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FRAM-FDM: A Quantitative Safety-II Framework for Runway Overrun Risk Assessment Using Functional Resonance Analysis and Flight Data Monitoring

Christianne Reiser
Embraer (Brazil)
Emilia Villani
Instituto Tecnológico de Aeronáutica (ITA)
Moacyr Machado Cardoso Junior
moacyr@ita.br

Instituto Tecnológico de Aeronáutica

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Abstract

Runway overruns rank among the most frequent and economically significant accident categories in commercial aviation, typically arising from the nonlinear combination of performance variabilities during the approach and landing phases. Existing risk models either rely on historical accident databases or treat runway overrun precursors as independent binary events, overlooking the interactive dynamics of everyday flight operations. This paper introduces FRAM-FDM, a quantitative methodology that integrates the Functional Resonance Analysis Method (FRAM) with Flight Data Monitoring (FDM) to assess and manage operational runway overrun risk from a Safety-II perspective. The methodology deconstructs the approach-and-landing sociotechnical system into functional couplings, quantifies their output variabilities using real flight data recorder (FDR) data, and aggregates them through: (i) linear regression combined with Monte Carlo Simulation (MCS) for probabilistic fleet-level risk estimation; (ii) logistic regression with odds-ratio analysis to rank precursor influence; and (iii) metadata-driven scenario simulation in the FRAM Model Visualiser (FMV). Applied to a case study of 110 landings — including one overrun event — from a business jet fleet, the framework identifies airspeed excess at the runway threshold and brake application profile as the dominant risk contributors, demonstrates synergistic risk amplification when multiple variabilities co-occur, and provides actionable guidance for training and procedure reinforcement. FRAM-FDM advances FRAM toward a fully quantitative, data-driven implementation and aligns FDM programmes with Safety-II principles.

1 Introduction

Runway overruns (ROs) occur when an aircraft rolls beyond the end of the runway surface during landing. They constitute the single most frequent accident category in commercial aviation, accounting for a disproportionate share of hull losses, fatalities, and infrastructure damage [1]. The EUROCONTROL/Flight Safety Foundation Global Action Plan for the Prevention of Runway Excursions (GAPPRE) estimates that ROs involve a complex interaction among airlines, aerodromes, aircraft manufacturers, air navigation service providers, and meteorological agencies, making their prevention inherently systemic [2].

Current Flight Data Monitoring (FDM) algorithms detect individual precursors — unstable approaches, long touchdowns, late or insufficient use of deceleration devices — by comparing parameters against pre-defined thresholds. Although technically robust, this event-centric strategy treats precursors as independent occurrences and leaves the cumulative, interactive risk of the monitored fleet unquantified. Most machine-learning and Bayesian-network models in the literature (e.g. [3]–[10]) either require a prior binary categorisation of variables, rely on historical accident databases, or model only a subset of the landing sequence, ignoring the deceleration run after touchdown.

The Functional Resonance Analysis Method (FRAM), developed by Hollnagel [11], offers an alternative systemic lens aligned with the Safety-II paradigm [12]. Rather than tracing failures to discrete causes, FRAM models the variability of everyday performance: things go right and wrong for the same reasons,

and unacceptable outcomes emerge when normally minor variabilities resonate. Despite growing use of FRAM in aviation [13, 14], all existing applications remain qualitative or semi-quantitative, and none has previously produced a full probabilistic fleet-level risk estimate grounded in real flight data.

Earlier steps toward a quantitative FRAM-FDM formulation were reported in [33] and [34]. Reiser et al. [33] applied a customised FRAM to 632 landings of a jet fleet using logistic regression as the sole aggregation mechanism, focusing on the flare and brake phases (50 feet AGL to 30 knots groundspeed) and identifying the brake application profile as the dominant contributor. A subsequent investigation [34] extended the approach to 288 landings and introduced Monte Carlo Simulation (MCS) for probabilistic risk estimation, concentrating on the flare phase and long-touchdown outcomes. Complementary findings were reported in [35]. The present work unifies and substantially extends this body of work into a single, integrated probabilistic framework spanning the complete approach-and-landing sequence.

Specifically, this paper introduces a methodology that: (i) models the entire approach-and-landing sequence as a FRAM network comprising 27 functions from decision height (500 feet AGL) to taxi speed; (ii) quantifies each function's output variability from real FDR data using novel FDM metrics for flare technique, brake effectiveness, and runway surface interaction; (iii) aggregates variabilities through linear regression combined with MCS, logistic regression with odds-ratio analysis, and metadata-driven FMV scenario simulation; and (iv) manages variability by providing actionable training and procedural recommendations grounded in the quantitative outputs. The framework is validated on a dataset of 110 landings from a business jet fleet, including one overrun event — the first FRAM model to comprehensively address all known precursors of a specific accident type using real flight data and deliver a full probabilistic fleet-level risk estimate.

