was administered to a panel of $N = 16$ subject matter experts out of 18 formally invited (87.5% completion rate). Panel members were selected based on strict expertise criteria across academia and industry in Zimbabwe:

- **Academic Experts ($n = 8$):** Engineering faculty holding PhDs in Aerospace, Mechanical, or Systems Engineering (mean experience: 17.125 years) drawn from universities hosting or establishing engineering degree programs.

- **Industrial Experts ($n = 8$):** Senior engineers and operations managers from mining, energy, agricultural technology, and aviation sectors (mean experience: 16.250 years).
- **Independence and COI:** All experts participated independently; none held financial or administrative stakes in the host institution or program accreditation outcomes.

3.4.2 Survey Instrument and Evaluation Metrics

Experts evaluated candidate living laboratory surrogates across the top clusters using two anchored Likert items (1 = Low to 5 = High):

1. **Relevance (The Bridge):** Degree to which the local asset serves as a functional pedagogical surrogate for the aerospace competency.
2. **Rigor (The Atom):** Degree to which the local asset maintains required mathematical and physical depth.

To adhere to ordinal survey data standards, results are reported using both non-parametric measures (**Medians** and **Interquartile Ranges – IQR**) and parametric metrics (**Means μ** , **Standard Deviations σ** , and **Coefficients of Variation CV**) [21].

The Coefficient of Variation was calculated using Equation 5:

$$CV = \left(\frac{\sigma}{\mu} \right) \times 100 \quad (5)$$

Following established survey methodology standards [21, 22], thresholds were defined as: $CV \leq 20\%$ indicating acceptable professional convergence, $CV \leq 10\%$ indicating high consensus, and $CV > 20\%$ indicating significant disagreement.

3.5 Ethics, Consent, Data Governance and Responsible AI

This study involved a minimal-risk expert survey and a text-mining component restricted to non-personal technical records. The authors state that the work was conducted in alignment with international ethical principles for human research and COPE standards. The following consent, privacy, copyright, and responsible-AI safeguards were applied:

1. **Data Protection and Privacy (Zero PII):** In accordance with Zimbabwe's *Cyber and Data Protection Act [Chapter 12:07]*, the diagnostic text-mining pipeline processed exclusively non-personal, technical operational failure metrics (e.g., mechanical breakdowns, electrical grid trips). No personally identifiable information (PII) or confidential records were extracted or stored.
2. **Copyright and Fair Dealing (Text Mining):** Newspaper text mining (*The Herald*, 2022–2026) complied strictly with Section 24 (*Fair Dealing for Research or Private Study*) of Zimbabwe's *Copyright and Neighboring Rights Act [Chapter 26:05]*. The pipeline extracted uncopyrightable factual occurrences and physical constants; no verbatim prose or articles are redistributed.
3. **Human Subject Ethics and Informed Consent:** Written digital informed consent was obtained from all $N = 16$ expert panelists prior to survey access. Participant identities were fully de-identified upon submission (EXP_01 to EXP_16). The unedited survey instrument and de-identified supporting documentation are archived in the replication repository (see Data Availability Statement).
4. **Responsible AI Governance and Model Provenance:** LLM interactions were executed via the official Google Vertex AI API using the Gemini 1.5 Pro foundation model. System execution logs capturing request IDs, endpoint metadata, and timestamps are archived in the replication repository (see Data Availability Statement). All AI outputs passed through mandatory Human-in-the-Loop audit gates (Gate A: Cohen's $\kappa = 0.812$; Gate B: Fleiss' $\kappa = 0.782$).

Overall, formal ethics committee review was not required.

4. Results and Discussion

4.1 Isomorphism Mapping

This section presents the results of the diagnostic text-mining of *The Herald* archive, identifying $N = 40$ discrete industrial friction points across Zimbabwe's economic sectors. These friction points were classified relative to the ten strategic priority pillars of the National Development Strategy 2 (NDS-2: 2026–2030) [1]. Sample size selection ($N = 40$) was governed by theoretical saturation (Section 3.1.3), where additional data ingestion yielded diminishing returns on new engineering physics atoms.

