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A Q-RUNG ORTHOPAIR FUZZY MULTI-CRITERIA MODEL INCORPORATING A HESITANCY-DOMINANT UNCERTAINTY MEASURE FOR PRIORITISING PATIENT-SAFETY RISKS IN NURSING CARE

HEMŞİRELİK BAKIMINDA HASTA GÜVENLİĞİ RİSKLERİNİN ÖNCELİKLENDİRİLMESİ İÇİN TEREDDÜT-BASKIN BİR BELİRSİZLİK ÖLÇÜSÜ İÇEREN Q-RUNG ORTOPAİR BULANIK ÇOK KRİTERLİ MODEL

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ABSTRACT
Background: Ward-level patient-safety scoring tools compress likelihood, harm and detectability into a single crisp number, which limits their capacity to express the vagueness of nursing judgement.
Objective: To propose an uncertainty measure for q-rung orthopair fuzzy (*q-ROF*) numbers that attains its unique maximum at complete hesitancy, to establish its properties with detailed proofs and to embed it in a transparent weighting and ranking model for prioritising patient-safety risks in nursing care.
Methods: Linguistic ratings of eight patient-safety risks on four criteria (likelihood, harm severity, detection difficulty and care burden) were represented as *q-ROF* numbers. The proposed measure supplied a matrix-derived criterion weight formed from certainty and contrast; this was blended with author-specified *SWARA* scenario-priority weights, and risks were ranked with *CRADIS*. Each matrix cell is an author-assigned, literature-informed scenario rating: the heterogeneous publications provide source facts and context but do not directly determine the fuzzy grade. Ratings are not taken from any experts.
Results: Under the constructed scenario inputs, missed venous thromboembolism (*VTE*) prophylaxis, unrecognised clinical deterioration and healthcare-associated infection (*HAI*) formed the leading group, with *CRADIS* indices of 1.00, 0.973 and 0.925. The *q-ROF TOPSIS* ranking coincided under identical inputs, which is an internal method-concordance check rather than external validation. Equal criterion weights produced an exact three-way top tie among R4, R6 and R8; average tied ranks gave a Spearman correlation of 0.976 with the blended-weight ranking. Across the q and blend grid, correlations ranged from 0.929 to 1.00; Monte Carlo mean correlations declined from 0.983 to 0.867 as perturbation increased, and the first-place identity became uncertain.
Conclusion: The hesitancy-dominant measure and matrix-derived certainty-contrast weighting provide a transparent workflow. The reported ordering is conditional on an author-constructed scenario, not a validated clinical hierarchy; the inputs and priority weights must be replaced or calibrated with local incident, audit, workload and multidisciplinary judgement data before clinical use.
Keywords: multi-criteria decision-making, q-rung orthopair fuzzy set, patient safety, nursing care, uncertainty measure

ÖZET
Arka Plan: Servis düzeyindeki hasta güvenliği puanlama araçları olasılık, zarar ve saptanabilirliği tek bir kesin sayıda birleştirmekte; bu durum hemşirelik yargısındaki belirsizliğin ifade edilmesini sınırlamaktadır.
Amaç: *q-ROF* (q-rung ortopair bulanık) sayılar için en yüksek değerine yalnızca tam tereddüt durumunda ulaşan bir belirsizlik ölçüsü önermek, özelliklerini ayrıntılı ispatlarla ortaya koymak ve bu ölçüyü hemşirelik bakımındaki hasta güvenliği risklerinin önceliklendirilmesine yönelik şeffaf bir ağırlıklandırma ve sıralama modeline yerleştirmektir.
Yöntem: Sekiz hasta güvenliği riskine ilişkin dilsel değerlendirmeler dört kriterde (olasılık, zarar şiddeti, saptama güçlüğü ve bakım yükü) *q-ROF* sayılarla temsil edilmiştir. Önerilen ölçüden kesinlik ve kontrasta dayalı matristen türetilmiş bir kriter ağırlığı elde edilmiş; bu ağırlık yazarca belirlenen *SWARA* senaryo-öncelik ağırlıklarıyla harmanlanmış ve riskler *CRADIS* ile sıralanmıştır. Matris hücreleri yazar tarafından atanmış, literatürden beslenen bir senaryo derecesidir; heterojen yayınlar kaynak bulgusu ve bağlam sağlamakta, ancak bulanık dereceyi doğrudan belirlememektedir. Uzmanlardan derecelendirme alınmamıştır.
Bulgular: Oluşturulan senaryo girdileri altında ihmal edilen venöz tromboemboli (*VTE*) profilaksisi, fark edilmeyen klinik kötüleşme ve sağlık hizmetiyle ilişkili enfeksiyon (*HAI*), sırasıyla 1,00, 0,973 ve 0,925 *CRADIS* indeksleriyle önde gelen grubu oluşturmuştur. Aynı girdilerle *q-ROF TOPSIS* sıralaması örtüşmüştür; bu, dış doğrulama değil yöntemler arası iç uyum kontrolüdür. Eşit kriter ağırlıkları R4, R6 ve R8 arasında tam bir üçlü üst sıra eşitliği oluşturmuş; ortalama eşit sıra kullanıldığında harmanlanmış sıralamayla Spearman

korelasyonu 0,976 olmuştur. q ve harmanlama ızgarasında korelasyonlar 0,929-1,00, Monte Carlo ortalamaları bozulma arttıkça 0,983'ten 0,867'ye düşmüş; bu sırada birinci sıradaki risk belirsizleşmiştir.

Sonuç: Tereddüt-baskın ölçü ve matristen türetilmiş kesinlik-kontrast ağırlıklandırması şeffaf bir iş akışı sunmaktadır. Diğer yandan, bildirilen sıralama yazarca oluşturulmuş senaryoya bağlıdır ve doğrulanmış (valide edilmiş) bir klinik hiyerarşi değildir; bu nedenle klinik kullanım öncesinde girdiler ve öncelik ağırlıkları yerel vaka kayıtları, denetim, iş yükü ve multidisipliner değerlendirme verileriyle değiştirilmeli veya kalibre edilmelidir.

Anahtar Kelimeler: çok kriterli karar verme, q-rung ortopair bulanık küme, hasta güvenliği, hemşirelik bakımı, belirsizlik ölçüsü

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INTRODUCTION

Improving patient safety depends on directing scarce ward resources to the risks that matter most, yet the crisp scoring tools used in ward-level risk assessment compress likelihood, harm and detectability into a single number and have limited capacity to express the vagueness of nurse judgement. Fuzzy methods have therefore been applied across healthcare risk management, including proactive risk management systems (En-Naaoui et al., 2024), multicriteria risk evaluation (Drnovšek et al., 2025), occupational health and safety assessment in hospitals (Badida et al., 2023; Gul et al., 2017), failure mode analysis in emergency departments (Chanamool & Naenna, 2016) and patient prioritisation (Chen et al., 2025; Perez-Aguilar et al., 2024; Rana et al., 2023). Building on the intuitionistic fuzzy set (*IFS*) (Atanassov, 1986), the *q-ROF* (q-rung orthopair fuzzy) set (Yager, 2017) requires only that the sum of the q-th powers of the membership and non-membership grades be at most one, so that an assessment can represent a high possibility of a serious event while retaining a genuine degree of doubt (Liu & Wang, 2018; Peng et al., 2018).

Two methodological gaps motivate this study. First, *q-ROF* criterion weighting can rely on entropy-derived quantities (Khan et al., 2021; Peng & Liu, 2019); average determinacy alone may assign substantial weight to a criterion that scarcely separates the alternatives. Second, recent healthcare research has already integrated circular q-*ROF* information with a modified Compromise ranking of alternatives from distance to ideal solution (*CRADIS*) method for hospital infection-control strategy ranking (M. Li et al., 2026), so the contribution claimed here is not the first healthcare use of *q-ROF CRADIS*. In the literature examined for this study, however, we did not identify the specific combination developed here: a hesitancy-dominant *q-ROF* uncertainty measure with a unique maximum at complete hesitancy; matrix-derived certainty-contrast weights blended with transparent, author-specified The stepwise weight assessment ratio analysis (*SWARA*) scenario priorities; *CRADIS* ranking of nursing patient-safety risks; and cell-level separation of source facts from author inference. The study establishes the measure's properties, demonstrates the workflow on an explicitly constructed scenario, and evaluates same-input concordance and synthetic robustness. Its intended users are researchers and, after local calibration, nurse managers, quality and safety officers and clinical governance teams. In a search of the scholarly indexes (which covers PubMed, Scopus, Semantic Scholar and ArXiv) and Crossref in May-August 2026 with the terms q-rung orthopair, *CRADIS*, uncertainty measure, hesitancy, patient safety and nursing, we did not identify this exact combination of a hesitancy-dominant uncertainty measure, matrix-derived certainty and contrast weighting and *CRADIS* ranking applied to nursing patient-safety prioritisation. A recent study applies a circular *q-ROF CRADIS* model to hospital infection management (M. Li et al., 2026); it differs in the uncertainty representation, the weighting construction and the application focus, and no claim of first healthcare use is made here.

MATERIALS AND METHODS

Preliminaries

A *q-ROF* number is a pair $A = (\mu, \nu)$with $\mu, \nu \in [0,1]$and $\mu^q + \nu^q \leq 1$for a rung $q \geq 1$, and its hesitancy is $\pi_A = (1 - \mu^q - \nu^q)^{1/q}$(Yager, 2017). Its score is $S(A) = \mu^q - \nu^q$(Peng et al., 2018). For

numbers $A_1, \dots, A_n$with weights $w_1, \dots, w_n$that sum to one, the *q-ROF* weighted averaging (*QROFWA*) operator (Liu & Wang, 2018) is

$$\mathrm{QROFWA}(A_1, \dots, A_n) = \left(\left(1 - \prod_{i=1}^{n}(1-\mu_i^q)^{w_i}\right)^{1/q},\ \prod_{i=1}^{n} \nu_i^{w_i}\right) \quad (1)$$

Equation (1) is reported for completeness and for future applications with multiple independent ratings per cell; no such aggregation was required for the present primary matrix. The base case uses $q = 3$throughout and the sensitivity analysis varies q.

The proposed hesitancy-dominant uncertainty measure

For a *q-ROF* number $A = (\mu, \nu)$the proposed uncertainty measure is

$$U(A) = \pi_A^q + \left(1 - \pi_A^q\right)\frac{1-|\mu^q - \nu^q|}{2}, \qquad \pi_A^q = 1 - \mu^q - \nu^q \quad (2)$$

The measure combines the hesitancy with the balance of the two grades: it peaks only at complete hesitancy and vanishes only at full determinacy, so more determinate ratings carry less rating uncertainty. The three properties that justify this reading are stated and proved below. Throughout the proofs, write $h = \pi_A^q = 1 - \mu^q - \nu^q \in [0,1]$for the hesitancy mass and $d = |\mu^q - \nu^q| \in [0,1]$for the determinacy gap, so that $U(A) = h + (1-h)(1-d)/2$.

Proposition 1 (Boundedness). *For every q-ROF number A,* $0 \le U(A) \le 1$.

Proof. Since $\mu, \nu \in [0,1]$and $\mu^q + \nu^q \le 1$, both $h \in [0,1]$and $d \le \mu^q + \nu^q = 1 - h$hold, and in particular $d \in [0,1]$. Both summands of $U(A) = h + (1-h)(1-d)/2$are non-negative, so $U(A) \ge 0$, with the first summand at most $h$and the second at most $(1-h)/2$because $(1-d)/2 \le 1/2$. Hence $U(A) \le h + (1-h)/2 = (1+h)/2 \le 1$. Equality $U(A) = 1$forces $h = 1$, which is examined in Proposition **2**. ■

Proposition 2 (Unique maximum at complete hesitancy). $U(A) = 1$*if and only if* $\mu = \nu = 0$, *that is, at complete hesitancy; at every other grade* $U(A) < 1$.