2 Theoretical Background

2.1 Safety-I vs. Safety-II in Aviation

The Safety-I paradigm defines safety as the minimisation of unacceptable outcomes, analysing deviations from normal functioning as the proximate cause of accidents. Safety-II, articulated by Hollnagel et al. [12], proposes instead that performance variability is ubiquitous and necessary: systems succeed because individuals continuously adjust their actions to match variable conditions. Both failures and successes share the same performance substrate. FRAM-FDM operationalises this vision by providing the quantitative apparatus to connect everyday FDM data to a systemic risk estimate.

2.2 The Functional Resonance Analysis Method

FRAM rests on four core principles [11]: (i) equivalence of successes and failures; (ii) performance adjustments as Efficiency-Thoroughness Trade-Offs (ETTOs); (iii) emergence of outcomes from resonating variabilities rather than linear causation; and (iv) context-specific functional dependencies. A FRAM model describes the system as a set of functions, each characterised by six aspects: Input (I),

Output (O), Precondition (P), Resource (R), Control (C), and Time (T). Functions are coupled when the output of one serves as an aspect of another, creating a network through which variability propagates.

2.3 Runway Overrun Mechanics and Precursors

A landing overrun results from insufficient runway remaining when the aircraft reaches taxi speed. The final remaining distance is determined by runway length, touchdown point, groundspeed at touchdown, and longitudinal deceleration rate. Flight Safety Foundation guidelines classify a landing as critical when the remaining distance is less than 2,500 feet at 80 knots groundspeed [17] — approximately 400 feet at 30 knots assuming constant deceleration of ≈ 0.11 g. This threshold is used as the outcome boundary in the present study. The risk increases nonlinearly when multiple precursors co-occur: each 10 feet of excess height at the threshold adds ≈ 200 feet of air-distance; each 10% of excess approach speed increases the unfactored landing distance (ULD) by ≈ 20%; each second of delay in applying deceleration devices adds ≈ 200 feet to the stopping distance [17].

2.4 Related Work and Positioning of This Study

Systematic literature reviews of FRAM in aviation [13, 14] identify the method as widely used for retrospective accident analyses and prospective risk assessment. Quantitative enhancements include the Resilience Analysis Matrix [18], Monte Carlo evolution of FRAM [19], and FRAM + Bayesian Network integration [20]. Runway overrun models fall into three categories: (1) post-hoc analysis of historical accident databases [21–23]; (2) machine-learning models for real-time prediction [24–27]; and (3) hazard-combination risk models using Bayesian networks, copula regression, or logistic/linear regression on flight data [3–10, 28].

Within category (3), the most directly related antecedents are three prior publications from this research group. Reiser et al. [33] published a customised FRAM applied to 632 landings using logistic regression, covering the flare-and-brake phase and identifying the brake application profile as the dominant contributor. Reiser et al. [34] extended the approach to 288 landings, introduced MCS for probabilistic risk estimation, and focused on the flare phase and long-touchdown outcomes. Reiser et al. [35] reported complementary findings combining FRAM with FDM metrics across a multi-fleet dataset. The present work builds explicitly on this foundation and extends it in four substantive directions:

- Scope extension — the FRAM model is expanded from the flare-and-brake phase (50 feet AGL → 30 knots) to the full approach-and-landing sequence (500 feet AGL → 30 knots), incorporating 27 functions versus the original 9, and including all known RO precursors (flight path, airspeed, configuration, vertical speed, flare technique, and deceleration).
- Probabilistic risk quantification — a multiple linear regression + normal copula + Monte Carlo Simulation module (n = 10,000) is added, producing a fleet-level probability of critical landing (R^2_{adj} = 0.925), compared to the qualitative risk classification of [33].
- Quantitative scenario simulation — the FRAM Model Visualiser (FMV) metadata facility is integrated, embedding regression equations as key-value formulas in functional couplings and enabling

conditional scenario branching via the "Activate" key — a capability absent in [33].

- Accident reconstruction — the actual overrun event in the dataset is reconstructed and its causal chain is quantitatively traced through the FRAM network, demonstrating the synergistic resonance of co-occurring variabilities; [33] did not include an overrun event in its sample.

No existing study — including [33–35] — applies FRAM to the full approach-and-landing sequence, covers the complete post-touchdown deceleration run, delivers a probabilistic fleet risk estimate grounded in real flight data, and adopts a Safety-II distribution-level perspective on FDM data simultaneously. Table 1 summarises the positioning of FRAM-FDM relative to the most relevant prior works.

Table 1
Positioning of this work relative to selected prior studies

Study	FRAM	Real FDR Data	Full Landing Run	Safety-II	Quantitative Risk
Patriarca et al. [19]	✓	✗	✗	Partial	MCS
Oliveira et al. [20]	✓	✗	✗	Partial	BN
Calle-Alonso et al. [3]	✗	✓	✗	✗	BN
Alnasser & Czado [8]	✗	✓	✗	Partial	Copula
Li et al. [9]	✗	✓	Partial	Partial	ML
Reiser et al. [33] (2024)	✓	✓	Partial	Partial	Logistic reg.
This work (FRAM-FDM)	✓	✓	✓	✓	**MCS + LR + FMV**

3 The FRAM-FDM Methodology

FRAM-FDM is a customised, quantitative FRAM comprising four steps that map onto the traditional FRAM process while introducing data-driven enhancements at each stage. The workflow is iterative: outputs of Step 3 inform the refinement of the functional model in Step 1. Figure 1 illustrates the four-step workflow.