Extraction yielded a total repository of 109 core engineering atoms across the dataset. Table 2 presents an illustrative extract of primary friction points, detailing their associated NDS-2 pillars, aerospace isomorphisms, and constituent atoms. Note that the frequency parameter f represents the *cumulative occurrence count of required problem-solving atoms* embedded across the $N = 40$ dataset statements. Because complex failures (e.g., Friction 01: Precision Planting) concurrently require multiple physics competencies (PID control, sensor fusion, closed-loop simulation), cumulative atom frequencies naturally exceed $N = 40$.

4.2 Clustering and Weighting

The 109 identified atoms were consolidated into 15 credit-bearing curriculum clusters (C_{01} to C_{15}) to balance pedagogical structure with operational agility [4]. The Cluster Weight (ω_k) aggregates the cumulative dataset frequencies of all constituent atoms within a cluster (Equation 1). Table 3 presents the primary functional clusters.

4.3 Isomorphic Alignment and Pillar Density Modeling

Pillar Density (ρ_j) measures the degree to which curriculum clusters address industrial frictions across the ten strategic priority pillars of NDS-2 [1]. Results are summarized in Table 4.

The highest alignment densities are observed in Pillar 5 (Technology, Innovation, and Human Capital Development, $\rho_5 = 0.92$) and Pillar 2 (Inclusive Economic Growth and Structural Transformation, $\rho_2 = 0.85$). Together, Pillars 5 and 2 reflect the supply-and-demand dynamics of Zimbabwe's technical ecosystem: Pillar 5 provides digital analytical tools (supply), while Pillar 2 represents physical industrial hardware in mining, manufacturing, and processing where those solutions are absorbed (demand).

The Aggregate Alignment Coefficient (Γ) evaluates overall strategic policy alignment across all ten NDS-2 pillars:

$$\Gamma = \frac{1}{10} \sum_{j=1}^{10} \rho_j = \frac{0.62 + 0.85 + 0.81 + 0.74 + 0.92 + 0.71 + 0.68 + 0.55 + 0.64 + 0.78}{10} = \mathbf{0.730}$$

An aggregate score of $\Gamma = 0.730$ indicates strong policy alignment. While technical and industrial pillars show high saturation ($\rho_j > 0.80$), the overall distribution across all ten NDS-2 pillars demonstrates that the curriculum equips graduates to address broad domestic industrial bottlenecks, rather than restricting career outcomes strictly to a mature domestic aerospace sector. The complete expert evaluation matrix used to derive these pillar density scores is available in the replication repository (see Data Availability Statement).

Table 2. Industrial Friction Points and Aerospace Isomorphic Mapping

ID	Industrial Friction (Zimbabwe)	<i>f</i>	NDS-2 Pillar	Aerospace Isomorphism (The Bridge)	Curriculum Atoms (Examples)
01	Precision Planting: Grain loss due to manual, imprecise seed distribution.	42	4	Precision Control Laws: PID-controlled Variable Rate Application from fuel-flow avionics.	PID Control, Closed-Loop Stability, Control Simulation, HIL Testing
02	Border Security Surveillance: Cross-border smuggling, illegal mining, and poaching.	38	10	Structural Optimization: Ultra-light, high-aspect-ratio wings for long-endurance UAVs.	Induced Drag, Wing Morphing, Aspect Ratio Optimization, Aeroelasticity
03	Mining Plant Downtime: Frequent bearing and gear-train failure in primary crushers.	35	2	High-Torque Rotordynamics: Aero-engine bearing life extension and vibration damping.	Tribology, Fatigue Analysis, Vibration Monitoring, Life-Cycle Assessment
04	Grid Vulnerability: Real-time monitoring gaps in national electricity grid pylons.	32	3	Remote Asset Telemetry: High-security satellite/UAV datalinks and sensor fusion.	Sensor Fusion, RF Propagation, Data Encryption, Link Budgeting
05	Automation Repair Gap: Industry unable to repair “Black Box” imported controllers.	27	5	Modular Controller Design: Utilizing Integrated Modular Avionics (IMA) architectures.	IMA Architecture, Real-Time OS (RTOS), Embedded Systems, HW/SW Integration
06	Underground Mine Safety: GPS-denied shafts causing machinery collisions.	23	5	SLAM Navigation: Implementing LiDAR-based navigation for autonomous indoor operations.	SLAM Algorithms, Sensor Fusion, Machine Vision, Path Planning
07	Heavy Soil Plowing: Tool wear and high fuel consumption in clay soils.	21	4	Aero-Surface Interaction: Applying Blade Element Momentum (BEM) to cutting tools.	BEM Theory, Composite Matrix Design, Structural Topology, Acceleration Math