Proof. If $\mu = \nu = 0$then $h = 1$and $U(A) = 1 + 0 = 1$. Conversely, from the proof of Proposition **1**, $U(A) \le (1+h)/2$with equality only when $d = 0$. If $U(A) = 1$then $(1+h)/2 \ge 1$, so $h \ge 1$, hence $h = 1$; then $\mu^q + \nu^q = 0$, which for $\mu, \nu \ge 0$forces $\mu = \nu = 0$. The maximum is therefore attained at the single grade $(0,0)$and nowhere else. This property replaces the standard maximality axiom of *q-ROF* entropies, which places the maximum at every balanced grade $\mu = \nu$(Khan et al., 2021; Peng & Liu, 2019); a balanced but fully determinate grade satisfies $h = 0$and $d = 0$and yields $U(A) = 1/2 < 1$. The measure is therefore hesitancy-dominant rather than balance-dominant. ■

Proposition 3 (Sharp minimum and symmetry). $U(A) = 0$*if and only if* (μ, ν)*is a fully determinate grade with* $\mu^q + \nu^q = 1$*and* $|\mu^q - \nu^q| = 1$, *that is,* $(1,0)$*or* $(0,1)$. *Moreover* $U(\mu, \nu) = U(\nu, \mu)$*for all grades.*

Proof. If $U(A) = 0$then both non-negative summands vanish: $h = 0$and $(1-h)(1-d)/2 = (1-d)/2 = 0$, so $d = 1$. Now $h = 0$gives $\mu^q + \nu^q = 1$and $d = 1$gives $|\mu^q - \nu^q| = 1$; these two equalities force $\{\mu^q, \nu^q\} = \{0,1\}$, hence $(\mu, \nu) \in \{(1,0), (0,1)\}$. The converse is immediate by substitution. Symmetry holds because Udepends on (μ, ν)only through $\mu^q + \nu^q$and $|\mu^q - \nu^q|$, both of which are invariant under exchanging $\mu$and ν. ■

Properties in Proposition **1** and Proposition **3** coincide with the boundary, sharpness and symmetry axioms of a *q-ROF* entropy (Peng & Liu, 2019). Proposition **2** differs deliberately from the standard maximality axiom (Khan et al., 2021; Peng & Liu, 2019). Supplementary section S5 compares the axioms, the treatment of hesitancy and balanced grades, the limiting cases and the ranking behaviour of the proposed measure with established *q-ROF* entropy and knowledge measures (Khan et al., 2021; Peng & Liu, 2019) and identifies cases in which the measures produce different orderings; a linear balance-only comparator corresponds to a published entropy and is retained only as an intuitive example. The coefficient one half in Equation (2) is the neutral midpoint of the balance term: at zero hesitancy the measure reduces to half of one minus the determinacy gap, so a fully determinate grade never exceeds one half, strictly below the unique

maximum of Proposition 2. A parametrised variant that replaces this coefficient with alpha, evaluated at 0.25, 0.50 and 0.75, left the ranking unchanged (Spearman 1.00; Supplementary section S7).

Distance, matrix-derived weights and blended weights

The following powered-grade Euclidean distance between *q-ROF* numbers is used:

$$d(A,B)=\sqrt{\frac{1}{2}\left[\left(\mu_A^q-\mu_B^q\right)^2+\left(\nu_A^q-\nu_B^q\right)^2+\left(\pi_A^q-\pi_B^q\right)^2\right]} \tag{3}$$

The matrix-derived weight of criterion $j$is formed from two coefficients over the $m=8$risks. The certainty coefficient $c_j$is one minus the mean uncertainty of the criterion ratings, so it is large when the ratings on criterion $j$are on average more determinate; because the proposed measure also depends on the balance of the two grades, $c_j$reflects both lower hesitancy and more determinate grades and is not a measure of hesitancy alone. The contrast coefficient $g_j$is the mean pairwise distance between the risk ratings on criterion j, so it is large when the criterion separates the risks:

$$c_j=1-\frac{1}{m}\sum_{i=1}^{m}U\left(A_{ij}\right),\qquad g_j=\frac{2}{m(m-1)}\sum_{i<i'}d\left(A_{ij},A_{i'j}\right),\qquad w_j^o=\frac{c_j g_j}{\sum_{k=1}^{n}c_k g_k} \tag{4}$$

which is zero for a constant column because such a column cannot distinguish any risk. If every contrast coefficient is zero, so that the denominator vanishes, equal matrix-derived weights are used by convention. Subjective weights $w_j^s$are obtained with *SWARA* (Keršulienė et al., 2010), in which the criteria are ordered by importance and successive comparative-importance ratios yield the weights. The order and ratios are author-specified scenario priorities; they were informed by general patient-safety considerations but were not estimated from the source statistics or elicited from a nurse or expert panel (Supplementary section S4). The final weight of criterion $j$blends the matrix-derived and the *SWARA* scenario-priority weights:

$$w_j=\frac{\delta w_j^o+(1-\delta)w_j^s}{\sum_{k=1}^{n}\left[\delta w_k^o+(1-\delta)w_k^s\right]} \tag{5}$$

with $\delta=0.5$in the base case.

***CRADIS* ranking and the benchmark**

Let A_j^+ and A_j^- be the ideal and the anti-ideal *q-ROF* value of criterion j, taken as the highest-score and the lowest-score rating. The weighted deviations from the two references and the compromise index (Puška et al., 2022) are

$$s_i^+=\sum_{j=1}^{n}w_j\,d(A_{ij},A_j^+),\qquad s_i^-=\sum_{j=1}^{n}w_j\,d(A_{ij},A_j^-)$$
$$K_i^+=\frac{s_{\min}^+}{s_i^+},\qquad K_i^-=\frac{s_i^-}{s_{\max}^-},\qquad Q_i=\frac{K_i^++K_i^-}{2} \tag{6}$$

As a same-input benchmark, an author-implemented *q-ROF* adaptation of *TOPSIS* was computed with the same criterion weights and the distance of Equation (3): the closeness coefficient of alternative $i$is $C_i=s_i^-/(s_i^++s_i^-)$and alternatives are ranked in decreasing order of C_i. The adaptation follows the Pythagorean fuzzy *TOPSIS* of Zhang and Xu (2014) and is reported as an internal concordance check rather than external or clinical validation. Figure 1 shows the framework.

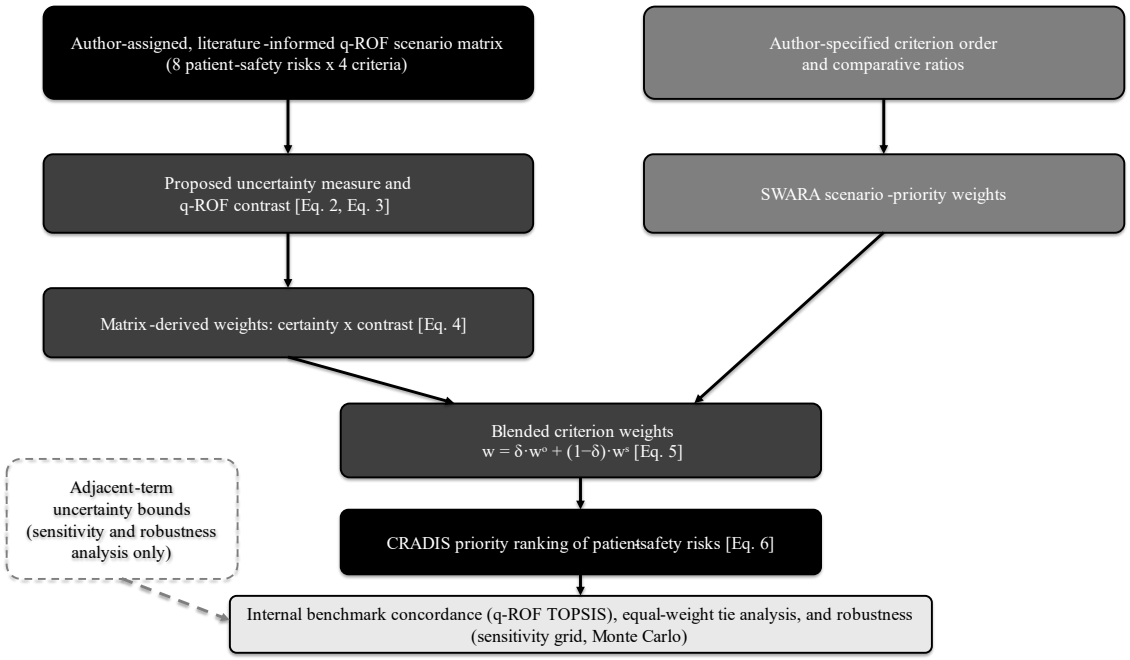

Figure 1. The proposed *q-ROF SWARA-CRADIS* framework. The matrix-derived certainty-contrast branch and the author-specified *SWARA* scenario-priority branch are independent and join only at the blended-weight stage; the dashed path shows that adjacent-term bounds feed sensitivity and robustness analyses only.

Data construction and provenance

Rather than convening a panel of nurses, we assigned each linguistic term through a documented source-to-cell workflow specified for this analysis. For every risk-criterion pair, the supplementary data file reports the source, setting and population, extracted statistic or statement, the construct directly measured, the author inference, the assigned term, adjacent-term range and evidence status. As an illustrative example, the likelihood term of R8 missed *VTE* prophylaxis was assigned from the reported finding that 10,643 of 82,269 prescribed prophylaxis doses (12.9%) were missed before an educational intervention (Haut et al., 2025); because this dose-level omission frequency comes from a single implementation study rather than from a population prevalence estimate, the ordinal judgement supported the central term high (*H*) rather than very high, and the adjacent-term range *MH-VH* was recorded for the sensitivity analyses. The primary matrix uses one author-assigned, literature-informed scenario rating per cell (Abraham et al., 2021; Al-Hameed et al., 2017; Al-Moteri et al., 2019; Berdot et al., 2013; Bouldin et al., 2013; Cantero et al., 2026; European Pressure Ulcer Advisory Panel et al., 2019; Haut et al., 2025; Heikkilä et al., 2023; Honarmand et al., 2024; Howanitz et al., 2002; Jessurun et al., 2023; Keers et al., 2013; LeLaurin & Shorr, 2019; F. Li et al., 2019; Z. Li et al., 2020; Morris et al., 2022; Sahle et al., 2023; Saint et al., 2016; Shipley et al., 2023; Song et al., 2019; Storr et al., 2017; Suetens et al., 2018; Suh et al., 2017; VanGilder et al., 2021; Yokoe et al., 2023); it is a methodological illustration and does not represent observations from a specific ward. Two multivariate profiles created by shifting selected terms one level are sensitivity scenarios only and are not averaged into the primary matrix; where future applications contain genuinely independent ratings for a cell, those ratings may be aggregated with Equation (1). The source studies use heterogeneous denominators, populations, settings and event definitions. No common epidemiological normalisation, universal numerical threshold or published conversion rule was applied; every fuzzy term is therefore an author judgement within the constructed scenario. Sensitivity comprised the q/blend grid, two multivariate shifts, one *HAI*-likelihood downgrade and Monte Carlo perturbation; it was not an exhaustive one-at-a-time test of all 32 cells.

