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A perception-sensitive framework for strategic risk prioritization in healthcare organizations: a Monte Carlo simulation

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A perception-sensitive framework for strategic risk prioritization in healthcare organizations: a Monte Carlo simulation

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Abstract

Background: Strategic risk prioritization in healthcare organizations often relies on judgment-dependent estimates of probability and consequence. Such estimates may be shaped by organizational attention, information access, professional responsibilities and sensemaking, yet these influences are rarely made explicit when risk rankings are produced. This study developed the Perception-sensitive Risk Integration in Strategic Management (PRISM-Risk) framework to examine the sensitivity of healthcare risk priorities to documented interpretive assumptions.
Methods: We evaluated a theory-informed proof-of-concept model using 10,000 Monte Carlo iterations across four synthetic hospital risks: ransomware-related disruption, healthcare-associated infection outbreak, medical oxygen interruption and emergency department/intensive-care capacity surge. A baseline score combining probability, impact and strategic unobservability was subjected to bounded log-odds shifts under three contrasting perceptual conditions and a simulated five-role multidisciplinary committee condition. Outcomes included score change, highest-priority probability, rank reversal, mean absolute rank change and Spearman rank correlation with baseline. Sensitivity analyses varied iteration count, shift variance, shift magnitude and committee aggregation.

Results: The recent cyber-incident, institutional-overconfidence and frontline clinical-salience conditions produced rank reversals in 66.0%, 72.4% and 77.7% of iterations, respectively. The simulated committee condition produced rank reversals in 31.4% of iterations and a mean Spearman correlation of 0.917 with baseline. Sensitivity analyses preserved the qualitative pattern. The committee result reflects its prespecified sparse shifts, lower member-level variance and aggregation rule and does not demonstrate superiority of multidisciplinary committees.
Conclusions: PRISM-Risk provides a transparent assumption-sensitivity approach for examining when judgment-dependent inputs may materially change healthcare risk priorities. It is not a validated prediction instrument and should not be used for personnel assessment or automated reprioritization. Empirical calibration with healthcare decision-makers and institutional data is required before operational use.
Keywords: healthcare organizations; healthcare governance; strategic risk management; decision support; risk perception; Monte Carlo simulation

Background

Strategic risk prioritization in healthcare is not only a technical problem of estimating likelihood and consequence; it is also an organizational problem of allocating limited managerial attention across competing threats. Risk-management standards embed risk assessment within governance, strategy and planning [1, 2]. Yet many healthcare organizations rely on semi-quantitative scores assembled from expert judgments about likelihood, consequence and related dimensions. Where reliable statistical evidence is incomplete, such judgments are often unavoidable, but the resulting scores can conceal the informational, role-based and organizational conditions under which they were produced.

The attention-based view argues that organizational action depends on which issues decision-makers notice and on how structures, rules, resources and relationships channel attention [3]. This is especially relevant in hospitals, where executives, clinicians, infection-prevention teams, information-technology specialists and facilities managers encounter different signals and operate under different responsibilities. Sensemaking theory further emphasizes that organizational actors interpret ambiguous circumstances in ways that enable action [4]. Strategic risk prioritization can therefore be understood as an organizational sensemaking process in which technical evidence and situated interpretation interact.

Enterprise risk management is similarly understood as a socio-technical process in which formal methods interact with organizational roles, routines and communication [5, 6]. Research on judgment under uncertainty shows that availability, anchoring, representativeness, confidence, familiarity, controllability, dread and trust can shape estimates of risk [7–12]. These influences are not necessarily errors. Experience and professional proximity may reveal weak signals that are absent from dashboards; the same mechanisms can nevertheless amplify salient risks, attenuate familiar risks or create inconsistent priorities.

Recent reviews link risk perception with risk-management behavior and enterprise risk-management performance [13–15]. Conventional probability-impact matrices may treat ordinal judgments as if they were precise measurements, produce identical scores for substantively different risks and hide uncertainty or assessor-dependent assumptions [16, 17]. Existing approaches commonly treat perceptual and organizational influences as sources of bias or as contextual explanations after a score has been generated. Less attention has been given to making those influences explicit at the parameter level and testing whether the resulting priority order is robust to plausible alternative interpretations.