3.1 Step 1 – Function Identification and Description

The sociotechnical system is decomposed into 27 functions representing tasks required to produce the landing outcome. Each function is characterised by six FRAM aspects (I, O, P, R, C, T) and classified as human, technological, or organisational. The initial model is constructed from expert knowledge and Standard Operating Procedures (SOPs), subsequently refined by the empirical correlation analysis in Step 3. Compared to the 9-function model of [33], which covered only the flare and brake phases, the present model extends coverage to the full approach-and-landing sequence from 500 feet AGL.

3.2 Step 2 – Performance Variability Characterisation via FDM

Flight data are decoded from ARINC 717 FDR binary files into 8-sps time-series tables processed by R routines [38]. Three novel FDM metrics, absent in [33], are introduced: (i) flare technique metrics — the area under the time-curve of TLA and pitch attitude during the flare phase (50 feet to touchdown), correlating with touchdown point ($\rho = 0.53$) and vertical speed at touchdown ($\rho = 0.69$); (ii) brake application index — arithmetic mean of brake pedal position normalised by groundspeed, encoding timing and magnitude of pedal application; and (iii) runway surface condition index — ratio of actual to designed brake pressure averaged over the landing run.

3.3 Step 3 – Variability Aggregation

Three complementary analytical modules aggregate variabilities into system-level risk estimates, extending the single-module logistic regression of [33]. Step 3a: a multiple linear regression model is fitted to remaining distance at 30 knots as the dependent variable; inter-predictor correlations are modelled by a normal copula; Monte Carlo integration over 10,000 simulated landings estimates the probability of a critical landing (remaining distance < 400 feet). Step 3b: a logistic regression model quantifies each precursor's influence on long-touchdown risk through Odds Ratios (ORs) — a methodological step that follows directly from [33], here applied to the approach sequence. Step 3c: FMV metadata simulation embeds regression equations as key-value formulas within FRAM functional couplings, enabling interactive scenario exploration and conditional branching via the "Activate" key.

3.4 Step 4 – Variability Management

The MCS-derived risk probability benchmarks the fleet and tracks the effect of interventions over time. Logistic regression ORs prioritise which precursors to address in training or procedures. FMV scenario simulations quantify the marginal benefit of specific operational changes, guiding cost-effective risk reduction strategies.

4 Case Study: Runway Overrun Risk Assessment

4.1 Dataset and Context

The dataset comprises 110 landings performed by a business jet fleet equipped with wheel brakes as the sole deceleration device (no thrust reverser, no ground spoilers, no autobrake) — the same fleet type studied in [33]. One of the 110 landings resulted in a runway overrun, an event not present in the 632-landing dataset of [33]. Flight data were decoded from ARINC 717 FDR files at 8 sps; an external database of ≈ 23,000 runways provided geometrical and infrastructure data (threshold coordinates, elevation, length, ILS/PAPI availability) for each landing.

4.2 Step 1 – FRAM Model

Twenty-seven functions were identified across the approach phase (purple), landing phase (blue), flare (teal), and deceleration run (amber). Entry functions include "To Approach" (triggered at 500 feet AGL) and background functions for runway infrastructure and environmental conditions. Exit functions are "To Taxi" (acceptable outcome, remaining distance ≥ 400 feet) and "To Taxi, if possible" (critical landing, remaining distance < 400 feet). The complete FRAM-FDM functional network is presented in Fig. 4 (Section 4.4.3).

4.3 Step 2 – Performance Variability Characterisation

Key findings from the variability characterisation of the 110 landings are summarised in Fig. 2. Panel (a): 75% of landings crossed the 50-feet mark above Vref, and 28% exceeded Vref + 5 knots. Panel (b): 89% touched down beyond the 1,000-feet aiming point (lognormal distribution). Panel (c): the median brake pedal application index was 44% — consistent with the ≈ 47% median reported in [33] for the same fleet type — with a negative correlation with runway length ($\rho = -0.44$), confirming an ETTO adaptive behaviour. Panel (d): 6 of 110 landings (5.5%) fell below the 400-feet critical threshold, including one actual overrun.