Note: *f* represents cumulative atom occurrence count across all problem statements in the dataset.

Table 3. Curriculum Clusters and Industrial Weightings (ω_k)

Index	Cluster	Constituent Atoms (Sample Units)	Weight (ω_k)
01	PHM (Predictive Health)	Tribology, NDT, Vibration Monitoring, Fatigue Analysis, Life-Cycle Assessment	163
02	ASTO (Structural Topology)	Wing Morphing, BEM, Structural Fatigue, Composites, Stress Intensity Factors	130
03	GNC (Guidance & Control)	PID Control, HIL, Closed-Loop Stability, SLAM Algorithms, Path Planning	115
04	SELC (Systems Lifecycle)	Mission Profiling, Risk Management, Integrated Logistics Support (ILS), Fleet Readiness	102
05	CFD (Fluid/Thermal)	Cavitation Modeling, Heat Transfer, Fluidics, Gas Dynamics, Boundary Layer Theory	98
06	AVIN (Avionic Integration)	Sensor Fusion, Telemetry, IMA Architecture, RTOS, Link Budgeting, Data Encryption	85
07	PROP (Propulsion Systems)	Brayton Cycle, BEM, Fuel-Flow Control, Thermal Barrier Coatings (TBC)	72
08	COMP (Computing Systems)	Machine Vision, Embedded Systems, Real-Time OS, HW/SW Integration	48

Note: Cluster Weight (ω_k) represents the cumulative frequency of constituent atoms across the $N = 40$ friction dataset.

Table 4. NDS-2 Strategic Pillar Density and Saturation Results (ρ_j)

ID (j)	NDS-2 Strategic Priority Area (Pillar)	Density (ρ_j)	Saturation Level
1	Macro-Economic Stability & Financial Sector Deepening	0.62	Moderate
2	Inclusive Economic Growth & Structural Transformation	0.85	Very High
3	Infrastructural Development & Housing	0.81	High
4	Agriculture, Food, Climate & Environment	0.74	High
5	Technology, Innovation, and Human Capital Development	0.92	Very High
6	Job Creation, Youth Entrepreneurship, Creative Industry, Sport	0.71	Moderate-High
7	Regional Development and Inclusivity through Devolution	0.68	Moderate
8	Social Development, Gender & Social Protection	0.55	Moderate
9	Image Building, International Relations and Trade	0.64	Moderate
10	Governance, Institution Building, Peace and Security	0.78	High
Aggregate Alignment Coefficient (Γ)		0.730	Strong Fit

Note: Density values represent mean instructional weights of clusters mapped to NDS-2 objectives. The unrounded aggregate score is $\Gamma = 0.728667$, reported as 0.730.

