Research Square

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A Composite Human-Readiness Index for Flight-Line Maintenance Personnel: Model Formulation and a Pre-Registered Validation Protocol

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Research Article

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Abstract

Flight-line aircraft maintenance is a safety-critical activity in which degradation of individual human readiness — through sleep loss, insufficient recovery, sustained workload, and reduced attention — can raise the probability of latent maintenance error. Supervisors currently lack a simple, defensible, forward-looking indicator that aggregates these factors at the person-month level. This paper formulates the Aggregated Personnel-readiness Number (APN), a transparent composite index that combines five routinely recordable inputs — sleep duration, physical exercise, verified task-completion rate, maintenance-error count, and a short standardized cognitive-vigilance score — into a bounded 0–10 score with three interpretive bands. We present the full normalization scheme, an interpretable weighted-sum daily model, and a monthly regularized-regression updating procedure that replaces expert-assigned weights with locally estimated coefficients as data accumulate. Because no field dataset yet exists, the numerical section is presented explicitly as a non-empirical illustrative worked example whose sole purpose is to demonstrate the computation; no performance claim is derived from it. The primary contribution of the paper is therefore twofold: (i) a fully specified, auditable index construction grounded in the maintenance-human-factors and fatigue-risk-management literature, and (ii) a pre-registered validation protocol — including sampling, outcome definition, statistical analysis plan, and stopping rules — designed so that a subsequent field study can confirm, refute, or recalibrate the index. We discuss ethical safeguards required for personnel monitoring and position APN as a candidate decision-support layer within maintenance safety management systems, subject to the empirical validation specified herein.

1. Introduction

Aircraft maintenance errors are distinctive among safety hazards because their consequences are frequently latent: a defect introduced or missed during a task may remain undetected until inspection, ground run, or flight. This temporal gap between action and consequence limits the usefulness of retrospective, event-triggered safety tools for day-to-day supervision. A flight-line officer-in-charge managing a maintenance team needs a proactive signal that indicates when the team's collective human readiness is declining, before that decline manifests as an error.

Established maintenance human-factors instruments — most prominently the Maintenance Error Decision Aid (MEDA) — are investigative in nature and are applied after an event has occurred. Fatigue-risk-management guidance from civil aviation authorities recognizes fatigue as a persistent, only partially eliminable hazard in continuous operations, but such guidance is typically framed at the organizational and scheduling level rather than at the level of an individual supervisor's monthly decision-making. There remains a practical gap: a lightweight, interpretable indicator that a line supervisor can compute from records already generated during normal operations.

This paper addresses that gap by formulating the Aggregated Personnel-readiness Number (APN). The acronym is retained for continuity with prior working documents; it is expanded here as a descriptive

term to make explicit that the index aggregates several personnel-readiness inputs rather than representing any single quantity or any individual. APN is not proposed as a validated operational tool in this paper. Rather, the paper makes two deliberately separable contributions. First, it provides a complete and auditable model specification: the choice of variables, their normalization, an interpretable initial weighting, and a principled mechanism for replacing those weights with locally estimated coefficients. Second, it provides a pre-registered validation protocol that specifies, in advance, exactly how a field study should be designed and analysed to test the index. Framing the work this way is intentional: it separates the reusable methodological contribution (available now) from the empirical claim (deferred until data exist), and it allows the eventual field study to be evaluated against pre-committed criteria rather than post-hoc rationalization.

The guiding principle throughout is that a low readiness score must trigger support and risk control, not blame. A technician may score low because of illness, night duty, family stress, inadequate tooling, unclear job cards, or unrealistic tasking. The value of an early signal lies in prompting a supervisory conversation and a management intervention before an avoidable error occurs.

2. Background and Variable Selection

The five APN inputs were selected because each is (a) supported by the maintenance-human-factors or fatigue literature as plausibly related to error risk or performance, and (b) obtainable from routine flight-line records or a brief daily entry, minimizing additional administrative burden.