4.4 Step 3 – Variability Aggregation

4.4.1 Risk Quantification via Monte Carlo Simulation

The best-subset linear regression for remaining distance achieved $R^2_{adj} = 0.9254$ with four regressors: longitudinal deceleration ($\beta = 9{,}246.54$, $p < 2\times10^{-16}$), touchdown point ($\beta = -1.075$, $p = 6.3\times10^{-14}$), groundspeed at touchdown ($\beta = -56.22$, $p < 2\times10^{-16}$), and runway length ($\beta = 0.992$, $p < 2\times10^{-16}$). A normal copula was fitted to account for inter-predictor correlations (e.g. $\rho = -0.16$ between deceleration and runway length; $\rho = 0.46$ between touchdown point and runway length). Best-fit parametric distributions were: longitudinal deceleration ~ Weibull (shape = 3.563, scale = 0.221); touchdown point ~ Lognormal ($\mu = 7.245$, $\sigma = 0.263$); groundspeed at touchdown ~ Lognormal ($\mu = 4.458$, $\sigma = 0.084$); runway length ~ Lognormal ($\mu = 8.671$, $\sigma = 0.274$). The MCS ($n = 10{,}000$) produced the distribution shown in Fig. 3, with 7.1% of simulated landings below the critical 400-feet threshold (median remaining distance: 2,741 feet). The R^2_{adj} of 0.925 represents a substantial improvement over the R^2_{adj} of 0.25–0.34 reported in [33], reflecting the richer predictor set and the linear (rather than logistic) regression on the continuous outcome variable.

4.4.2 Precursor Influence Identification via Logistic Regression

The logistic regression for critical touchdown point (> 1,000 feet from threshold) yielded the odds ratios summarised in Table 2. For each additional knot of ΔVref at 50 feet AGL, the probability of a long touchdown increases by approximately 113.5% (OR = 2.135). Height at the runway threshold (OR = 1.845, $p = 0.021$) is the most statistically significant predictor. Headwind (OR = 0.834) and crosswind (OR =

0.728) exert protective effects. The model achieved $R^2adj = 0.702$ (Pearson) / 0.805 (Nagelkerke). In contrast to [33], where the brake application profile was identified as the most influential predictor of the system output (remaining distance), the present logistic model targets the touchdown point specifically, and the most influential approach-phase predictor is airspeed excess — a finding that extends and complements [33] by capturing upstream precursors invisible to the original model.

Table 2
Logistic regression results: predictors of critical touchdown point (> 1,000 feet from threshold)

Predictor	Coefficient	Odds Ratio	OR Interpretation	p-value
Height at threshold (ft)	0.612	1.845	↑ 84.5% per ft	0.021
Vertical speed at 50 ft (ft/s)	−0.000018	1.000	≈ 0	0.998
Pitch area (deg·s)	0.156	1.169	↑ 16.9%	0.174
Thrust area (deg·s)	0.080	1.083	↑ 8.3%	0.083
ΔVref at 50 ft (kt)	0.759	2.135	↑ 113.5% per kt	0.102
Reference speed Vref (kt)	0.096	1.101	↑ 10.1%	0.794
Crosswind (kt)	−0.318	0.728	↓ 27.2% per kt	0.303
Headwind (kt)	−0.182	0.834	↓ 16.6% per kt	0.115
Runway length (ft)	0.000447	1.000	↑ 0.045% per ft	0.419

4.4.3 Scenario Simulation via FMV Metadata and FRAM Network

Linear regressions for three technological sub-functions — "To Touchdown" ($R^2adj = 0.754$), "To Decelerate the Aircraft" ($R^2adj = 0.814$), and "To Stop the Aircraft" ($R^2adj = 0.925$) — were embedded as FMV metadata formulas. The conditional "Activate" key triggers the "Taxi, if possible" exit function only for critical landings (remaining distance < 400 feet). The complete 27-function FRAM-FDM network is presented in Fig. 4. This FMV-based scenario simulation capability represents a methodological advance over [33], which used the FRAM Model Visualiser only for diagram visualisation without quantitative metadata.

Simulation of the actual overrun event identified the following causal chain: the aircraft crossed the threshold 8 knots above Vref; it touched down long over a contaminated runway; brake application was initially light (standard deceleration profile, consistent with the ≈ 47% median reported in [33]); an 18-knot tailwind compounded the excess kinetic energy. FMV simulation confirmed that: (a) the same conditions on a dry runway would not have produced a critical landing; (b) crossing at Vref instead of Vref + 8 knots would still have resulted in a critical but non-overrunning landing; and (c) aggressive brake application

from wheel spin-up would have been sufficient to avoid the critical outcome — in alignment with the dominant role of the brake profile identified in [33].

4.5 Step 4 – Variability Management

The quantitative outputs translate directly into actionable risk management measures. Speed control on approach is the most operationally controllable precursor in the extended model (OR = 2.135 per knot): a 5-knot reduction in threshold crossing speed reduces long-touchdown probability by approximately 57%. FMV simulations confirm that immediate, maximum-effort brake application from wheel spin-up is the most effective single intervention under adverse conditions — reinforcing the central finding of [33] and extending it with quantified scenario analysis. Enhanced crew training on runway surface condition reporting interpretation (GRF/RWYCC) is also recommended, as the overrun analysis suggests the crew applied a standard deceleration profile without recognising the contaminated runway state.

5 Discussion

5.1 Advances Over Existing Approaches

FRAM-FDM makes four substantive advances over the prior literature, including its direct predecessor [33]. First, it is the first study to model the full approach-and-landing sequence — including the post-touchdown deceleration run — within a single unified framework, compared to the flare-and-brake scope of [33] and the touchdown-only or approach-only scope of [3–10, 24–27]. Second, FRAM-FDM explicitly represents interactive couplings among precursors as functional dependencies, capturing synergistic risk amplification that is missed by independent-precursor analyses including [33]. Third, the MCS-based probabilistic risk estimate — absent in [33] — provides a fleet-level benchmark that safety managers can track over time and use to evaluate the impact of interventions. Fourth, the FMV metadata facility enables visual, interactive scenario exploration, bridging quantitative modelling and operational decision-making in a way not available in [33].