The model was demonstrated on eight patient-safety risks on a general ward: patient falls, pressure injury, medication administration error, healthcare-associated infection (*HAI*), patient misidentification, unrecognised clinical deterioration, catheter-associated urinary tract infection (*CAUTI*) and missed venous thromboembolism (*VTE*) prophylaxis. Four criteria were used (Table 2): likelihood of occurrence, harm severity, detection difficulty and care burden; for all four a higher value

increases the priority of a risk. The seven-point linguistic scale ranging from very low (*VL*) to very high (*VH*) and its *q-ROF* numbers are given in Table 1.

Table 1. Linguistic scale and the corresponding *q-ROF* numbers.

Term	***VL***	***L***	***ML***	***M***	***MH***	***H***	***VH***
q-ROF number	(0.15, 0.85)	(0.35, 0.75)	(0.45, 0.65)	(0.55, 0.55)	(0.65, 0.45)	(0.75, 0.35)	(0.90, 0.20)

VL: very low, *L*: low, *ML*: medium low, *M*: medium, *MH*: medium high, *H*: high, *VH*: very high.

Table 2. Decision criteria, descriptions and priority orientation.

Criterion	**Description**	**Priority orientation**
Likelihood	How often the safety event occurs on the ward.	Higher values increase priority
Harm severity	The severity of harm to the patient if the event occurs.	Higher values increase priority
Detection difficulty	The difficulty of detecting the event before it causes harm.	Higher values increase priority
Care burden	The nursing workload required to prevent, monitor, detect and manage the patient-safety risk.	Higher values increase priority

Sensitivity, robustness and statistical analysis

The base case used $q = 3$and $\delta = 0.5$; the sensitivity analysis recomputed the complete pipeline for $q \in \{2,3,4\}$and $\delta \in \{0,0.5,1\}$. The base-case value $\delta = 0.5$was prespecified so that the matrix-derived and *SWARA* scenario-priority weights receive equal influence, because no prior evidence indicated that either weighting source was more credible for this constructed scenario; the grid endpoints 0 and 1 recover each source alone. The analysis also evaluated two multivariate term-shift scenarios and one cell-specific downgrade of *HAI* likelihood. The analysis further included a one-at-a-time weak-cell analysis that varied the nine lower-certainty cells one adjacent level in each feasible direction (14 runs) and a parametrised variant of the balance coefficient of Equation (2) evaluated at 0.25, 0.50 and 0.75. A Monte Carlo study perturbed every grade with independent Gaussian noise at standard deviations 0.01, 0.03, 0.05 and 0.10, with 4000 replications each and a fixed seed. The four perturbation levels were prespecified to represent increasing severities of input uncertainty on the [0,1]grade scale rather than estimated error magnitudes: $\sigma = 0.01$represents near-negligible imprecision, $\sigma = 0.03$and $\sigma = 0.05$represent moderate uncertainty in an author-assigned grade and $\sigma = 0.10$is a deliberate stress level approaching the 0.10 to 0.15 membership-grade spacing between adjacent linguistic terms. Spearman correlation quantified whole-ranking agreement; average ranks were used for exact ties. Standalone framework components are provided in the supplement (Sections S7-S9).

RESULTS

Weights

The proposed uncertainty measure of Equation (2) gave the certainty coefficient of each criterion, the mean pairwise distance of Equation (3) gave the contrast coefficient, and Equation (4) combined them into the matrix-derived weight. *SWARA* supplied the author-specified scenario-priority weights from the order harm severity, detection difficulty, likelihood and care burden; Equation (5) blended the two with $\delta = 0.5$. The matrix-derived, *SWARA* scenario-priority and blended criterion weights are reported in Table 3: the matrix-derived weight is largest for likelihood and the *SWARA* scenario-priority weight largest for harm severity; after blending, harm severity remains the most heavily weighted criterion. Figure S1 shows the three weight sets.

Table 3. Certainty and contrast coefficients and the matrix-derived, *SWARA* scenario-priority and blended criterion weights.

Coefficient or weight	Likelihood	Harm severity	Detection difficulty	Care burden
Certainty coefficient c_j	0.354	0.315	0.302	0.354
Contrast coefficient g_j	0.271	0.264	0.261	0.250
Matrix-derived weight (certainty × contrast)	0.277	0.240	0.227	0.256
SWARA scenario-priority weight	0.231	0.319	0.266	0.185
Blended weight ($\delta = 0.5$)	0.254	0.279	0.247	0.220

The matrix-derived weight is the normalised product of the certainty coefficient and mean-pairwise-distance contrast coefficient; *SWARA* values are author-specified scenario priorities and the blend uses $\delta = 0.5$.

Ranking and benchmark concordance

Table 4 reports the compromise index and rank of each risk. Under the constructed scenario, missed *VTE* prophylaxis had the highest index, followed closely by unrecognised clinical deterioration and *HAI*. These three risks form the leading scenario-dependent group. To assess same-input method concordance, the constructed matrix was also analysed with *q-ROF TOPSIS* and with an equal-weight *CRADIS* ranking. The proposed ranking coincides exactly with *q-ROF TOPSIS* on the same inputs (Spearman correlation 1.00), an internal method-concordance check rather than external or clinical validation. Under equal criterion weights, R4 *HAI*, R6 unrecognised clinical deterioration and R8 missed *VTE* prophylaxis all attained *CRADIS* index 1.00 and shared average rank 2.0; the overall Spearman correlation with the blended-weight ranking was 0.976. Figure 2 shows the priority indices and Figure S2 in the supplementary file compares the rankings across methods. Figure 3 shows the whole decision pattern as a heat map of the priority-oriented normalised criterion scores; darker cells indicate higher normalised criterion values, not weighted contributions to the final compromise index.

Table 4. Priority index, proposed ranking and same-input method-concordance ranks; exact ties receive average ranks.

Patient-safety risk	*CRADIS* index	Proposed rank	*q-ROF TOPSIS*	Equal-weight rank
R8 Missed *VTE* prophylaxis	1.00	1	1	2.0
R6 Unrecognised clinical deterioration	0.973	2	2	2.0
R4 *HAI*	0.925	3	3	2.0
R2 Pressure injury	0.602	4	4	4
R3 Medication administration error	0.555	5	5	5
R1 Patient falls	0.437	6	6	6
R7 *CAUTI*	0.345	7	7	7
R5 Patient misidentification	0.240	8	8	8

A larger *CRADIS* index denotes a higher illustrative priority. Under equal weights R4, R6 and R8 each reached index 1.00 and shared average rank 2.0 (the average of positions 1-3).

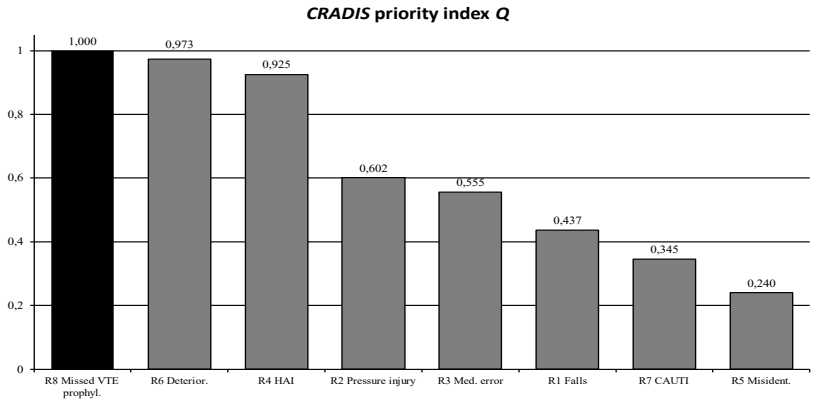

Figure 2. Illustrative *CRADIS* priority indices under the constructed inputs; a larger value denotes a higher illustrative priority. *VTE*: venous thromboembolism; *HAI*: healthcare-associated infection; *CAUTI*: catheter-associated urinary tract infection.

Patient-safety risk	Likelihood	Harm severity	Detection difficulty	Care burden
R8 Missed VTE prophyl.	0.62	1.00	1.00	0.20
R6 Deterior.	0.20	1.00	1.00	0.62
R4 HAI	1.00	0.62	0.20	1.00
R2 Pressure injury	0.62	0.41	0.00	1.00
R3 Med. error	1.00	0.00	0.41	0.41
R1 Falls	0.62	0.20	0.00	0.62
R7 CAUTI	0.00	0.20	0.20	0.62
R5 Misident.	0.00	0.20	0.20	0.00

Darker cells indicate a higher normalised q-ROF criterion score (min-max normalised per criterion).

Figure 3. Heat map of the priority-oriented normalised *q-ROF* criterion scores for all risks; darker cells indicate higher normalised criterion values, not weighted contributions to the final compromise index. *VTE*: venous thromboembolism; *HAI*: healthcare-associated infection; *CAUTI*: catheter-associated urinary tract infection.

Sensitivity and robustness

A sensitivity study varied the rung over $q \in \{2,3,4\}$and the blend over $\delta \in \{0,0.5,1\}$and recomputed the pipeline. Across this grid the Spearman rank correlation with the baseline ranged from 0.929 to 1.00; missed *VTE* prophylaxis ranked first when $\delta$was 0 or 0.5, whereas *HAI* ranked first when $\delta = 1$. In addition, the *HAI* likelihood term, an author-performed ordinal classification of a broad hospital-wide infection category rather than a direct numerical comparison with the pressure-injury prevalence estimate, was tested one level lower as a cell-specific condition: with this single cell changed from very high to high, the Spearman rank correlation with the baseline was 0.976; *HAI* retained third rank, while the two near-tied leaders reversed order: unrecognised clinical deterioration rose to first and missed *VTE* prophylaxis fell to second. This reversal shows that a whole-ranking correlation as high as 0.976 can coexist with a change in the first-ranked risk. The Monte Carlo study is summarised in

Table 5: as the standard deviation increased from 0.01 to 0.10, the mean Spearman correlation with the baseline fell from 0.983 to 0.867 and the probability that missed *VTE* prophylaxis was ranked first fell from 0.66 to 0.36, with unrecognised clinical deterioration and *HAI* the next most frequent leaders. Missed *VTE* prophylaxis had the highest first-place probability at every tested perturbation size, but that probability fell to 0.364 at $\sigma = 0.10$, compared with 0.339 for R6 and 0.276 for R4. Thus average whole-ranking concordance remained comparatively high while first-place identity was uncertain. These perturbations act on constructed grades and do not represent observed disagreement among clinical staff. A one-at-a-time weak-cell analysis varied the nine lower-certainty cells one adjacent level in each feasible direction (14 runs): the leading group was unchanged in every run, Spearman correlations remained between 0.905 and 1.00 and the first-place identity changed only when the deterioration likelihood rose one level or the *VTE* detection term fell one level (Supplementary section S7).

Table 5. Same-input benchmark concordance and synthetic-perturbation robustness of the proposed ranking.

Comparison or test	Spearman rank correlation
q-ROF TOPSIS (same inputs)	1.00
Equal-weight *CRADIS* (same inputs; average ties)	0.976
Monte Carlo, $\sigma = 0.01$(4000 runs), mean	0.983
Monte Carlo, $\sigma = 0.03$(4000 runs), mean	0.958
Monte Carlo, $\sigma = 0.05$(4000 runs), mean	0.940
Monte Carlo, $\sigma = 0.10$(4000 runs), mean	0.867

The *q-ROF TOPSIS* and equal-weight rows are same-input concordance checks; the Monte Carlo rows are mean robustness statistics under synthetic perturbation of the constructed inputs (4000 replications each) and are not comparison methods. Minimum Spearman correlations ranged from 0.881 at $\sigma = 0.01$to 0.238 at $\sigma = 0.10$. Average whole-ranking correlation should not be interpreted as stability of the first-ranked risk.