4.4 Substitution Fidelity Benchmarking (F_s)

To address physical laboratory deficits, candidate non-aerospace industrial assets (“living laboratories”) were evaluated using the Substitution Fidelity Index (F_s , Equation 4). Table 5 presents the Resource Substitution and Fidelity Matrix for primary curriculum clusters, detailing individual parameter breakdowns (Coverage Ratio, $\bar{A}$, $\bar{I}$) and 95% Confidence Intervals.

Table 5. Expanded Resource Substitution & Fidelity Matrix (RSFM) with Parameter Breakdowns

Cluster	Required Asset (RSA)	Living Lab Isomorph	Coverage	$\bar{A}$	$\bar{I}$	F_s	(95% CI)	Isomorphic Logic
PHM	Aero-Engine Test Cell	Heavy Haul Truck Telematics	1.00	0.95	0.96	0.912	[0.884, 0.938]	Identical sensor-fusion and vibration data protocols.
ASTO	High-Cycle Fatigue Rig	Vibratory Recovery Screens	0.95	0.96	0.98	0.893	[0.861, 0.922]	Mimics multi-axial mechanical oscillations of airframes.
SELC	Mission Control Center	Security Operations Center	0.92	0.95	0.98	0.857	[0.822, 0.889]	Shared system-of-systems telemetry and fleet logistics logic.
GNC	Flight Test Range	Agritech Unmanned Field Range	0.90	0.96	0.97	0.838	[0.801, 0.871]	Isomorphic PID tuning and terrain-following path planning.
CFD	Subsonic Wind Tunnel	Industrial Cooling Fluidics	0.88	0.95	0.98	0.820	[0.781, 0.854]	Shares mathematical boundary layer physics and pressure gradients.

Note: Coverage = $\sum A_{isomorph} / \sum A_{required}$; $\bar{A}$ = Mean Accessibility; $\bar{I}$ = Mean Instrumentation. Confidence intervals generated via non-parametric percentile bootstrap (2,000 iterations).

Fidelity scores for primary clusters reached $\bar{F}_s = 0.820\text{--}0.912$, demonstrating that domestic industrial infrastructure offers high fidelity for hosting fundamental aerospace engineering physics. Importantly, the F_s screening mechanism actively rejects low-fidelity assets. For instance, underground haulage vehicles possessed complete structural physics (1.00) but were rejected due to underground safety access restrictions ($\bar{A} = 0.20 \implies F_s = 0.180$). Similarly, uninstrumented machine shop lathes were rejected due to a lack of electronic telemetry ($\bar{I} = 0.15 \implies F_s = 0.135$).

4.5 Single-Round Expert Validation Survey

Survey responses were collected from $N = 16$ Zimbabwean subject matter experts (87.5% completion rate across 8 academic and 8 industrial leaders). Table 6 presents expert evaluation metrics across ordinal non-parametric (**Medians**, **IQRs**) and parametric (**Means** μ , **Standard Deviations** σ , **Coefficients of Variation** CV) distributions [21].

With Coefficients of Variation below the established 20% threshold (14.1% for both Relevance and

Table 6. Statistical Distribution of Expert Ratings and Consensus Metrics ($N = 16$)

Validation Variable	Mean (μ)	Median	IQR	Std. Dev (σ)	CV (%)
Relevance (The Bridge)	4.38	4.0	1.0	0.62	14.1%
Rigor (The Atom)	4.06	4.0	1.0	0.57	14.1%

Note: Scores evaluated on a 5-point anchored Likert scale (1 = Low to 5 = High). $CV \leq 20\%$ confirms strong panel consensus [21, 22]. De-identified individual responses are archived in the replication repository (see Data Availability Statement).

Rigor), the expert panel demonstrated strong convergence, confirming that living laboratory surrogates maintain required academic rigor while providing high regional relevance [21, 22].

4.6 Washington Accord and CDIO Accreditation Mapping

To verify that the living laboratory framework satisfies international engineering accreditation requirements, all 15 curriculum clusters were mapped directly against the 12 Washington Accord Graduate Attributes (WA1–WA12) and the Conceive-Design-Implement-Operate (CDIO) standards [3]. Table 7 presents the mapping for the eight primary functional clusters.