Recent DOI-indexed studies from 2021–2026 strengthen the rationale for APN variable selection. Aircraft-maintenance research now reports fatigue as a measurable operational hazard, links safety leadership and safety climate with maintenance-technician safety behaviour, and identifies proactive hazard reporting, learning from past events, and human-factor integration within SMS as continuing needs (Aktas & Kagnicioglu, 2023; Chawdhury & Sultan, 2026; Coban, 2025; da Silva et al., 2024; Malakis et al., 2023; Tyagi et al., 2023a, 2023b; Under & Gerede, 2021). Recent work on digital maintenance, predictive classification, aviation-maintenance ecosystems, and ergonomics further supports a simple auditable indicator that can sit beside formal maintenance records rather than replacing supervisory judgement (Hovanec et al., 2024; Kabashkin, 2024; Rosadi et al., 2024).

Sleep and fatigue. Fatigue-risk-management guidance for aviation maintenance identifies extended duty, night work, and circadian disruption as contributors to degraded maintainer performance. Sleep duration is therefore included as a proxy for acute fatigue state, with the normalization centred on a physiologically typical target because both curtailed and unusually extended sleep can signal disturbed recovery, illness, or scheduling imbalance.

Physical readiness. Regular physical activity is associated with alertness and resilience to fatigue in shift-work settings. Exercise is included as a modifiable readiness input, capped so that the index rewards reasonable activity rather than excessive exertion.

Productivity and error. Task-completion rate captures throughput, but throughput alone is an inadequate and potentially hazardous target: speed uncoupled from quality is precisely the condition under which latent errors are introduced. APN therefore pairs a productivity term with an explicit error-count penalty, so that safe productivity — not raw speed — is rewarded. This reflects the multi-factorial view of maintenance error embodied in MEDA, in which errors typically arise from several contributing conditions rather than a single careless act.

Cognitive vigilance. A short, standardized, time-bound attention-and-arithmetic test provides a direct daily probe of vigilance state. Such brief cognitive probes are used in fatigue research as sensitive indicators of impairment; the requirement here is a fixed rubric applied identically to all personnel within a measurement period, with learning effects monitored.

The sleep and cognition terms are also supported by recent DOI-indexed sleep-science evidence: both short and excessive sleep duration have been associated with poorer executive function, stable sleep of at least seven hours improves working memory and response inhibition, and even one night of sleep restriction can impair sustained attention (Ren et al., 2025; Tai et al., 2022; Wust et al., 2024; Zimmerman et al., 2024). The exercise term is retained as a practical recovery and readiness input because recent work continues to report associations between physical activity and cognitive functioning (Barakou et al., 2023; Kekalainen et al., 2023).

A related prior modelling effort by the present author and a colleague developed a literature-informed logistic model for task-level maintenance-error probability on a simulation-derived dataset (Chawdhury & Sultan, 2026). That work operated at the level of individual task risk; APN differs in target and intended use, aggregating readiness to a person-month score designed for direct supervisory interpretation. The prior model is cited as conceptual precedent for the regression logic adopted here, not as empirical validation of APN.

Table 1
Mapping of literature-supported evidence to APN design decisions.

Evidence base	Relevance to error/performance	APN design decision
Maintenance error investigation (MEDA)	Errors are multi-factorial; average of several contributing conditions per event	Error treated as a penalized, multi-factor signal — not individual blame
FAA / ICAO fatigue-risk-management guidance	Duty length, night work, and circadian disruption degrade maintainer performance	Sleep and cognitive-vigilance terms as core readiness inputs
Fatigue-management guidance for continuous operations	Fatigue is predictable and must be actively managed, not eliminated	APN framed as a recurring monthly management indicator
Prior task-level error-probability model (Chawdhury & Sultan, 2026)	Regression links human-factor inputs to error likelihood	Regularized regression adopted to localize weights from data

3. Data-Collection Protocol

At the end of each duty day, each participating team member completes a brief record designed to take under two minutes. A supervisor or authorized data clerk independently verifies the task count and error entries against work orders, inspection notes, and rectification records, so that the two outcome-relevant fields do not rely on self-report alone. The cognitive probe is a fixed-format, time-bound test (for example, a three-minute arithmetic-and-attention task) applied identically to all personnel within a measurement period. Table 2 defines the variables, their sources, and their expected direction of effect.

Table 2
APN input variables, measurement sources, and expected direction of effect.