The brake application profile identified as the dominant contributor in [33] is confirmed here as a critical intervention lever (FMV simulations show that 100% brake from wheel spin-up is sufficient to avoid criticality in most adverse scenarios). The extended model additionally reveals that airspeed control during approach is the most actionable upstream precursor — a finding only accessible because the present model covers the full approach phase.

5.2 Interpretation of Findings

Several predictors in the logistic regression show strong ORs but p-values > 0.05, reflecting the limited sample size (110 landings) and the rarity of critical touchdowns. The R^2adj values of 0.70–0.81 are nevertheless substantial for a complex sociotechnical phenomenon. The finding that height at the runway threshold (OR = 1.845) is a significant predictor — even though 81% of landings already cross below the recommended 50 feet AGL — illustrates the ETTO concept: crews are systematically

displacing their approach geometry to extend the available runway margin, a Safety-II adaptation that partially compensates for the observed tendency to fly fast approaches.

5.3 Limitations

Principal limitations: (a) sample size — 110 landings with a single overrun event constrains statistical power; (b) fleet specificity — the aircraft lacks thrust reversers, ground spoilers, and autobrake, limiting direct generalisation to other fleet types; (c) organisational and environmental functions are modelled as background constants rather than active variability sources; and (d) pilot decision-making during the approach — particularly the go-around decision — was not quantitatively modelled.

5.4 Future Work

Extensions include: applying FRAM-FDM to hard landings, runway veer-offs, and tail-strike events; integrating STPA [31] to complement variability analysis with constraint-based hazard identification; formally modelling the "To Evaluate the Approach" function (go-around decision) via the Perceptual Cycle Model (PCM) [30]; and expanding the dataset to multi-fleet, multi-operator samples to consolidate OR estimates and improve statistical power. Applying the method to fleets with thrust reversers, ground spoilers, or autobrake is also a direct extension, requiring only the addition of the corresponding FRAM functions and FDM metrics.

6 Conclusion

This paper introduced an extended FRAM-FDM methodology that integrates FRAM with FDM to assess runway overrun risk from a Safety-II perspective. Building on an initial logistic-regression-only formulation published in The Aeronautical Journal [33], the present work adds MCS-based probabilistic risk quantification, copula-modelled predictor dependencies, FMV metadata-driven scenario simulation, and extends the scope from the flare-and-brake phase to the full approach-and-landing sequence. Applied to 110 landings including one overrun event, the framework demonstrated: (1) a measurable critical-landing probability of 7.1% (MCS, n = 10,000); (2) airspeed excess at the 50-feet mark as the most operationally controllable upstream precursor (OR = 2.135 per knot); (3) aggressive brake application from wheel spin-up as the most effective single intervention — confirming the central finding of [33]; and (4) the overrun resulted from the simultaneous co-occurrence of excess speed, long touchdown, wet or contaminated runway, and tailwind — a combination undetectable by independent FDM event algorithms but captured by the FRAM functional coupling structure. FRAM-FDM advances FRAM toward a fully quantitative, probabilistic, data-driven implementation and aligns FDM programmes with Safety-II principles.

Declarations

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Author contributions (CRediT)

Christianne Reiser: Conceptualisation, Methodology, Software (R routines), Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Visualisation. Emilia Villani: Conceptualisation, Supervision, Writing – Review & Editing, Project Administration. Moacyr Machado Cardoso Jr.: Conceptualisation, Supervision, Writing – Review & Editing.

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Data availability

Flight data were provided by the aircraft operator under a confidentiality agreement and cannot be shared publicly. The runway infrastructure database is available from commercial providers. The R analysis scripts and the FRAM-FDM model files are available from the corresponding author upon reasonable request.