DISCUSSION

The model converts author-assigned, literature-informed *q-ROF* scenario values into an auditable illustrative ordering rather than a single crisp score. Under the stated inputs, missed *VTE* prophylaxis, unrecognised deterioration and *HAI* form the leading group. For R8, the literature directly supports a substantial missed-dose frequency and serious *VTE*-associated outcomes (Al-Hameed et al., 2017; Haut et al., 2025; Sahle et al., 2023), while the very-high detection-difficulty term remains an author scenario judgement: the corrected Suh study provides prophylaxis-adherence context, not a measure of omission-detection performance (Suh et al., 2017). For R6, the sources support severe consequences and recognition delays, but the likelihood anchor is conditional on a selected cardiac-arrest cohort rather than a general ward incidence (Al-Moteri et al., 2019; Honarmand et al., 2024; Shipley et al., 2023). *HAI* prevalence and mortality association are supported (Cantero et al., 2026; Suetens et al., 2018), whereas its detection and care-burden terms remain indirect mappings. The ordering must therefore be interpreted as conditional on the constructed inputs, not as evidence that one hazard is universally more important than another.

The second point is illustrated by the weighting. A criterion whose ratings are determinate but nearly identical across risks has a high certainty coefficient and a low contrast coefficient, so its matrix-derived weight is small; a criterion that separates the risks receives more weight. Compared with entropy-only weighting (Khan et al., 2021; Peng & Liu, 2019), this certainty-contrast construction makes the source of each matrix-derived weight visible and therefore easier to inspect in a safety committee. Supplementary section S5 shows that at a balanced but fully determinate grade the Peng-Liu *E1* and *E4* measures attain their maximum values, whereas the proposed measure and the Khan-derived entropy do not; this difference illustrates the proposed measure's emphasis on complete hesitancy.

Relevance for practitioners. The framework offers three practical benefits after local calibration. First, it converts linguistic judgements into an explicit calculation that can be checked line by line. Second, the revised provenance record separates the source finding, the construct directly measured and the author inference, so a safety committee can see precisely where published evidence ends and scenario judgement begins. Third, the sensitivity outputs distinguish whole-ranking concordance from uncertainty in the first-ranked risk. A ward may replace the supplied scenario values with local incident, audit, surveillance and workload data and elicit *SWARA* priorities from a multidisciplinary group without altering the mathematical workflow; the supplied matrix itself should not be used operationally.

This study is subject to several limitations. No nurses, clinical experts or patient records were used; the matrix contains author-assigned scenario ratings informed by selected publications and does not represent any specific ward. The cited studies use heterogeneous denominators and constructs, and no common epidemiological normalisation or fixed numerical cut-offs were applied. Several detection-difficulty and care-burden cells are supported only indirectly, and wristband defects or selected cardiac-arrest cases serve as proxies rather than direct incidence measures. Every fuzzy term therefore remains an author judgement even where the underlying source statistic is verified. The scenario priority order used in *SWARA* is also author-specified and would need multidisciplinary elicitation in a deployment. Only eight risks and four criteria are considered under one linguistic scale, and the results depend on the rung $q$and the blend parameter δ. The proposed measure satisfies the boundary, sharpness and symmetry properties of established *q-ROF* entropies; unlike them, it attains its maximum only at complete hesitancy rather than at every balanced grade, so it quantifies hesitancy-dominant uncertainty and is not a standard entropy. The *q-ROF TOPSIS* agreement and equal-weight analysis are same-input checks, not clinical validation. Average whole-ranking concordance did not imply a stable first-place identity. Future work should elicit ratings and priorities from clinical stakeholders, test criterion-specific anchors, calibrate against ward data and prospectively evaluate decision usefulness before clinical adoption.

CONCLUSION

A hesitancy-dominant uncertainty measure for *q-ROF* numbers was proposed and its boundedness, unique maximum at complete hesitancy, sharp minimum and symmetry were established. Within the author-constructed scenario, matrix-derived certainty-contrast weights, author-specified *SWARA* priorities and *CRADIS* produced a reproducible leading group of missed *VTE* prophylaxis, unrecognised clinical deterioration and *HAI*. *q-ROF TOPSIS* gave the same primary ordering under identical inputs, whereas equal weights produced a three-way top tie. Mean rank concordance remained high under synthetic perturbation, but the first-place identity became uncertain. These outputs are a methodological demonstration, not a validated clinical hierarchy; local evidence and multidisciplinary elicitation are prerequisites for use.

Declarations

Ethics approval and consent to participate: Not applicable. The study used only published literature, author-constructed literature-informed ratings and illustrative perturbations and involved no participants, identifiable data or clinical intervention.

Consent for publication: Not applicable; the study contains no individual person's data or images.

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Data and code availability: The manuscript includes the supplementary pages containing data and code. The supplementary section pages contain the scale, transparent source-to-cell provenance, the primary matrix, *SWARA* trail, uncertainty-measure comparison, full results, sensitivity and robustness outputs, environment details and the complete model.py listing. The sources supporting the supplementary provenance appear in the same reference list. The supplementary section cites the same references as the main article.

Author contributions: The author designed the study, performed the analysis and wrote the manuscript.

Use of artificial intelligence (*AI*): No *AI* tools were used to generate any content for this manuscript.

Clinical disclaimer: The framework and its outputs must not be used as patient-specific or ward-specific safety decisions without local calibration and validation.

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Supplementary Material

Supplementary Data and Code
A q-rung orthopair fuzzy multi-criteria model incorporating a hesitancy-dominant uncertainty measure for prioritising patient-safety risks in nursing care
The material contains no patient records, identifiable information or clinical outcome dataset.

Clinical disclaimer: The framework and its outputs must not be used as patient-specific decisions without local calibration and clinician validation.
This material is provided for academic use only. If the data, the linguistic mappings, the calculation logic or the code in this document is used, the article above should be cited.

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Abbreviations: q-rung orthopair fuzzy (*q-ROF*); step-wise weight assessment ratio analysis (*SWARA*); compromise ranking of alternatives from distance to ideal solution (*CRADIS*); technique for order preference by similarity to ideal solution (*TOPSIS*); venous thromboembolism (*VTE*); healthcare-associated infection (*HAI*); catheter-associated urinary tract infection (*CAUTI*); linguistic terms very low (*VL*), low (L), medium low (*ML*), medium (M), medium high (*MH*), high (H) and very high (*VH*).

S1. Linguistic scale and documented author-assignment workflow

Linguistic terms were mapped to the seven *q-ROF* pairs shown in Table S1 of the main text. For each risk-criterion cell, the author: (1) selected a hazard-specific source; (2) recorded the source finding and the construct directly measured; (3) documented the inference needed to apply that finding to the target criterion; (4) assigned a central term and adjacent-term range; and (5) classified the evidence as direct, indirect/proxy or author scenario judgement. The studies use noncommensurate denominators, settings and event definitions, so no common epidemiological normalisation, fixed numerical cut-offs or published conversion rule was used. The terms are therefore author-assigned, literature-informed scenario values rather than literature-derived measurements. Sensitivity comprised two multivariate shifts, a one-level downgrade of the *HAI*-likelihood cell, the q/blend grid and Monte Carlo perturbation; it should not be assumed as an exhaustive one-at-a-time test of all 32 cells.

S2. Source-to-cell provenance for all 32 constructed cells

Table S-PROV summarises the central term, adjacent range, evidence status and source. The following 32 narratives separately state the source finding, what the source directly measured and the author inference that produced the scenario assignment. References follow the author-date style of the main article; the sources cited in this section appear in the main reference list. All care-burden terms are author-assigned burden ratings informed by the activities each hazard requires; nursing workload was not directly measured and the two very high burden terms are varied in the weak-cell analysis (Section S7).

No	Risk	Criterion	Term	Range	Evidence status	Source
1	R1 Patient falls	Likelihood	*H*	*MH-VH*	Direct statistic; author term	Bouldin 2013
2	R1 Patient falls	Harm severity	*M*	*ML-MH*	Direct harm evidence; author term	Bouldin 2013
3	R1 Patient falls	Detection difficulty	*ML*	*L-M*	Indirect evidence; author term	Heikkilä 2023
4	R1 Patient falls	Care burden	*H*	*MH-VH*	Indirect workload evidence; author term	LeLaurin 2019; Morris 2022
5	R2 Pressure injury	Likelihood	*H*	*MH-VH*	Direct statistic; author term	Z. Li 2020
6	R2 Pressure injury	Harm severity	*MH*	*M-H*	Direct association; author term	Song 2019
7	R2 Pressure injury	Detection difficulty	*ML*	*L-M*	Indirect evidence; author term	Z. Li 2020
8	R2 Pressure injury	Care burden	*VH*	*H-VH*	Indirect workload evidence; author term	EPUAP/NPIAP/PPPIA 2019; VanGilder 2021
9	R3 Medication administration error	Likelihood	*VH*	*H-VH*	Direct statistic; author term	Keers 2013
10	R3 Medication administration error	Harm severity	*ML*	*L-M*	Indirect harm evidence; author term	Berdot 2013
11	R3 Medication administration error	Detection difficulty	*MH*	*M-H*	Criterion mismatch; author term	Jessurun 2023
12	R3 Medication administration error	Care burden	*MH*	*M-H*	Indirect burden evidence; author term	Jessurun 2023
13	R4 Healthcare-associated infection	Likelihood	*VH*	*H-VH*	Direct statistic; author term	Suetens 2018
14	R4 Healthcare-associated infection	Harm severity	*H*	*MH-VH*	Direct association; author term	Cantero 2026
15	R4 Healthcare-associated infection	Detection difficulty	*M*	*ML-MH*	Indirect evidence; author term	Suetens 2018
16	R4 Healthcare-associated infection	Care burden	*VH*	*H-VH*	Indirect workload evidence; author term	Storr 2017; Yokoe 2023
17	R5 Patient misidentification	Likelihood	*ML*	*L-M*	Process proxy; author term	Howanitz 2002
18	R5 Patient misidentification	Harm severity	*M*	*ML-MH*	Author-assigned scenario	Abraham 2021
19	R5 Patient misidentification	Detection difficulty	*M*	*ML-MH*	Indirect evidence; author term	Abraham 2021
20	R5 Patient misidentification	Care burden	*ML*	*L-M*	Author-assigned burden	Howanitz 2002
21	R6 Unrecognised clinical deterioration	Likelihood	*M*	*ML-MH*	Selected-cohort proxy; author term	Shipley 2023

No	Risk	Criterion	Term	Range	Evidence status	Source
22	R6 Unrecognised clinical deterioration	Harm severity	*VH*	*H-VH*	Indirect severe-outcome evidence; author term	Shipley 2023
23	R6 Unrecognised clinical deterioration	Detection difficulty	*VH*	*H-VH*	Direct qualitative evidence; author term	Al-Moteri 2019
24	R6 Unrecognised clinical deterioration	Care burden	*H*	*MH-VH*	Indirect workload evidence; author term	Honarmand 2024
25	R7 Catheter-associated UTI	Likelihood	*ML*	*L-M*	Direct statistic; author term	Saint 2016
26	R7 Catheter-associated UTI	Harm severity	*M*	*ML-MH*	Indirect harm evidence; author term	F. Li 2019
27	R7 Catheter-associated UTI	Detection difficulty	*M*	*ML-MH*	Criterion mismatch; author term	Saint 2016
28	R7 Catheter-associated UTI	Care burden	*H*	*MH-VH*	Indirect burden evidence; author term	Saint 2016
29	R8 Missed *VTE* prophylaxis	Likelihood	*H*	*MH-VH*	Direct statistic; author term	Haut 2025
30	R8 Missed *VTE* prophylaxis	Harm severity	*VH*	*H-VH*	Direct association; author term	Al-Hameed 2017; Sahle 2023
31	R8 Missed *VTE* prophylaxis	Detection difficulty	*VH*	*H-VH*	Adherence context only; author term	Suh 2017
32	R8 Missed *VTE* prophylaxis	Care burden	*M*	*ML-MH*	Indirect burden evidence; author term	Haut 2025