Table 7. Mapping of top Curriculum Clusters to Washington Accord Graduate Attributes (WA1–WA12) and CDIO Standards

Cluster	Washington Accord Attribute	CDIO Standard	Living Lab Delivery Mode
PHM	Engineering Knowledge (WA1), Problem Analysis (WA2)	CDIO Std 3 (Integrated Curriculum)	Heavy Mining Telematics / Power Turbines
ASTO	Design/Development (WA3), Tool Usage (WA5)	CDIO Std 5 (Design-Implement)	Vibratory Processing Rigs / Structural Testbeds
GNC	Complex Problem Analysis (WA2), Modern Tools (WA5)	CDIO Std 7 (Integrated Learning)	Agritech Unmanned Aerial/-Ground Systems
SELC	Teamwork (WA9), Communication (WA10), Project Mgmt (WA11)	CDIO Std 8 (Active Learning)	Integrated Security Operations Control
CFD	Investigation (WA4), Engineering & Society (WA6)	CDIO Std 4 (Intro to Engineering)	Industrial Cooling Fluidics / Pumping Infrastructure
AVIN	Modern Tool Usage (WA5), Ethics (WA7)	CDIO Std 6 (Engineering Workspaces)	Telemetry Systems / Embedded Controller Rigs
PROP	Engineering Knowledge (WA1), Sustainability (WA7)	CDIO Std 3 (Integrated Curriculum)	Hwange Power Station Thermal Turbines
COMP	Individual & Team Work (WA9), Lifelong Learning (WA12)	CDIO Std 11 (Learning Assessment)	Industrial PLC Automation / Edge Computers

Note: WA1–WA12 refer to International Engineering Alliance (IEA) Graduate Attributes.

As shown in Table 7, living laboratory surrogates fulfill core analytical, technical, and investigative competencies (WA1–WA8). Specialized professional attributes that require institutional environments (such as WA9 Individual/Team Work and WA10 Communication) are fulfilled through integrated capstone design projects and industry-partnered team internships.

5. Conclusion

This research establishes a validated isomorphic framework for aerospace engineering education in emerging economies, contributing a data-driven methodology that enables a transition in curriculum architecture from a resource-dependent model to one driven by atomic mapping and Generative Artificial Intelligence. Applied within the context of Zimbabwe, the framework deconstructs global aerospace engineering benchmarks (Washington Accord Graduate Attributes WA1–WA12 and CDIO standards) into irreducible engineering “atoms” and anchors these atoms within local industrial “living laboratories”—capitalizing on physical equivalences such as the thermodynamic parity between Hwange Thermal Power Station turbines and aerospace gas turbine cycles. In this manner, national industrial friction points are transformed into high-rigor pedagogical assets.

The resulting curriculum architecture was evaluated against the ten strategic priority pillars of Zimbabwe’s National Development Strategy 2 (NDS-2: 2026–2030), yielding an Aggregate Alignment Coefficient of $\Gamma = 0.730$. Framework viability was further validated through a Single-Round Expert Validation Survey ($N = 16$, 87.5% completion rate), demonstrating strong professional consensus across both Industrial Relevance (Median = 4.0, $\mu = 4.38/5.0$, CV = 14.1%) and Academic Rigor (Median = 4.0, $\mu = 4.06/5.0$, CV = 14.1%), alongside high Equipment Substitution Fidelity ($F_s = 0.912$, 95% CI: [0.884, 0.938]). Rather than serving as an autonomous accreditation mechanism or fully demonstrated classroom intervention, these findings confirm that the framework provides a transparent, data-driven decision-support template for emerging economies to navigate infrastructural barriers and co-design technically rigorous, industry-aligned engineering curricula.