Variable	Symbol	Unit	Preferred source	Expected direction
Sleep duration	S	h/day	Self-entry, optionally confirmed via fatigue log	Readiness peaks near a physiological target
Physical exercise	E	h/day	Self-entry or unit physical-training record	Improves readiness up to a practical cap
Completed tasks	T	tasks/day	Work order / job card (verified)	Improves score only when error is controlled
Working time	W	h/day	Duty roster	Used to compute task rate
Error count	M	count/day	Quality / supervisor record (verified)	Penalizes the score
Cognitive-vigilance score	C	0–100	Time-bound standardized test	Higher score improves readiness

4. Model Formulation

4.1 Normalization of daily inputs

Because the inputs have heterogeneous units, each is first mapped to a dimensionless value in [0, 1]. The following definitions are proposed for the first field trial and are themselves treated as tunable during validation:

$S^* = \max\{ 0, 1 - |S - S_0| / a \}$ (sleep readiness, centred at target $S_0 \approx 7.5$ h, tolerance $a \approx 3.5$ h)

$E^* = \min(E / E_{cap}, 1)$ (exercise readiness, cap $E_{cap} \approx 0.75$ h)

$P = T / W$; $P^* = (P - P_{min}) / (P_{max} - P_{min})$ (normalized productivity rate)

$C^* = C / 100$ (cognitive-vigilance readiness)

$M^* = \min(M / M_{max}, 1)$ (error penalty)

The sleep term is centred on a target rather than treated as monotonic, because both curtailed and unusually long sleep may indicate disturbed recovery. The exercise term is capped to reward reasonable activity rather than excess. The productivity range parameters (P_min, P_max) are set from the unit's own historical task-rate distribution and reported explicitly so the normalization is reproducible.

4.2 Interpretable daily model

A transparent initial daily index is defined as a bounded weighted sum:

$$APN_d = clip_{0}^{10}\{\, 10 \cdot [\, w_S \cdot S^* + w_E \cdot E^* + w_P \cdot P^* + w_C \cdot C^* - w_M \cdot M^* + b \,] \,\}$$

where the weights (w_S, w_E, w_P, w_C, w_M) encode the relative operational importance of each term, b is a small baseline constant, and the result is clipped to [0, 10]. For the illustrative example in Section 5 only, the initial values w_S = 0.25, w_E = 0.15, w_P = 0.25, w_C = 0.25, w_M = 0.20, b = 0.10 are used. These expert-assigned values are placeholders whose only role is to make the worked computation concrete; they carry no empirical claim and are expected to be replaced during validation (Section 4.3). The sign on the error term is negative by construction, encoding the design commitment that the index rewards safe productivity rather than speed.

4.3 Monthly regularized-regression update

After the first measurement period, the expert-assigned weights are replaced by coefficients estimated from local data, so that the index reflects the unit's actual operating relationships rather than prior assumptions. For a continuous supervisor-verified performance outcome Y for technician i on day t:

$$Y_it = \beta_0 + \beta_1 S^*_it + \beta_2 E^*_it + \beta_3 P^*_it + \beta_4 C^*_it - \beta_5 M^*_it + \varepsilon_it$$

When the outcome is binary (for example, error / no-error on a task), a logistic specification is preferred:

$$Pr(Error_it = 1) = 1 / [\, 1 + exp(\, -(\, \alpha_0 + \alpha_1 S^*_it + \alpha_2 E^*_it + \alpha_3 P^*_it + \alpha_4 C^*_it + \alpha_5 M^*_it \,)\,)\,]$$

Because unit sizes are typically small relative to the number of predictors and the predictors may be correlated, coefficients are estimated with L2 (ridge) regularization to stabilize the solution:

$$\beta = argmin_\beta \{\, \Sigma\, (\, Y - X\beta \,)^2 + \lambda\, \Sigma\, \beta_j^2 \,\}$$

with the penalty strength λ selected by cross-validation (Section 6). The monthly index for a technician is the mean of that technician's valid daily values:

$$APN_month,i = (\, 1 / n_i \,)\, \Sigma_t\, APN_d,it$$

5. Illustrative Worked Example (Non-Empirical)

Important: The dataset in this section is fabricated for illustration only. It is not field data and contains no measured observations. Its sole purpose is to demonstrate, step by step, how APN is computed from the

kind of records a unit would collect. No performance, predictive, or validity claim is made or should be inferred from these numbers. Empirical evaluation is deferred to the validation study specified in Sections 6–7.