Cell 1 (R1 Patient falls, Likelihood). Source finding: 3.56 falls per 1000 patient-days in US adult medical/surgical units. Direct construct: Ward fall frequency. Author inference: *H* was assigned relative to the other scenario hazards; no published H cut-off exists. Assignment: *H* (adjacent range *MH-VH*); status: Direct statistic; author term. Source: Bouldin 2013.
Cell 2 (R1 Patient falls, Harm severity). Source finding: 26.1% of falls were injurious; 0.93 injurious falls per 1000 patient-days; most injuries were not severe. Direct construct: Observed injury frequency and profile. Author inference: *M* summarises the relative harm profile in this scenario. Assignment: *M* (adjacent range *ML-MH*); status: Direct harm evidence; author term. Source: Bouldin 2013.
Cell 3 (R1 Patient falls, Detection difficulty). Source finding: Specialty-specific fall rates and identifiable fall risk factors were reported. Direct construct: Fall frequency and risk factors, not detection performance. Author inference: Routine screening and overt event recognition were used to assign *ML*. Assignment: *ML* (adjacent range *L-M*); status: Indirect evidence; author term. Source: Heikkilä 2023.
Cell 4 (R1 Patient falls, Care burden). Source finding: Reviews describe multicomponent prevention including rounding, supervision and education. Direct construct: Prevention components and effectiveness. Author inference: Nursing workload was not quantified; H is a scenario burden judgement. Assignment: *H* (adjacent range *MH-VH*); status: Indirect workload evidence; author term. Source: LeLaurin 2019; Morris 2022.
Cell 5 (R2 Pressure injury, Likelihood). Source finding: Pooled pressure-injury prevalence was 12.8%; hospital-acquired prevalence was 8.4%. Direct construct: Occurrence prevalence. Author inference: *H* is an author conversion without a universal threshold. Assignment: *H* (adjacent range *MH-VH*); status: Direct statistic; author term. Source: Z. Li 2020.
Cell 6 (R2 Pressure injury, Harm severity). Source finding: Pressure injury was associated with mortality (pooled hazard ratio (*HR*) 1.78; stage 3-4 *HR* 2.41). Direct construct: Mortality association. Author inference: *MH* represents substantial relative harm; causation is not claimed. Assignment: *MH* (adjacent range *M-H*); status: Direct association; author term. Source: Song 2019.

Cell 7 (R2 Pressure injury, Detection difficulty). Source finding: The prevalence review reports stage distribution. Direct construct: Prevalence and stage distribution, not detection sensitivity. Author inference: Routine skin assessment and possible missed deep-tissue injury informed *ML*. Assignment: *ML* (adjacent range *L-M*); status: Indirect evidence; author term. Source: Z. Li 2020.
Cell 8 (R2 Pressure injury, Care burden). Source finding: Guidance recommends repositioning, skin assessment, support surfaces and nutrition; a large survey provides prevalence context. Direct construct: Prevention components and prevalence. Author inference: Workload was not measured; *VH* is an author burden judgement. Assignment: *VH* (adjacent range *H-VH*); status: Indirect workload evidence; author term. Source: EPUAP/NPIAP/PPPIA 2019; VanGilder 2021.
Cell 9 (R3 Medication administration error, Likelihood). Source finding: Median medication-administration error prevalence was 19.6% including timing errors and 8.0% excluding timing errors. Direct construct: Dose-level process error frequency. Author inference: *VH* is an author scenario category. Assignment: *VH* (adjacent range *H-VH*); status: Direct statistic; author term. Source: Keers 2013.
Cell 10 (R3 Medication administration error, Harm severity). Source finding: The review found frequent administration errors, no fatal errors in included reports and predominantly minor assessed consequences. Direct construct: Observed consequence profile. Author inference: *ML* summarises low-to-moderate harm in the sampled evidence. Assignment: *ML* (adjacent range *L-M*); status: Indirect harm evidence; author term. Source: Berdot 2013.
Cell 11 (R3 Medication administration error, Detection difficulty). Source finding: About 11.8% of observed errors were judged potentially harmful. Direct construct: Potential harm, not the proportion missed or undetected. Author inference: *MH* detection difficulty is retained only as an explicit author scenario judgement. Assignment: *MH* (adjacent range *M-H*); status: Criterion mismatch; author term. Source: Jessurun 2023. Treated as an unsupported author scenario input and varied one level lower and higher in the weak-cell analysis (Section S7).
Cell 12 (R3 Medication administration error, Care burden). Source finding: Complex pharmaceutical forms and specific administration times were associated with errors; interruptions and patient-to-nurse ratio were not supported as claimed. Direct construct: Error determinants in the studied wards. Author inference: Verification effort informed *MH*, but workload was not directly measured. Assignment: *MH* (adjacent range *M-H*); status: Indirect burden evidence; author term. Source: Jessurun 2023.
Cell 13 (R4 Healthcare-associated infection, Likelihood). Source finding: 6.5% of acute-care inpatients had at least one *HAI* in the European point-prevalence survey. Direct construct: *HAI* prevalence. Author inference: *VH* is an author classification across noncommensurate hazard denominators and was tested at *H*. Assignment: *VH* (adjacent range *H-VH*); status: Direct statistic; author term. Source: Suetens 2018.
Cell 14 (R4 Healthcare-associated infection, Harm severity). Source finding: *HAI* was associated with inpatient death (adjusted odds ratio (*OR*) about 1.70). Direct construct: Mortality association. Author inference: *H* represents substantial relative harm; causation is not claimed. Assignment: *H* (adjacent range *MH-VH*); status: Direct association; author term. Source: Cantero 2026.
Cell 15 (R4 Healthcare-associated infection, Detection difficulty). Source finding: The survey applied clinical, microbiological and surveillance case definitions. Direct construct: Case ascertainment method, not detection difficulty. Author inference: Need for surveillance/culture informed *M*. Assignment: *M* (adjacent range *ML-MH*); status: Indirect evidence; author term. Source: Suetens 2018.
Cell 16 (R4 Healthcare-associated infection, Care burden). Source finding: World Health Organization (*WHO*) and compendium sources describe multicomponent ward-wide infection-prevention programmes. Direct construct: Programme components and recommendations. Author inference: No nursing workload estimate was reported; *VH* is an author burden judgement. Assignment: *VH* (adjacent range *H-VH*); status: Indirect workload evidence; author term. Source: Storr 2017; Yokoe 2023.
Cell 17 (R5 Patient misidentification, Likelihood). Source finding: Across 1,757,730 wristbands, 45,197 errors were identified; the mean error rate fell from 7.40% in quarter 1 to 3.05% in quarter 8 and 71.6% of errors were missing wristbands. Direct construct: Identification-process defects, not wrong-patient harm incidence. Author inference: The process proxy informed *ML* likelihood; it is varied in the weak-cell analysis (Section S7). Assignment: *ML* (adjacent range *L-M*); status: Process proxy; author term. Source: Howanitz 2002.
Cell 18 (R5 Patient misidentification, Harm severity). Source finding: The study described incident types and contributory factors, but patient and institutional consequence data were scarce. Direct

construct: Incident typology; consequence data scarce. Author inference: The M harm term is an author-assigned scenario value and is varied in the weak-cell analysis (Section S7). Assignment: *M* (adjacent range *ML-MH*); status: Author-assigned scenario. Source: Abraham 2021.

Cell 19 (R5 Patient misidentification, Detection difficulty). Source finding: Identification failures were sometimes discovered downstream or at transfers. Direct construct: Discovery circumstances, not detection sensitivity. Author inference: Downstream discovery informed *M*. Assignment: *M* (adjacent range *ML-MH*); status: Indirect evidence; author term. Source: Abraham 2021.

Cell 20 (R5 Patient misidentification, Care burden). Source finding: Continuous wristband monitoring reduced identification defects. Direct construct: Monitoring activity, not two-identifier-check workload. Author inference: *ML* care burden is an explicit author scenario judgement. Assignment: *ML* (adjacent range *L-M*); status: Author-assigned burden. Source: Howanitz 2002.

Cell 21 (R6 Unrecognised clinical deterioration, Likelihood). Source finding: 79.4% of selected cardiac-arrest cases outside the intensive care unit (*ICU*) had met rapid-response criteria earlier. Direct construct: Conditional proportion among patients who arrested, not ward incidence. Author inference: *M* is a constructed likelihood value and the 79.4% figure is not an occurrence estimate. Assignment: *M* (adjacent range *ML-MH*); status: Selected-cohort proxy; author term. Source: Shipley 2023.

Cell 22 (R6 Unrecognised clinical deterioration, Harm severity). Source finding: The source supplies qualitative severe-outcome context in a selected cardiac-arrest cohort. No quantitative data were extracted. Direct construct: Qualitative severe-outcome context. Author inference: The "*VH*" term is a qualitatively supported, author-assigned scenario judgement; the uncertainty of this specific assignment is explicitly evaluated in the weak-cell analysis (Section S7). Assignment: VH (adjacent range H-VH); status: Indirect severe-outcome evidence; author term. Source: Shipley 2023.

Cell 23 (R6 Unrecognised clinical deterioration, Detection difficulty). Source finding: The systematic review found that deterioration may be missed despite charting and that recognition/response delays persist. Direct construct: Qualitative evidence on recognition failure. Author inference: *VH* is an author ordinal choice based on this direct qualitative evidence. Assignment: *VH* (adjacent range *H-VH*); status: Direct qualitative evidence; author term. Source: Al-Moteri 2019.

Cell 24 (R6 Unrecognised clinical deterioration, Care burden). Source finding: Guidance supports timely vital signs, education, escalation criteria and rapid response team (*RRT*) or medical emergency team (*MET*) systems. Direct construct: Recommended response-system components. Author inference: No workload measure was reported; H is an author burden judgement. Assignment: *H* (adjacent range *MH-VH*); status: Indirect workload evidence; author term. Source: Honarmand 2024.

Cell 25 (R7 Catheter-associated UTI, Likelihood). Source finding: Non-*ICU CAUTI* rates decreased from about 2.28 to 1.54 per 1000 catheter-days in the national programme. Direct construct: Catheter-day incidence in participating units. Author inference: *ML* is an author scenario category, not a published threshold. Assignment: *ML* (adjacent range *L-M*); status: Direct statistic; author term. Source: Saint 2016.

Cell 26 (R7 Catheter-associated UTI, Harm severity). Source finding: The meta-analysis reports *CAUTI* associated with increased mortality and identifies risk factors including longer hospital/*ICU* stay. Direct construct: Associations and risk factors; not proof that *CAUTI* caused longer stay. Author inference: *M* summarises the reported harm context. Assignment: *M* (adjacent range *ML-MH*); status: Indirect harm evidence; author term. Source: F. Li 2019.

Cell 27 (R7 Catheter-associated UTI, Detection difficulty). Source finding: The cited programme evaluates prevention and does not measure diagnostic or pre-harm detection difficulty. Direct construct: Prevention-programme outcome. Author inference: *M* detection difficulty is retained as an explicit author scenario judgement. Assignment: *M* (adjacent range *ML-MH*); status: Criterion mismatch; author term. Source: Saint 2016. Treated as an unsupported author scenario input and varied one level lower and higher in the weak-cell analysis (Section S7).