Limitations and Future Research Directives

The contributions of this study must be interpreted within its methodological boundaries:

1. **Corpus Bounds:** Friction extraction relied on an audited state-archive screening pool ($N = 1,420$ public records, 2022–2026) yielding $N = 40$ core industrial friction points. While cross-verified against official regulatory bulletins (ZERA, OAG, Parliamentary notices), future iterations should incorporate automated real-time ingestion from broader multi-sector maintenance logs and enterprise asset management systems (see Data Availability Statement).
2. **LLM Architecture Scope:** The diagnostic engine was evaluated using Google Gemini 1.5 Pro. Comparative benchmarking across alternative architectures (e.g., GPT-4o, Claude 3.5 Sonnet) and open-weight domain-adapted models remains an important area for future investigation.
3. **Implementation Horizon:** As a validated decision-support framework and proof-of-concept template, this study evaluates structural feasibility and expert-perceived plausibility. Future work should pilot a multi-year longitudinal implementation across participating universities in Zimbabwe to empirically measure graduate learning outcomes, Washington Accord competency acquisition, and workplace integration.

Appendix A: GenAI Isomorphic Prompting and Execution Protocol

This appendix provides the computational and prompt engineering specifications required to replicate the diagnostic text-mining pipeline described in the methodology.

A.1 LLM Configuration and Execution Environment

All text-mining and isomorphic extraction runs were executed via the Google Vertex AI API using the Gemini 1.5 Pro model and the parameters specified in Table 8.

Table 8. Generative AI Execution Hyperparameters and Environment

Parameter	Configuration Value / Specification
Model Architecture	Gemini 1.5 Pro (Vertex API)
Execution Period	February 15, 2026 – March 10, 2026
Temperature (T)	0.00 (Deterministic / Minimum-Entropy Mode)
Top- P Sampling	0.95
Max Output Tokens	2,048 tokens per API call
Context Window	Full corpus ingestion ($N_{\text{screened}} = 1,420$ total records)
Replication Protocol	3 independent runs per document chunk (88.4% atom overlap)
Inter-Rater Reliability	Gate A (Cohen’s $\kappa = 0.812$); Gate B (Fleiss’ $\kappa = 0.782$)

A.2 System Prompt Template (Domain-Bounded Heuristic Steering)

The System Prompt imposes *Domain-Bounded Heuristic Steering* on the model, restricting its reasoning space to accredited engineering physics and Zimbabwe’s National Development Strategy 2 (NDS-2: 2026–2030) priority areas [1].

SYSTEM PROMPT:

You are an expert Systems Engineer and Curriculum Architect specializing in Aerospace Engineering and Industrial Isomorphisms in emerging economies. Your role is to perform high-recall diagnostic text-mining on industrial failure logs and decompose them into fundamental, domain-agnostic engineering physics principles (“atoms”).

Core Operational Rules:

1. **No Hallucination / Strict Physical Grounding:** You must only extract engineering principles that are mathematically and physically verifiable. Do not invent non-existent equations or fictitious mechanical failure modes.
2. **Atomic Decomposition:** Deconstruct every complex failure into irreducible physics/math units (e.g., Navier-Stokes boundary conditions, closed-loop PID control, Fast Fourier Transform vibration spectra, structural fatigue tensors).
3. **Theoretical Isomorphism Mapping:** Map each extracted industrial atom directly to a corresponding high-rigor aerospace application (e.g., map mining crusher bearing friction to aero-engine turbopump rotordynamics).
4. **Strategic Steering:** Align every mapped friction item against at least one of the 10 Strategic Priority Pillars of Zimbabwe’s National Development Strategy 2 (NDS-2: 2026–2030) and the Washington Accord Graduate Attributes (WA1–WA12).
5. **JSON Output Standard:** Return all outputs strictly in structured JSON format following the schema provided.

A.3 User Prompt Template (Friction Ingestion and Extraction)

The User Prompt supplies the raw, time-stamped text chunks extracted from *The Herald* newspaper archive (2022–2026) and instructs the model to execute isomorphic extraction.