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Figures

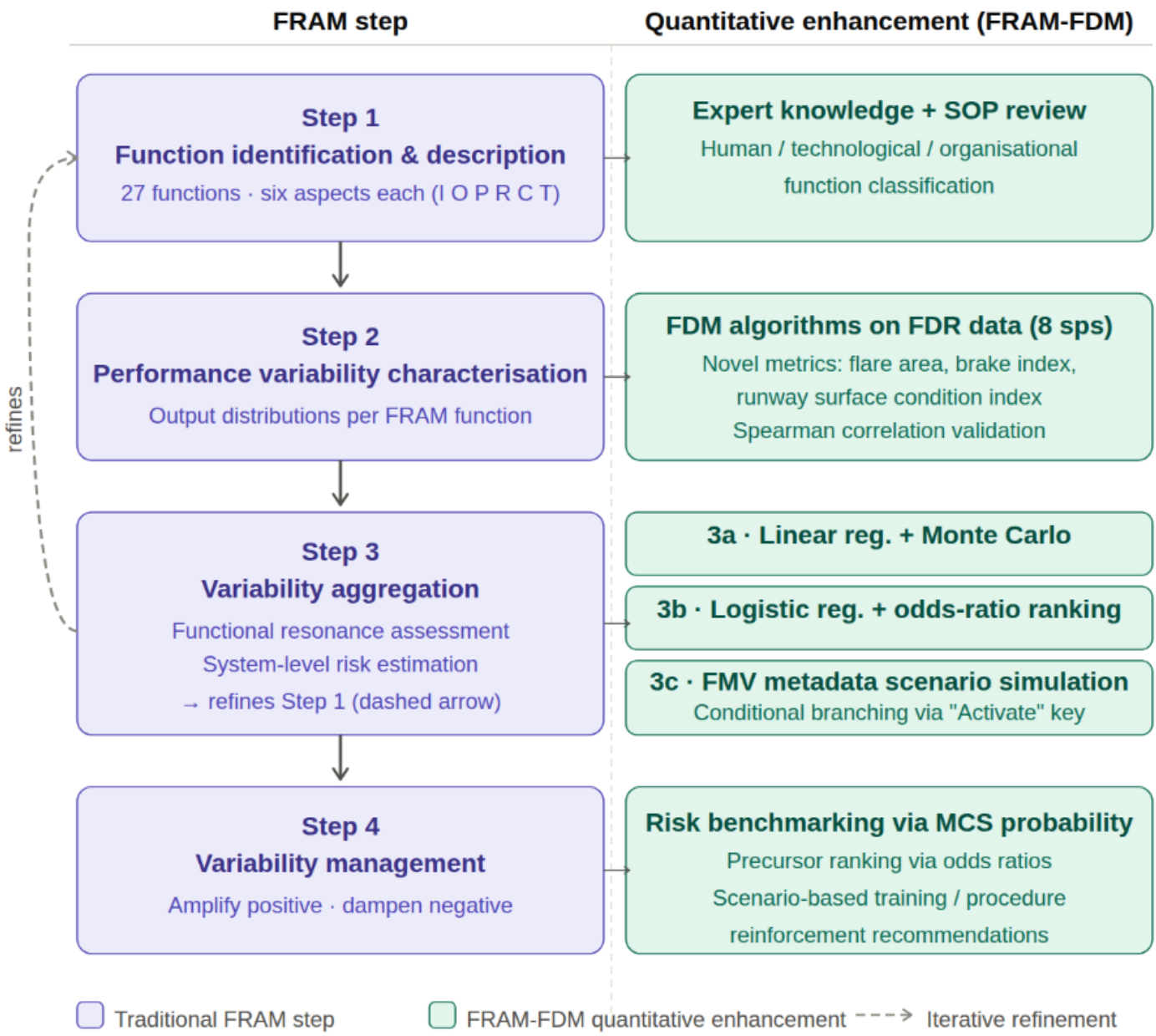


Figure 1

FRAM-FDM four-step workflow. Traditional FRAM steps (purple) are paired with quantitative enhancements (teal). The dashed feedback arrow from Step 3 back to Step 1 represents iterative model refinement as empirical correlation analysis validates and adjusts the functional structure