The twelve illustrative technician-months in Table 3 were constructed so that the input directions are internally consistent with the qualitative relationships described in the literature (Section 2). This internal consistency is a property of how the example was built; it is emphatically not evidence that the index works, and reviewers and readers should treat the table strictly as a computational demonstration.

Table 3
Illustrative (non-empirical) worked-example inputs and computed APN values.

ID	Sleep	Exercise	Tasks	Hours	Errors	Cognitive	APN	Risk index
T01	5.2	0.0	5	8.5	2	61	2.50	0.86
T02	6.0	0.2	6	8.0	1	68	4.81	0.64
T03	6.4	0.4	7	8.0	1	72	5.98	0.48
T04	7.1	0.5	7	7.5	0	78	7.68	0.26
T05	7.5	0.8	9	8.0	0	86	9.26	0.13
T06	8.0	0.7	9	8.0	0	83	8.73	0.17
T07	4.8	0.0	4	9.0	3	55	0.95	0.94
T08	5.8	0.1	5	8.5	2	63	3.17	0.81
T09	7.8	0.6	8	8.0	0	82	8.26	0.21
T10	6.9	0.3	7	8.0	1	75	6.22	0.45
T11	7.3	0.9	10	8.0	0	88	9.56	0.11
T12	5.5	0.2	6	8.5	2	66	3.60	0.77

5.1 Step-by-step computation for T01

For T01: S = 5.2 h, E = 0.0 h, T = 5, W = 8.5 h, M = 2, C = 61. The task rate is P = 5 / 8.5 = 0.588 tasks/h. Using the example range P_min = 0.444 and P_max = 1.250, the normalized productivity is P* = (0.588 − 0.444) / (1.250 − 0.444) = 0.179. Sleep readiness is S* = 1 − |5.2 − 7.5| / 3.5 = 0.343. Exercise readiness is E* = 0. Cognitive readiness is C* = 0.61. With M_max = 3, the error penalty is M* = 2 / 3 = 0.667. Substituting into the daily model:

$$APN_d = 10 \cdot [\, 0.25(0.343) + 0.15(0) + 0.25(0.179) + 0.25(0.61) - 0.20(0.667) + 0.10 \,] = 2.49$$

This places the illustrative technician in the lowest interpretive band. As specified in Section 8, the intended supervisory response is not sanction but review: confirm sleep debt, examine workload and

task allocation, determine whether errors were procedural or environmental, and consider rest, reassignment, or mentoring.

6. Illustrative Visualization

Figures 1–3 visualize the worked example only; like Table 3 they carry no empirical claim. They are included to show the form of output a validated deployment would produce.

7. Interpretation Bands and Intended Supervisory Response

The 0–10 score is partitioned into three interpretive bands. The band boundaries are initial proposals to be tested and, if necessary, recalibrated during validation (Section 6); they are not asserted as validated cut-points.

Table 4
Proposed interpretation bands and intended supervisory response.

Band	Interpretation	Intended supervisory response
0–5	Lower readiness / elevated risk	Supportive review: check rest and medical/personal factors, redistribute workload, increase oversight of complex tasks.
5–7	Regular readiness	Continue monitoring; give feedback; encourage sleep hygiene and activity; review recurrent minor errors.
7–10	High readiness	Suitable for demanding tasks where appropriate; guard against over-tasking high performers into fatigue.

The index is explicitly not a stand-alone disciplinary instrument. It must be interpreted alongside maintenance context, supervisor judgement, and the unit's safety-reporting culture.

8. Ethical and Governance Considerations

Any index that monitors individual personnel can become unfair or harmful if deployed without governance. Before field use, deployment requires: written rules stating what is measured, why, who may access the data, and how scores are used; informed consent and appropriate command or institutional authority, particularly for any health-adjacent data; access controls limiting score visibility to authorized supervisors; and periodic bias audits across shifts, trades, seniority, and task difficulty, since a junior technician assigned difficult rectification work should not be compared naively with a senior technician on routine inspection. The field study described below is subject to ethical review and command approval prior to any data collection, and no personally identifying performance data are published.