Cell 28 (R7 Catheter-associated UTI, Care burden). Source finding: The programme supports appropriate-use review, aseptic maintenance and catheter-removal activity. Direct construct: Implementation and prevention components. Author inference: *H* reflects inferred continuing care burden; workload was not quantified. Assignment: *H* (adjacent range *MH-VH*); status: Indirect burden evidence; author term. Source: Saint 2016.

Cell 29 (R8 Missed *VTE* prophylaxis, Likelihood). Source finding: Before the intervention, 10,643 of 82,269 prescribed prophylaxis doses (12.9%) were missed. Direct construct: Dose-level omission

frequency in one implementation study. Author inference: *H* is an author category and not a universal patient-level prevalence. Assignment: *H* (adjacent range *MH-VH*); status: Direct statistic; author term. Source: Haut 2025.

Cell 30 (R8 Missed *VTE* prophylaxis, Harm severity). Source finding: Hospital-acquired *VTE* mortality was about 14.3%; omitted early prophylaxis was associated with hospital death (adjusted *OR* 1.35) in a separate *ICU* registry. Direct construct: Mortality and adjusted association. Author inference: *VH* reflects severe relative harm; causation is not claimed. Assignment: *VH* (adjacent range *H-VH*); status: Direct association; author term. Source: Al-Hameed 2017; Sahle 2023.

Cell 31 (R8 Missed *VTE* prophylaxis, Detection difficulty). Source finding: Hospital-acquired venous thromboembolism (*HA-VTE*) cases had lower prior prophylaxis than controls (54.0% vs 79.2%). Direct construct: Prior prophylaxis adherence, not omission-detection performance. Author inference: *VH* detection difficulty is an author scenario judgement; the source supplies adherence context only. Assignment: *VH* (adjacent range *H-VH*); status: Adherence context only; author term. Source: Suh 2017. Treated as an unsupported author scenario input and varied one level lower and higher in the weak-cell analysis (Section S7).

Cell 32 (R8 Missed *VTE* prophylaxis, Care burden). Source finding: The implementation bundle included nurse/patient education and real-time follow-up of missed doses. Direct construct: Intervention activity. Author inference: *M* represents inferred implementation burden; workload was not directly measured. Assignment: *M* (adjacent range *ML-MH*); status: Indirect burden evidence; author term. Source: Haut 2025.

S3. Primary decision matrix

Patient-safety risk	Likelihood	Harm severity	Detection difficulty	Care burden
R1 Patient falls	H (0.75, 0.35)	M (0.55, 0.55)	*ML* (0.45, 0.65)	H (0.75, 0.35)
R2 Pressure injury	H (0.75, 0.35)	*MH* (0.65, 0.45)	*ML* (0.45, 0.65)	*VH* (0.90, 0.20)
R3 Medication administration error	*VH* (0.90, 0.20)	*ML* (0.45, 0.65)	*MH* (0.65, 0.45)	*MH* (0.65, 0.45)
R4 Healthcare-associated infection	*VH* (0.90, 0.20)	H (0.75, 0.35)	M (0.55, 0.55)	*VH* (0.90, 0.20)
R5 Patient misidentification	*ML* (0.45, 0.65)	M (0.55, 0.55)	M (0.55, 0.55)	*ML* (0.45, 0.65)
R6 Unrecognised clinical deterioration	M (0.55, 0.55)	*VH* (0.90, 0.20)	*VH* (0.90, 0.20)	H (0.75, 0.35)
R7 Catheter-associated urinary tract infection	*ML* (0.45, 0.65)	M (0.55, 0.55)	M (0.55, 0.55)	H (0.75, 0.35)
R8 Missed venous thromboembolism prophylaxis	H (0.75, 0.35)	*VH* (0.90, 0.20)	*VH* (0.90, 0.20)	M (0.55, 0.55)

S4. *SWARA* scenario-priority weight trail

SWARA used the author-specified scenario-priority order harm severity, detection difficulty, likelihood and care burden. Neither the order nor the comparative ratios were estimated from the heterogeneous source statistics or elicited from nurses or a clinical expert panel.

Position	Criterion	Comparative importance	Coefficient	Recalculated weight	Final weight
1	Harm severity	-	1.000	1.0000	0.3187
2	Detection difficulty	0.20	1.200	0.8333	0.2656
3	Likelihood	0.15	1.150	0.7246	0.2309
4	Care burden	0.25	1.250	0.5797	0.1848

S5. Comparison with published *q-ROF* measures

The proposed measure is compared with the Peng-Liu ratio entropy *E1*, the Peng-Liu linear entropy *E4*, and the Khan-derived entropy *EK* (complement of a knowledge measure) (Khan et al., 2021; Peng & Liu, 2019). With the determinacy gap and hesitancy mass of the main text, the comparators are $E1 = (h + 1 - d)/(h + 1 + d)$, $E4 = 1 - d$and $EK = 1 - (0.5(d + (2/\pi)\, arccos\, h))\text{^}(1/q)$. At a balanced but fully determinate grade the Peng-Liu *E1* and *E4* measures attain their maximum value 1.000 whereas the proposed measure gives 0.500 and the Khan-derived entropy 0.206; it should be pointed out that this difference illustrates the proposed measure's emphasis on complete hesitancy.

Grade (*mu*, *nu*)	Description	U (proposed)	*E1*	*E4*	*EK*
(0.90, 0.20)	Determinate positive	0.366	0.273	0.279	0.081
(0.20, 0.90)	Determinate negative	0.366	0.273	0.279	0.081
(0.55, 0.55)	Balanced, moderate hesitancy	0.834	1.000	1.000	0.356
(0.30, 0.30)	Balanced, high hesitancy	0.973	1.000	1.000	0.528
(0.00, 0.00)	Complete hesitancy	1.000	1.000	1.000	1.000
(0.7937, 0.7937)	Balanced, zero hesitancy	0.500	1.000	1.000	0.206
(0.85, 0.60)	Mild positive, low hesitancy	0.420	0.492	0.602	0.136

S6. Full *CRADIS* results

Blended weights were likelihood 0.254, harm severity 0.279, detection difficulty 0.247 and care burden 0.220. The primary *CRADIS* ranking and *q-ROF TOPSIS* ranking coincide at all eight positions. Under equal weights R4, R6 and R8 each attain index 1.000; the corrected average-tie convention assigns rank 2.0 to all three and yields Spearman correlation 0.976 with the blended ranking.

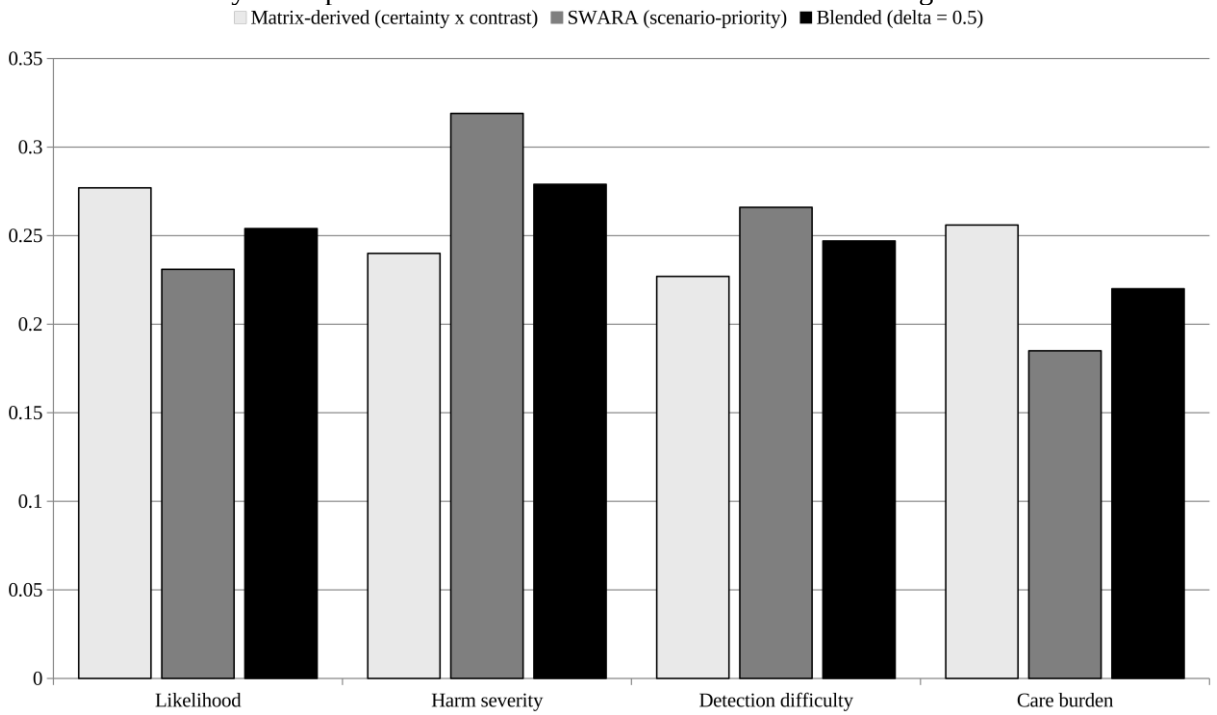


Figure S1. Matrix-derived certainty-contrast, author-specified *SWARA* scenario-priority and blended criterion weights (greyscale design).

S7. Sensitivity, cell-specific and Monte Carlo robustness

Rung q	Blend delta	Leading risk	Spearman vs baseline
2	0	R8 Missed *VTE* prophylaxis	1.000
2	0.5	R8 Missed *VTE* prophylaxis	1.000
2	1.0	R4 Healthcare-associated infection	0.929
3	0	R8 Missed *VTE* prophylaxis	1.000
3	0.5	R8 Missed *VTE* prophylaxis	1.000
3	1.0	R4 Healthcare-associated infection	0.929
4	0	R8 Missed *VTE* prophylaxis	1.000
4	0.5	R8 Missed *VTE* prophylaxis	1.000
4	1.0	R4 Healthcare-associated infection	0.929

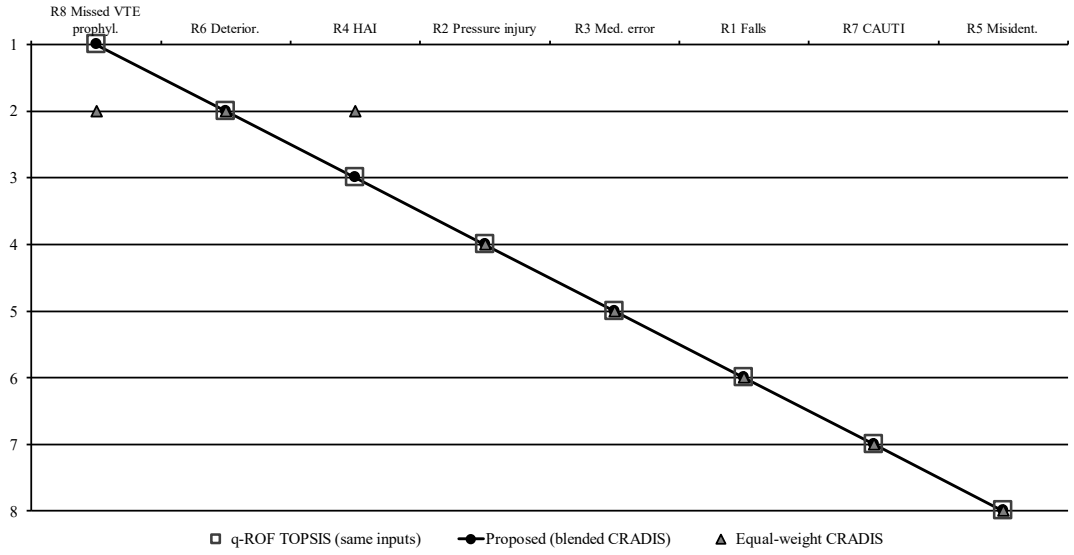
Under the two multivariate variants specified for this analysis, missed *VTE* prophylaxis remains first (Variant A Spearman 0.952; Variant B 1.000). Downgrading the author-assigned *HAI* likelihood term from very high to high, with all weights recomputed, gives Spearman 0.976; *HAI* remains rank 3 and R6 and R8 exchange positions. These scenarios do not constitute exhaustive cell-by-cell sensitivity testing.