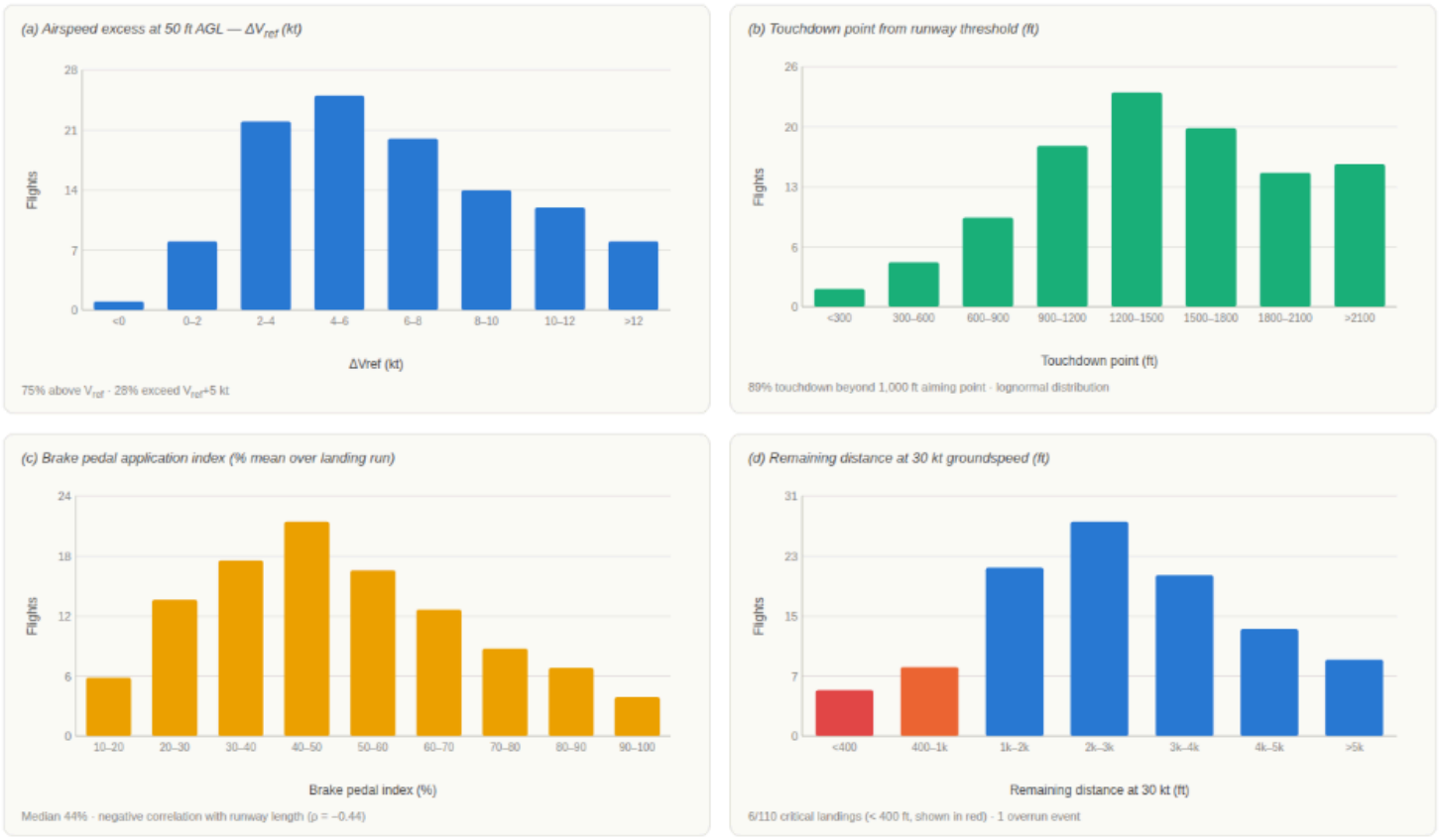


Figure 2

Performance variability distributions for key FRAM function outputs across the 110-landing dataset. (a) Airspeed excess ΔVref at 50 feet AGL; (b) touchdown point from runway threshold (lognormal distribution); (c) brake pedal application index — median 44%, consistent with Reiser et al. [33]; (d) remaining distance at 30 knots — critical landings (< 400 feet) in red, near-critical in orange

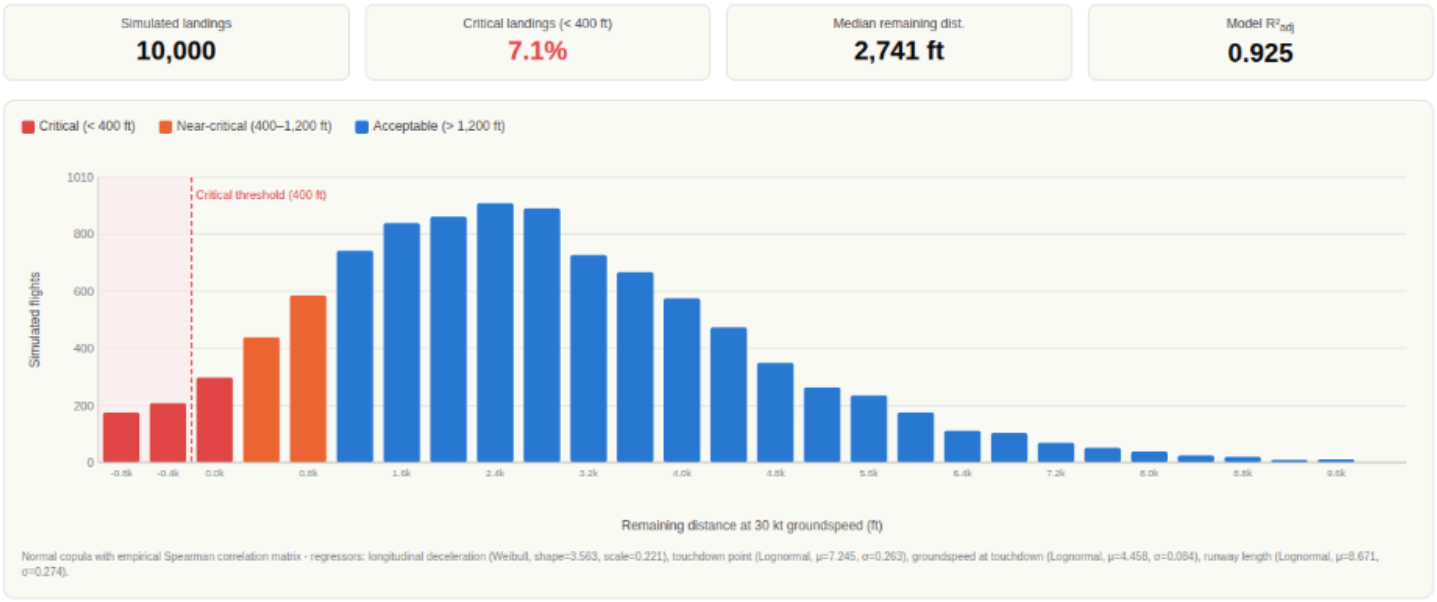


Figure 3

Monte Carlo Simulation results (n = 10,000 simulated landings). Distribution of remaining runway distance at 30 knots groundspeed. Red bars: critical zone (< 400 feet); orange bars: near-critical (400–1,200 feet); blue bars: acceptable (> 1,200 feet). KPI cards show the estimated critical-landing rate (7.1%), median remaining distance (2,741 feet), and model R²adj (0.925)