9. Pre-Registered Validation Protocol

The following protocol is stated in advance so that the planned field study can be evaluated against pre-committed design and analysis choices. It constitutes the paper's second principal contribution and converts APN from a proposed construct into a testable hypothesis.

9.1 Design, participants, and duration

A prospective observational cohort study of 60–150 flight-line maintenance personnel across one or more units, with daily data collection for 6–12 months. The lower bound supports estimation of a multivariable model with five predictors at an acceptable events-per-variable ratio; the duration spans seasonal and roster variation. Inclusion criteria, roster coverage, and handling of leave and detachment are recorded prospectively.

9.2 Outcomes

The primary outcome is a supervisor-verified maintenance-quality event (documented error, rework, or re-inspection finding) attributable to a technician-day. Secondary outcomes are supervisor-rated readiness and on-time completion. Outcomes are ascertained from records independent of the self-reported inputs to limit common-method bias.

9.3 Analysis plan

Confirmatory analyses, specified in advance: (1) association of APN with the primary outcome via mixed-effects logistic regression with a technician-level random intercept to account for repeated measures; (2) discrimination via the area under the ROC curve with confidence intervals; (3) calibration via calibration curves; (4) internal validation via repeated k-fold and, where units permit, leave-one-unit-out cross-validation, with ridge penalty λ tuned inside each training fold to avoid leakage; (5) sensitivity analyses on the normalization parameters (S_0, a, E_cap, M_max) and on the band thresholds; and (6) responsiveness analysis testing whether APN rises following documented interventions (rest, workload rebalancing). Missing data handling, outlier rules, and the primary hypothesis test are fixed before data lock.

This validation plan follows the same direction as recent aviation-safety literature calling for evidence-based human-factor interventions, better safety-behaviour measurement, and stronger integration of human performance into SMS practice (Chan et al., 2023; Chionis & Karanikas, 2022; Okine et al., 2025).

9.4 Success, futility, and recalibration criteria

Pre-committed decision rules: the index is considered supported if the primary-outcome model shows a statistically significant association in the expected direction and out-of-sample AUC meets a pre-specified threshold (for example, ≥ 0.70) with a lower confidence bound above chance. If discrimination is inadequate, the regression coefficients and normalization parameters are recalibrated and re-validated on held-out data rather than the model being abandoned or silently re-fitted to the full sample. If no configuration achieves the threshold, that null result is reported. These rules are stated now precisely so that the eventual empirical paper cannot be accused of post-hoc selection.

10. Discussion

APN is deliberately simple. A flight-line supervisor rarely needs an elaborate dashboard; more often a single interpretable score is enough to open a useful, timely conversation about rest, workload, or readiness. The design commitments — a target-centred sleep term, a capped exercise term, an explicit error penalty, locally estimated weights, and honestly labelled illustrative numbers — are all in service of a tool that is auditable and resistant to misuse.

The methodological posture of this paper is that a construct like APN earns the right to be deployed only after it survives a pre-registered test. By separating the reusable formulation from the deferred empirical claim, the work offers something usable now — a complete, reproducible index specification and protocol that other units could adopt or adapt — without overstating what has been demonstrated. The index also creates a bridge between maintenance quality assurance and personnel welfare: a persistently low score should prompt support (leave, medical review, reduced night duty, workload rebalancing) rather than sanction, consistent with the multi-factorial, non-punitive philosophy of modern maintenance-error management.

11. Limitations

This paper contributes a model specification and a validation protocol, not an externally validated operational tool; the numerical section is illustrative and non-empirical. Self-reported sleep and exercise are subject to reporting bias, mitigated only partially by independent verification of the outcome-relevant fields. The cognitive probe must be standardized and monitored for learning effects. Error counts may be under-reported where reporting culture is weak, biasing the penalty term. Task difficulty is not yet represented, so a single complex troubleshooting task and several routine tasks are treated equivalently; incorporating a difficulty weight is identified as a priority refinement. Finally, the initial weights and band thresholds are provisional and acquire empirical meaning only after the validation study.