This challenge is acute in hospitals, where strategic decisions span patient safety, infection prevention, workforce and capacity, digital infrastructure, supply continuity and critical utilities. Health services management requires attention to efficiency, sustainability, equity and organizational stewardship [18], while adaptive planning benefits from explicit decision support as evidence and operating conditions change [19]. Health-sensitive risk frameworks also emphasize that fragility and risk cannot be separated from service context and governance [20]. Simulation and model-based decision support are increasingly used for hospital resource planning and governance under uncertainty [21–23]. Hospitals are also dependent on interconnected electricity, water, transport and information systems [24]. In such settings, prioritization is a health-services governance choice because organizational visibility, escalation and representation can influence which threats receive attention, preparedness resources and management action.

This study develops the Perception-sensitive Risk Integration in Strategic Management (PRISM-Risk) framework as a transparent and ethically bounded way to examine this organizational problem. Drawing on the attention-based view, sensemaking and risk-perception research, PRISM-Risk treats judgment-dependent risk assessment as a governed organizational process rather than a purely technical calculation. It asks: (1) how can organizational attention and assessor-dependent interpretation be represented transparently at the parameter level; (2) how do prespecified perceptual conditions affect scores and rankings; (3) when do those assumptions produce rank reversals; and (4) how does a prespecified simulated committee aggregation condition behave relative to individual scenario profiles? The study is a proof-of-concept simulation of model behavior, not an empirical comparison of healthcare professionals or committees.

Organizational attention, sensemaking and risk prioritization

The attention-based view provides the primary organizational lens for PRISM-Risk. Its central premise is that organizational behavior reflects how attention is distributed across issues and possible responses [3]. In healthcare organizations, risk registers, dashboards, committee agendas, incident reports and escalation routines can be understood as attention structures: they influence which threats become visible, how frequently they are discussed and whose expertise enters the decision process. A technically identical signal may therefore receive different organizational weight depending on its salience, the role of the assessor and the information channels through which it is encountered.

Sensemaking complements this perspective by focusing on how ambiguous circumstances are interpreted and converted into a basis for action [4]. A recent cyber incident, confidence in established controls or frontline exposure to capacity constraints can alter which cues appear consequential without implying that one interpretation is inherently irrational. Similar use of organizational theory to illuminate healthcare coordination demonstrates the value of making the mechanisms that connect context, interpretation and collective action explicit [25]. In PRISM-Risk, attention and sensemaking do not supply empirically validated coefficients; they provide the theoretical rationale for testing how documented interpretive assumptions could alter risk parameters and priorities.

Risk-perception research specifies additional mechanisms through which judgments may vary, including availability, anchoring, familiarity, trust, perceived controllability and confidence [7–10]. PRISM-Risk groups these influences into three explanatory domains. Cognitive influences include availability, anchoring, representativeness, overconfidence and experience-based complacency. Socio-organizational influences include trust, professional norms, hierarchy,

communication, conformity and perceived preparedness. Decision-context influences include professional responsibility, relevant expertise, information access, workload and incident experience. These domains are organizing constructs for sensitivity analysis, not psychometrically validated scales or classifications of individuals.

Scope and architecture of PRISM-Risk

PRISM-Risk is intended for judgment-dependent assessments in which quantitative evidence is incomplete and expert interpretation contributes to parameter estimates. It is not designed to alter probabilities or consequences produced by validated actuarial, engineering, reliability or clinical prediction models. In those settings it may support interpretation and communication, but it is not a replacement for established quantitative methods.

The framework separates two analytically distinct layers. The baseline technical layer represents the best available assessment derived from records, surveillance, technical analysis and structured expert judgment. The perception-sensitive layer represents documented conditions that may change how the same parameters are estimated or interpreted. This separation does not imply that the baseline is perception-free or objectively correct; it creates a transparent benchmark against which assumption sensitivity can be examined.

Baseline and perception-sensitive scores

For risk r, the baseline technical risk score (BTRS) is:

$$BTRS_r = P_r \times I_r \times U_r$$

where P is probability, I is impact, and U is strategic unobservability; each is standardized between 0 and 1. Strategic unobservability is a proposed scenario construct representing the extent to which a threat remains insufficiently detected, monitored, communicated, escalated, or represented in organizational decisions. It is broader than technical detectability. Multiplying U

by probability and impact makes under-observed threats more prominent, but this equal multiplicative role is an unvalidated modeling choice rather than an established measurement rule.