Sigma	Mean Spearman	Minimum Spearman	P(top = R8)	P(top = R6)	P(top = R4)
0.01	0.983	0.881	0.658	0.279	0.063
0.03	0.958	0.833	0.439	0.331	0.231
0.05	0.940	0.643	0.387	0.335	0.278
0.10	0.867	0.238	0.364	0.339	0.276

At each of 4000 replications per perturbation size, independent Gaussian noise was added to both grades, values were clipped to [0.02, 0.98], inadmissible pairs were radially rescaled and matrix-derived weights and ranks were recomputed while *SWARA* scenario-priority weights remained fixed. The primary and Monte Carlo rankings contained no exact ties. The equal-weight deterministic check produced a three-way maximum; those alternatives receive average rank 2.0, and all rank correlations use the resulting average ranks.

Weak-cell one-at-a-time analysis. Each of the nine lower-certainty cells (8, 11, 16, 17, 18, 21, 22, 27 and 31) was varied one adjacent linguistic level in each feasible direction and the complete pipeline was recomputed; four upward shifts were infeasible because the cells already carry the highest term, giving 14 runs. The leading group(missed *VTE* prophylaxis, unrecognised clinical deterioration and healthcare-associated infection) was unchanged in all 14 runs and Spearman correlations with the baseline ranged from 0.905 to 1.000. The first-place identity changed only twice: raising cell 21 to *MH* placed unrecognised clinical deterioration first (Spearman 0.976) and lowering cell 31 to *H* placed healthcare-associated infection first (Spearman 0.905). Run-level results: cell 8 to *H* 0.976; cell 11 to *M* 1.000; cell 11 to *H* 0.976; cell 16 to *H* 1.000; cell 17 to *L* 1.000; cell 17 to *M* 1.000; cell 18 to *ML* 1.000; cell 18 to *MH* 1.000; cell 21 to *ML* 0.976; cell 21 to *MH* 0.976 (leader change); cell 22 to *H* 0.976; cell 27 to *ML* 1.000; cell 27 to *MH* 1.000; cell 31 to *H* 0.905 (leader change); all leaders otherwise missed *VTE* prophylaxis. Stored in the weak-cell sensitivity output.

Coefficient sensitivity of the uncertainty measure. The coefficient one half is the neutral midpoint of the balance term: at zero hesitancy the measure reduces to half of one minus the determinacy gap, so a fully determinate grade never exceeds one half, strictly below the unique maximum at complete hesitancy. A parametrised variant that replaces this coefficient with alpha, evaluated at 0.25, 0.50 and 0.75, left the ranking unchanged at all three values (Spearman 1.000, leader unchanged).



Equal weights: R4 = R6 = R8 at average rank 2.0 (three-way top tie; Spearman rho = 0.976).
Blended CRADIS and q-ROF TOPSIS agree at all eight ranks.

Figure S2. Same-input ranking concordance (greyscale design): blended *CRADIS*, *q-ROF TOPSIS* and equal-weight *CRADIS*. Rank 1 denotes highest priority; exact ties use average ranks, so the three equal-weight leaders are plotted at rank 2.0.

S8. Environment, seed and checksums

Environment tested for this archive: Python 3.13.5, NumPy 2.3.5 and Matplotlib 3.10.8. Monte Carlo draws use *numpy.random.seed(9)* with *MT19937*; the four perturbation batches run sequentially in ascending sigma without reseeding.
SHA-256: model.py 1d026bf6d396981c255ca14f85b3cf91f0e35968c7b64e3ef2e343e6b17fa22b; inputs.csv 2037b95e71f01cb4a787f8036a4aed58b224e3b358c74ee78ad006c9362a20fd; results.json 45254efb59b351b38ff6f378fad9b02af9464ad65476e2dc74c6c3c61b670154; make_figures.py 4c318f03ba917c2c3ae92f9719b724e762584cf3e2bca95b5e89d07d40433e4f.