12. Conclusion

This paper formulated the Aggregated Personnel-readiness Number, a transparent composite index that combines sleep, exercise, verified task rate, error count, and a cognitive-vigilance score into a bounded 0–10 monthly indicator for flight-line maintenance personnel, together with a monthly regularized-regression procedure for localizing its weights. The index is presented with an explicitly non-empirical worked example and, critically, a pre-registered validation protocol that specifies how a field study should test, recalibrate, or refute it. In this form the contribution is honest about its status: a reusable, auditable method and a committed empirical plan, ready to be validated. Subject to that validation, APN is positioned as a candidate proactive decision-support layer for fatigue management, workload planning, personnel welfare, and maintenance-error prevention within aviation safety management systems.

Declarations

Data availability. No empirical data were used in this study. The illustrative worked-example values in Section 5 are fabricated for demonstration and are fully reproducible from the equations in Section 4.

Ethics. This paper reports no human-subjects data collection. The prospective field study specified in Section 9 will be conducted only after ethical review and appropriate institutional and command approval.

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Conflicts of interest. The author declares no conflict of interest.

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Figures

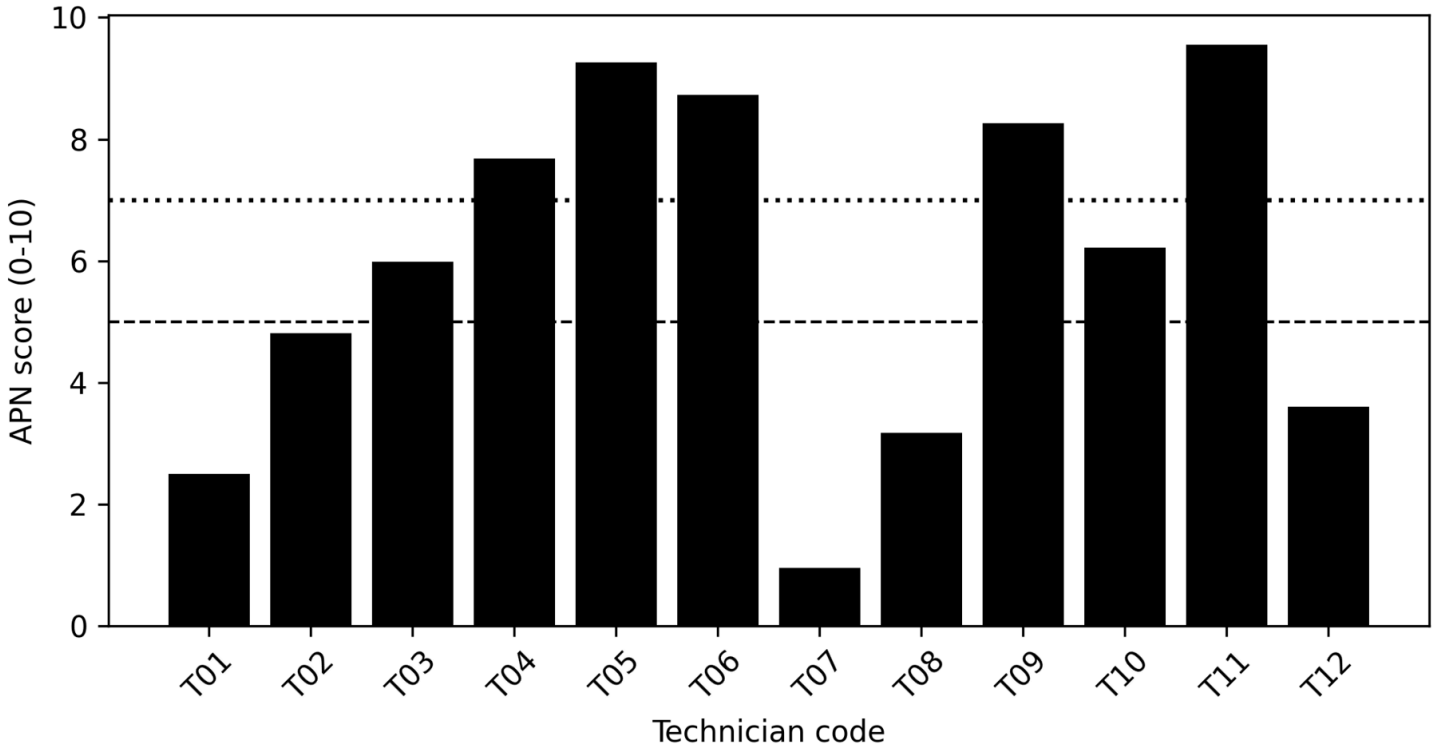


Figure 1

Computed APN values for the illustrative worked example. Reference lines mark the 5 and 7 band thresholds. (Non-empirical illustration.)

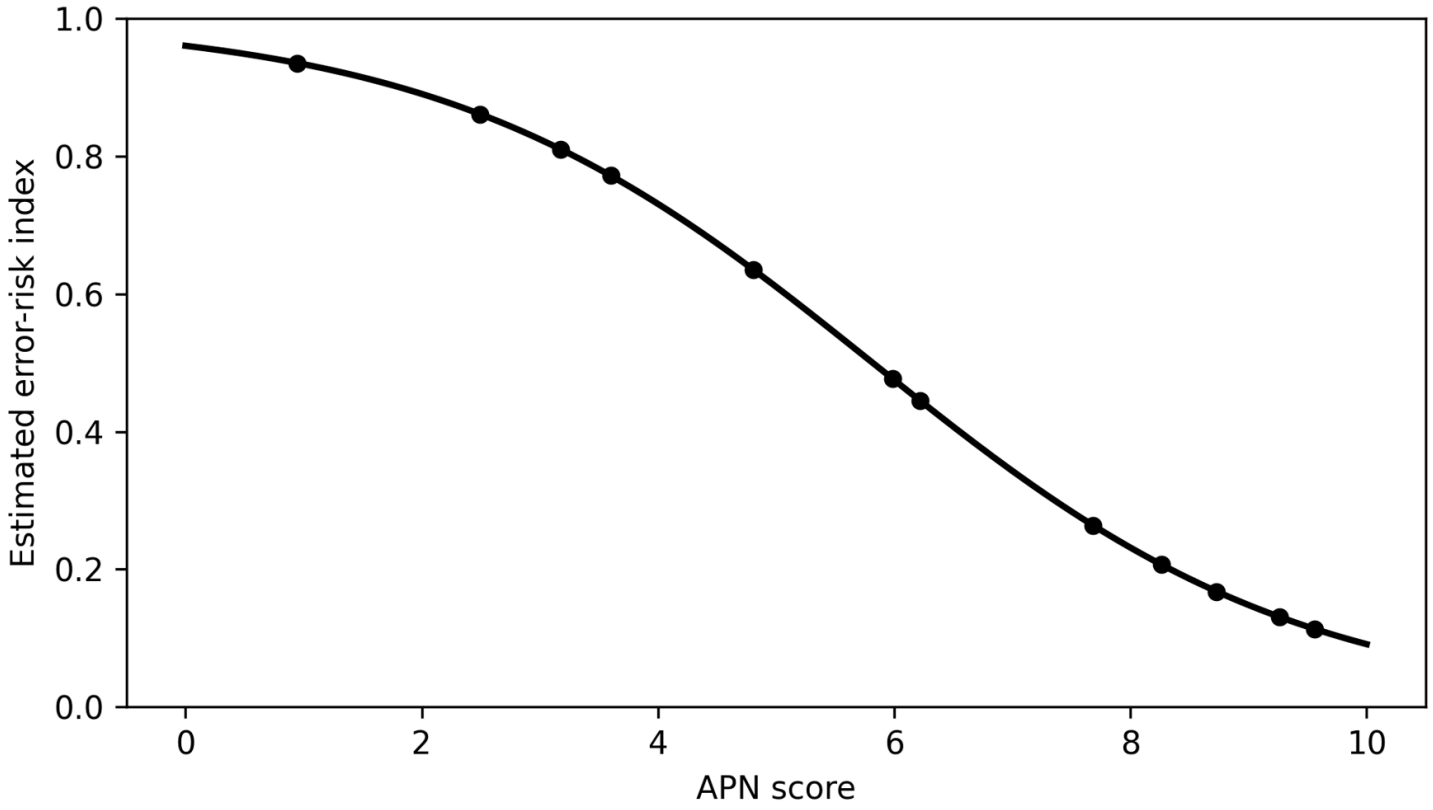


Figure 2

Illustrative relationship between APN and a notional error-risk index. The curve is schematic and must be recalibrated against real error records during validation. (Non-empirical illustration.)