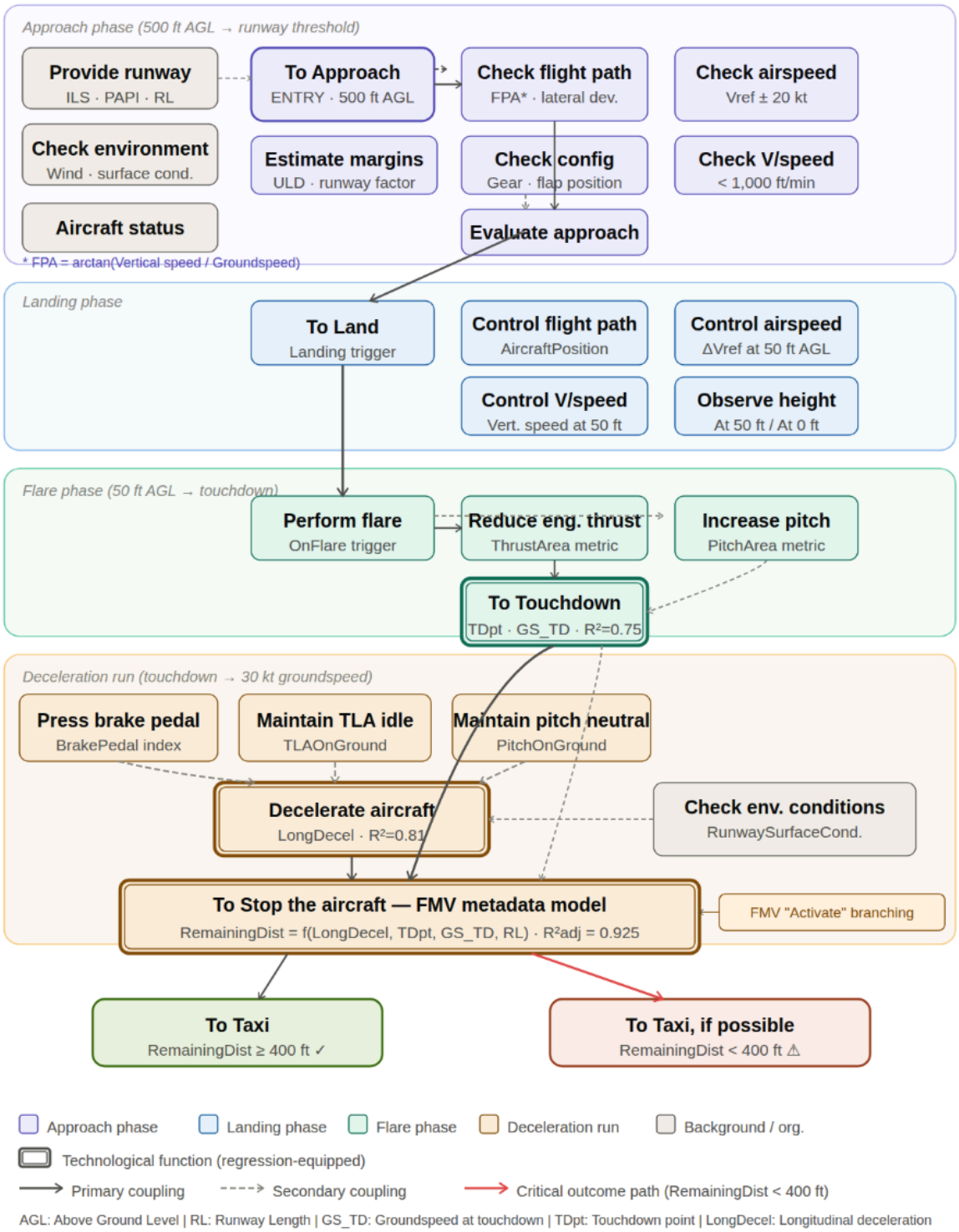


Figure 4

FRAM-FDM functional network diagram (27 functions). Phase colour-coding: purple = approach (500 ft AGL → runway threshold), blue = landing, teal = flare (50 ft AGL → touchdown), amber = deceleration run (touchdown → 30 knots). Flight Path Angle FPA = arctan(vertical speed / groundspeed). AGL = Above Ground Level. Double-bordered functions are technological functions equipped with regression metadata (R^2adj values shown). Solid black arrows = primary functional couplings; dashed grey arrows = secondary couplings; red arrow = critical outcome path. The FMV "Activate" conditional branching annotation is shown at the "To Stop the Aircraft" function