S9. Complete reproduction code

The listing below is identical to the standalone model.py file. Underscores are programming identifiers, not mathematical notation; exact deterministic ties receive average ranks. The plotting utilities that generate the figures are omitted from this listing because of space constraints.

```
# -*- coding: utf-8 -*-
"""Reproduce the q-ROF SWARA-CRADIS methodological illustration.

This material is provided for academic use only.
The framework and its outputs must not be used as patient-specific or ward-specific safety decisions without local calibration and validation.
If you use the data, the linguistic mappings, the calculation logic or the code in this document, please cite the article above.
Copyright (c) 2026 Şengül, D.
INTELLECTUAL PROPERTY & USAGE POLICY
This script is the intellectual property of the author and is developed
strictly for academic and research purposes.
ATTRIBUTION
Any usage, modification, adaptation, or distribution of this code must be
properly referenced and attributed to the author.
DISCLAIMER OF LIABILITY
No responsibility or liability is assumed for any commercial application,
real-life implementation, or operational usage of this code. This software is
provided "as is" without warranty of any kind, express or implied. The author
shall not be held liable for any damages or consequences arising from the use
of this script outside of its intended academic scope.

The primary matrix contains one author-assigned, literature-informed scenario
rating per cell. Published sources provide heterogeneous facts and context;
they do not directly generate the seven-level fuzzy terms. Variant profiles
and Gaussian perturbations are sensitivity analyses only.
"""
from __future__ import annotations

import csv
import json
```

```
import math
from pathlib import Path
from typing import Iterable

import numpy as np

SEED = 9
Q = 3
DELTA = 0.5
np.random.seed(SEED)  # RandomState/MT19937; batches run sequentially.

SC = {
    "VL": (0.15, 0.85), "L": (0.35, 0.75), "ML": (0.45, 0.65),
    "M": (0.55, 0.55), "MH": (0.65, 0.45), "H": (0.75, 0.35),
    "VH": (0.90, 0.20),
}
ORD = ["VL", "L", "ML", "M", "MH", "H", "VH"]
RF = [
    "R1 Patient falls", "R2 Pressure injury",
    "R3 Medication administration error", "R4 Healthcare-associated infection",
    "R5 Patient misidentification", "R6 Unrecognised clinical deterioration",
    "R7 Catheter-associated UTI", "R8 Missed VTE prophylaxis",
]
RK = [f"R{i}" for i in range(1, 9)]
CRIT = ["Likelihood", "Harm severity", "Detection difficulty", "Care burden"]


def shift(term: str, delta: int) -> str:
    index = min(max(ORD.index(term) + delta, 0), len(ORD) - 1)
    return ORD[index]


def load_base(path: str | Path = "inputs.csv") -> dict[str, list[str]]:
    values: dict[str, dict[str, str]] = {}
    with Path(path).open(newline="", encoding="utf-8") as stream:
        for row in csv.DictReader(stream):
            values.setdefault(row["risk_id"], {})[row["criterion"]] = row["linguistic_term"]
    missing = [(risk, criterion) for risk in RK for criterion in CRIT
               if risk not in values or criterion not in values[risk]]
    if missing:
        raise ValueError(f"Missing input cells: {missing}")
    return {risk: [values[risk][criterion] for criterion in CRIT] for risk in RK}


BASE = load_base()


def primary_matrix() -> np.ndarray:
    matrix = np.empty((8, 4), dtype=object)
    for i, risk in enumerate(RK):
        for j in range(4):
            matrix[i, j] = SC[BASE[risk][j]]
    return matrix


def uncertainty(number: tuple[float, float], q: int = Q) -> float:
    mu, nu = number
    hesitation = max(0.0, 1 - mu**q - nu**q)
    return hesitation + (1 - hesitation) * (1 - abs(mu**q - nu**q)) / 2


def distance(a: tuple[float, float], b: tuple[float, float], q: int = Q) -> float:
    mu1, nu1 = a
    mu2, nu2 = b
    pi1 = max(0.0, 1 - mu1**q - nu1**q)
    pi2 = max(0.0, 1 - mu2**q - nu2**q)
    return math.sqrt(0.5 * ((mu1**q - mu2**q)**2 +
                            (nu1**q - nu2**q)**2 + (pi1 - pi2)**2))


def contrast_mean_pair(column: Iterable[tuple[float, float]], q: int = Q) -> float:
    values = list(column)
    distances = [distance(values[a], values[b], q)
                 for a in range(len(values)) for b in range(a + 1, len(values))]
    return float(np.mean(distances)) if distances else 0.0


def matrix_weights(matrix: np.ndarray, q: int = Q):
    """Certainty x contrast weights derived from the constructed matrix."""
    certainty = np.array([
        1 - np.mean([uncertainty(matrix[i, j], q) for i in range(8)])
        for j in range(4)
    ])
    contrast = np.array([
        contrast_mean_pair([matrix[i, j] for i in range(8)], q)
        for j in range(4)
    ])
    product = certainty * contrast
    weights = np.ones(4) / 4 if product.sum() == 0 else product / product.sum()
    return weights, certainty, contrast


def swara_weights() -> np.ndarray:
```

```
    """Author-specified scenario-priority weights; no expert panel was used."""
    order = [1, 2, 0, 3]  # harm, detection, likelihood, care burden
    comparative = [0.0, 0.20, 0.15, 0.25]
    raw = [1.0]
    for position in range(1, 4):
        raw.append(raw[-1] / (1 + comparative[position]))
    ordered = np.array(raw) / sum(raw)
    result = np.zeros(4)
    for position, criterion_index in enumerate(order):
        result[criterion_index] = ordered[position]
    return result


def blended_weights(matrix: np.ndarray, delta: float = DELTA, q: int = Q):
    matrix_w, certainty, contrast = matrix_weights(matrix, q)
    swara_w = swara_weights()
    blended = delta * matrix_w + (1 - delta) * swara_w
    return blended / blended.sum(), matrix_w, swara_w, certainty, contrast


def cradis(matrix: np.ndarray, weights: np.ndarray, q: int = Q) -> np.ndarray:
    ideal, anti = [], []
    for criterion in range(4):
        column = [matrix[i, criterion] for i in range(8)]
        scores = [mu**q - nu**q for mu, nu in column]
        ideal.append(column[int(np.argmax(scores))])
        anti.append(column[int(np.argmin(scores))])
    dist_ideal = np.array([
        sum(weights[c] * distance(matrix[i, c], ideal[c], q) for c in range(4))
        for i in range(8)
    ])
    dist_anti = np.array([
        sum(weights[c] * distance(matrix[i, c], anti[c], q) for c in range(4))
        for i in range(8)
    ])
    positive = np.divide(dist_ideal.min(), dist_ideal, out=np.zeros_like(dist_ideal),
                         where=dist_ideal != 0)
    positive[dist_ideal == 0] = 1.0
    negative = np.ones_like(dist_anti) if dist_anti.max() == 0 else dist_anti / dist_anti.max()
    return (positive + negative) / 2


def average_ranks(values: np.ndarray, higher_better: bool = True) -> np.ndarray:
    """Return one-based average ranks; exact ties receive the same average rank."""
    values = np.asarray(values, dtype=float)
    sort_values = -values if higher_better else values
    order = np.argsort(sort_values, kind="mergesort")
    ranks = np.empty(len(values), dtype=float)
    start = 0
    while start < len(values):
        end = start + 1
        while end < len(values) and sort_values[order[end]] == sort_values[order[start]]:
            end += 1
        ranks[order[start:end]] = (start + 1 + end) / 2
        start = end
    return ranks


def json_ranks(ranks: np.ndarray) -> list[int | float]:
    return [int(value) if float(value).is_integer() else round(float(value), 4)
            for value in ranks]


def spearman(rank_a: np.ndarray, rank_b: np.ndarray) -> float:
    a, b = np.asarray(rank_a, float), np.asarray(rank_b, float)
    if np.std(a) == 0 or np.std(b) == 0:
        return 1.0 if np.array_equal(a, b) else 0.0
    return float(np.corrcoef(a, b)[0, 1])


def topsis(matrix: np.ndarray, weights: np.ndarray, q: int = Q) -> np.ndarray:
    ideal, anti = [], []
    for criterion in range(4):
        column = [matrix[i, criterion] for i in range(8)]
        scores = [mu**q - nu**q for mu, nu in column]
        ideal.append(column[int(np.argmax(scores))])
        anti.append(column[int(np.argmin(scores))])
    dist_ideal = np.array([
        sum(weights[c] * distance(matrix[i, c], ideal[c], q) for c in range(4))
        for i in range(8)
    ])
    dist_anti = np.array([
        sum(weights[c] * distance(matrix[i, c], anti[c], q) for c in range(4))
        for i in range(8)
    ])
    return dist_anti / (dist_ideal + dist_anti)


matrix = primary_matrix()
weights, w_matrix, w_swara, certainty, contrast = blended_weights(matrix)
indices = cradis(matrix, weights)
ranks = average_ranks(indices)
topsis_ranks = average_ranks(topsis(matrix, weights))
```

```
equal_ranks = average_ranks(cradis(matrix, np.array([0.25] * 4)))
concordance = {
    "topsis": round(spearman(ranks, topsis_ranks), 3),
    "equalw": round(spearman(ranks, equal_ranks), 3),
}

# Two multivariate term-shift scenarios; not one-at-a-time testing of every cell.
VARIANT = {"A": [1, 0, -1, 0], "B": [-1, 1, 0, -1]}
variant_sensitivity = []
for tag, shifts in VARIANT.items():
    variant = np.empty((8, 4), dtype=object)
    for i, risk in enumerate(RK):
        for j in range(4):
            variant[i, j] = SC[shift(BASE[risk][j], shifts[j])]
    variant_w, *_ = blended_weights(variant)
    variant_ranks = average_ranks(cradis(variant, variant_w))
    variant_sensitivity.append({
        "variant": tag, "top": RF[int(np.argmin(variant_ranks))],
        "sp": round(spearman(ranks, variant_ranks), 3),
        "rank": json_ranks(variant_ranks),
    })

# One cell-specific condition: R4 likelihood VH -> H.
r4_matrix = matrix.copy()
r4_index, likelihood_index = RK.index("R4"), CRIT.index("Likelihood")
r4_matrix[r4_index, likelihood_index] = SC["H"]
r4_weights, *_ = blended_weights(r4_matrix)
r4_indices = cradis(r4_matrix, r4_weights)
r4_ranks = average_ranks(r4_indices)
r4_sensitivity = {
    "cell": "R4 Likelihood", "from": "VH", "to": "H",
    "top": RF[int(np.argmin(r4_ranks))],
    "sp": round(spearman(ranks, r4_ranks), 3),
    "rank": json_ranks(r4_ranks), "R4_rank": json_ranks(r4_ranks)[r4_index],
    "weights": {CRIT[j]: round(float(r4_weights[j]), 3) for j in range(4)},
    "Q": [round(float(value), 4) for value in r4_indices],
}


def monte_carlo(sd: float, runs: int = 4000):
    top_counts = np.zeros(8)
    correlations, baseline_leader_ranks = [], []
    baseline_leader = int(np.argmin(ranks))
    for _ in range(runs):
        perturbed = np.empty_like(matrix)
        for i in range(8):
            for j in range(4):
                mu, nu = matrix[i, j]
                mu2 = min(0.98, max(0.02, mu + np.random.normal(0, sd)))
                nu2 = min(0.98, max(0.02, nu + np.random.normal(0, sd)))
                if mu2**Q + nu2**Q > 1:
                    scale = (mu2**Q + nu2**Q)**(1 / Q)
                    mu2, nu2 = mu2 / scale, nu2 / scale
                perturbed[i, j] = (mu2, nu2)
        perturbed_w, *_ = blended_weights(perturbed)
        perturbed_ranks = average_ranks(cradis(perturbed, perturbed_w))
        correlations.append(spearman(ranks, perturbed_ranks))
        top_counts[int(np.argmin(perturbed_ranks))] += 1
        baseline_leader_ranks.append(float(perturbed_ranks[baseline_leader]))
    top_frequency = {RK[i]: round(float(top_counts[i] / runs), 3)
                     for i in range(8) if top_counts[i] > 0}
    leader_distribution = {
        str(rank): round(baseline_leader_ranks.count(rank) / runs, 3)
        for rank in sorted(set(baseline_leader_ranks))
    }
    return {
        "sd": sd, "runs": runs,
        "mean_spearman": round(float(np.mean(correlations)), 3),
        "min_spearman": round(float(np.min(correlations)), 3),
        "top_rank_freq": top_frequency,
        "leader_rank_dist": leader_distribution,
    }


robustness = [monte_carlo(sd) for sd in (0.01, 0.03, 0.05, 0.10)]

sensitivity = []
for q_value in (2, 3, 4):
    for delta_value in (0.0, 0.5, 1.0):
        sensitivity_matrix = primary_matrix()
        sensitivity_w, *_ = blended_weights(sensitivity_matrix, delta_value, q_value)
        sensitivity_ranks = average_ranks(cradis(sensitivity_matrix, sensitivity_w, q_value))
        sensitivity.append({
            "q": q_value, "delta": delta_value,
            "top": RF[int(np.argmin(sensitivity_ranks))],
            "sp": round(spearman(ranks, sensitivity_ranks), 3),
        })


def proposed_measure(mu: float, nu: float, q: int = Q) -> float:
    return uncertainty((mu, nu), q)
```

```
def peng_liu_e1(mu: float, nu: float, q: int = Q) -> float:
    hesitation = max(0.0, 1 - mu**q - nu**q)
    gap = abs(mu**q - nu**q)
    return (hesitation + 1 - gap) / (hesitation + 1 + gap)


def peng_liu_e4(mu: float, nu: float, q: int = Q) -> float:
    return 1 - abs(mu**q - nu**q)


def khan_entropy(mu: float, nu: float, q: int = Q) -> float:
    hesitation = max(0.0, 1 - mu**q - nu**q)
    gap = abs(mu**q - nu**q)
    knowledge = (0.5 * (gap + (2 / math.pi) * math.acos(min(1.0, max(0.0, hesitation)))))**(1 / q)
    return 1 - knowledge


measure_cases = []
for label, mu, nu in [
    ("Determinate positive", 0.90, 0.20),
    ("Determinate negative", 0.20, 0.90),
    ("Balanced, moderate hesitancy", 0.55, 0.55),
    ("Balanced, high hesitancy", 0.30, 0.30),
    ("Complete hesitancy", 0.00, 0.00),
    ("Balanced, zero hesitancy", 0.7937, 0.7937),
    ("Mild positive, low hesitancy", 0.85, 0.60),
]:
    hesitation = max(0.0, 1 - mu**Q - nu**Q)
    measure_cases.append({
        "label": label, "mu": mu, "nu": nu,
        "pi_q": round(hesitation, 4), "abs_diff": round(abs(mu**Q - nu**Q), 4),
        "U_proposed": round(proposed_measure(mu, nu), 4),
        "E1_PengLiu": round(peng_liu_e1(mu, nu), 4),
        "E4_PengLiu_linear": round(peng_liu_e4(mu, nu), 4),
        "E_Khan": round(khan_entropy(mu, nu), 4),
    })

order, comparative = [1, 2, 0, 3], [None, 0.20, 0.15, 0.25]
coefficients, raw = [1.0], [1.0]
for position in range(1, 4):
    coefficients.append(1 + comparative[position])
    raw.append(raw[-1] / coefficients[-1])
normalised_raw = [value / sum(raw) for value in raw]
swara_trail = [{
    "position": p + 1, "criterion": CRIT[order[p]], "s_j": comparative[p],
    "k_j": round(coefficients[p], 3), "w_raw": round(raw[p], 4),
    "weight": round(normalised_raw[p], 4),
} for p in range(4)]

primary_export = {
    RK[i]: {CRIT[j]: {
        "term": BASE[RK[i]][j], "mu": round(matrix[i, j][0], 4),
        "nu": round(matrix[i, j][1], 4),
        "U": round(uncertainty(matrix[i, j]), 4),
    } for j in range(4)} for i in range(8)
}
weight_derivation = {
    CRIT[j]: {
        "certainty_c": round(float(certainty[j]), 4),
        "contrast_g": round(float(contrast[j]), 4),
        "w_matrix": round(float(w_matrix[j]), 4),
        "w_obj_legacy_key": round(float(w_matrix[j]), 4),
        "w_swara": round(float(w_swara[j]), 4),
        "w_blend": round(float(weights[j]), 4),
    } for j in range(4)
}

output = {
    "meta": {
        "q": Q, "delta": DELTA, "seed": SEED,
        "note": "Primary matrix uses one author-assigned, literature-informed scenario rating per cell; published statistics do not directly determine the linguistic grades.",
    },
    "factors": RF, "criteria": CRIT, "primary_matrix": primary_export,
    "weight_derivation": weight_derivation,
    "weights": {CRIT[j]: round(float(weights[j]), 3) for j in range(4)},
    "w_matrix": {CRIT[j]: round(float(w_matrix[j]), 3) for j in range(4)},
    "w_obj": {CRIT[j]: round(float(w_matrix[j]), 3) for j in range(4)},
    "w_swara": {CRIT[j]: round(float(w_swara[j]), 3) for j in range(4)},
    "certainty": {CRIT[j]: round(float(certainty[j]), 3) for j in range(4)},
    "contrast": {CRIT[j]: round(float(contrast[j]), 3) for j in range(4)},
    "Q": [round(float(value), 4) for value in indices],
    "rank": json_ranks(ranks), "rank_topsis": json_ranks(topsis_ranks),
    "rank_equalw": json_ranks(equal_ranks), "spearman": concordance,
    "robustness": robustness, "sensitivity": sensitivity,
    "variant_sensitivity": variant_sensitivity,
    "r4_likelihood_cell_sensitivity": r4_sensitivity,
    "swara_trail": swara_trail, "measure_cases": measure_cases,
    "provenance_base": {risk: list(BASE[risk]) for risk in RK},
    "variant_rule": {
        "A": "+1,0,-1,0 level shifts on (Likelihood,Harm,Detection difficulty,Care burden)",
        "B": "-1,+1,0,-1 level shifts",
    },
}
```

```
Path("results.json").write_text(json.dumps(output, indent=2, ensure_ascii=False) + "\n", encoding="utf-8")

print("WEIGHTS blend:", output["weights"])
print("matrix-derived:", output["w_matrix"], " SWARA:", output["w_swara"])
print("--- CRADIS ranking ---")
for index in np.argsort(ranks):
    print(f"#{json_ranks(ranks)[index]} {RF[index]} Q={indices[index]:.4f}")
print("Spearman vs TOPSIS/equal weights:", concordance)
for item in robustness:
    print("robustness", item)
```