USER PROMPT TEMPLATE:

Context Input:

Below is a text batch containing documented industrial, infrastructure, and mechanical failure events extracted from Zimbabwean national records:

[INSERT TEXT BATCH HERE]

Task Instructions:

1. Identify discrete **Industrial Friction Points** (mechanical breakdowns, sensor losses, structural wear, thermal outages, logistics failures).
2. For each identified friction point, perform functional decomposition to extract 3 to 5 fundamental **Aerospace Curriculum Atoms** (irreducible engineering science principles).
3. Formulate the **Aerospace Isomorphism (The Bridge)** explaining how this local non-aerospace asset can serve as a functional surrogate for an aerospace laboratory module.
4. Tag the relevant **NDS-2 Strategic Priority Pillar** (1 through 10).

Required JSON Output Schema:

```
{
  "frictions": [
    {
      "friction_id": "STRING (e.g., FRIC_01)",
      "industrial_description": "STRING",
      "nds2_pillar_id": "INTEGER (1-10)",
      "aerospace_isomorphism": "STRING",
      "extracted_atoms": [
        "STRING (Atom 1)",
        "STRING (Atom 2)",
        "STRING (Atom 3)"
      ]
    }
  ]
}
```

A.4 Human-in-the-Loop (HITL) Adjudication and Audit Protocol

All candidate JSON outputs generated by Gemini 1.5 Pro were subjected to a two-tier human expert audit prior to quantitative indexing ($\omega_k, \rho_j, \Gamma, F_s$):

- **Gate A (Academic Expert Audit – Rigor Gate):** Two senior engineering academics independently reviewed candidate atoms to confirm mathematical depth, deleting hallucinatory atoms or overly generic descriptions (Cohen’s $\kappa = 0.812$).
- **Gate B (Industry Expert Audit – Relevance Gate):** Panel of $N = 16$ domain experts evaluated the practical fidelity of proposed non-aerospace living laboratory assets (F_s) and NDS-2 policy mapping (Fleiss’ $\kappa = 0.782$).

Table 9 illustrates an anonymized sample of raw LLM outputs versus expert-adjudicated final outputs.

Table 9. Sample Raw LLM Output vs. Expert-Adjudicated Final Output

Friction Event	Raw LLM Extraction	Expert Adjudicated Out-put	Audit Verdict
Hwange Thermal Station Turbine Vibration (Friction 03)	Extracted Atoms: 1. Rotordynamics 2. Tribology 3. <i>Quantum Phase Shift (Hallucination)</i> 4. FFT Vibration Analysis	Extracted Atoms: 1. Rotordynamics 2. Tribology 3. FFT Vibration Analysis	Purged: Quantum Phase Shift removed (Gate A Rigor Gate).
Grain Loss in Precision Seeders (Friction 01)	Isomorphism: “Seeder can replace an actual flight control tower.”	Isomorphism: “Seeder fuel-flow avionics map to closed-loop PID control laws.”	Revised: Reframed to precise PID control isomorphism (Gate B Relevance Gate).

Author contributions

- Piwai N. Chikasha: Conceptualization, Methodology, Software (GenAI Prompt Engineering), Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Visualization.
- Kemlall Ramdass: Supervision, Validation, Review & Editing.
- The authors reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Funding statement

The authors received no specific funding for this work.

Conflict of interest statement

The authors declare no conflicts of interest.

Open data statement

All research datasets, raw extraction payloads, API execution logs, anonymized rater-by-item matrices, expert survey instruments, and executable Python analytical code supporting the conclusions of this article are permanently archived in the Zenodo open-access repository under persistent DOI: 10.5281/zenodo.21914900.

Reproducibility statement

Information on how to reproduce this research is archived in the Zenodo open-access repository under persistent DOI: 10.5281/zenodo.21914900.

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