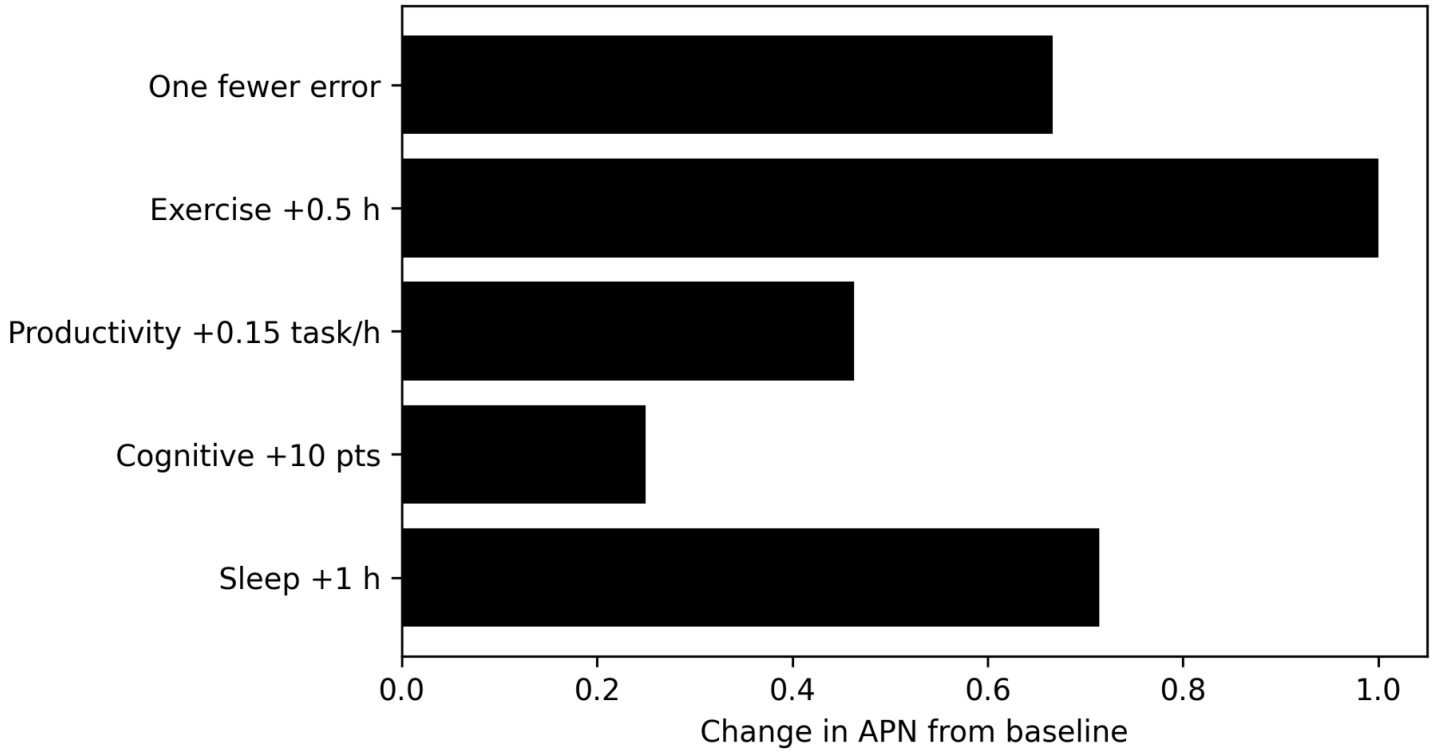


Figure 3

Illustrative sensitivity example showing how modifiable inputs (sleep, exercise, workload balancing) shift APN from a low-to-moderate baseline. (Non-empirical illustration.)