For profile j, the perceptual influence vector is $PIV_{rj} = (\Delta P_{rj}, \Delta I_{rj}, \Delta U_{rj})$. Positive values amplify and negative values attenuate the corresponding baseline parameter on the log-odds scale. The transformed value is:

$$X^*_{rj} = \text{logit}^{-1}[\text{logit}(X_r) + \Delta X_{rj}]$$

where X represents P, I, or U; $\text{logit}(X) = \ln[X/(1 - X)]$; and $\text{logit}^{-1}(z) = 1/(1 + e^{-z})$. The transformation preserves the 0-1 bounds without truncation. The perception-adjusted risk score (PARS) is:

$$PARS_{rj} = P^*_{rj} \times I^*_{rj} \times U^*_{rj}$$

PARS is directly comparable with BTRS, but it is not presumed to be a corrected or more accurate score. Its purpose is to show how a documented set of interpretive assumptions changes parameter values and priorities. The difference can be summarized as $D_{rj} = PARS_{rj} - BTRS_r$ and, when BTRS is greater than zero, as a percentage relative change.

Ranking, aggregation and governance safeguards

Because planning decisions concern competing threats, PRISM-Risk evaluates score change together with rank reversal, defined as any change in the ordering of risks relative to the iteration-specific baseline. A reversal is a signal of assumption sensitivity, not proof that either ordering is correct. It should prompt review of evidence, parameter definitions and the decision consequences of alternative rankings.

Committee estimates may be summarized using medians, means, weighted rules, consensus or Delphi procedures. Aggregation can limit extreme estimates but can also suppress minority

information, and real committees may be affected by hierarchy, conformity, unequal expertise and information withholding. No aggregation rule is assumed to be inherently superior.

The framework is intended for team- and scenario-level deliberation. It should not be used for psychological profiling, personnel selection, disciplinary evaluation, demographic adjustment or automated judgments about individual competence. Professional role and experience may be documented only as sources of information and responsibility. Local use requires confidentiality, an audit trail, a stated evidence hierarchy and a process for contesting both baseline and adjusted assumptions.

Methods

Study design and scenarios

This study combined theory-informed conceptual model development with an exploratory Monte Carlo simulation. All inputs were prespecified synthetic scenario assumptions; no patient-level, employee-level or institutional data were used. The analysis was designed to test internal model behavior and does not estimate the real incidence, severity, observability or perception of hospital risks. The theoretical mechanisms described above informed the construction of stress-test conditions but were not themselves empirically tested.

Four strategic scenarios represented different planning domains: (1) ransomware-related disruption of electronic records, laboratory communication, medication processes and administration; (2) a healthcare-associated infection outbreak requiring surveillance, isolation and operational reorganization; (3) medical oxygen interruption caused by infrastructure, logistics, equipment or supply failure; and (4) an emergency department and intensive-care capacity surge exceeding available staff, beds, equipment or critical-care capacity. The scenarios provided a heterogeneous test set rather than an exhaustive hospital risk register.

Baseline parameters and technical uncertainty

The baseline means and standard deviations are reported in Table 1. They were chosen to create distinct but overlapping risk-score distributions and should not be interpreted as hospital estimates. Probability, impact, and strategic unobservability were sampled independently from beta distributions. For a specified mean μ and variance σ^2, shape parameters were calculated as:

$$\alpha = \mu[\mu(1 - \mu)/\sigma^2 - 1]$$

$$\beta = (1 - \mu)[\mu(1 - \mu)/\sigma^2 - 1]$$

One value for each parameter and risk was sampled per iteration and multiplied to obtain BTRS. Independence was adopted for transparency and is a simplifying assumption; correlated parameters, cascading events, and common-cause failures were not modeled.

The baseline parameter assumptions are shown in Table 1.

Individual perceptual conditions

Three deliberately contrasting conditions were constructed as experimental stress tests, not classifications of real professionals. The recent cyber-incident condition represented attentional salience and anchoring after a recent event and included small negative shifts for other risks to represent attention displacement. The institutional-overconfidence condition applied negative shifts to represent strong confidence in existing controls. The frontline clinical-salience condition represented role-situated attention by amplifying infection, oxygen and capacity risks and slightly attenuating ransomware probability. Mean log-odds shifts are reported in Table 2.

At each iteration, the shift for parameter X under profile j was sampled as $\Delta X_{rj} \sim N(\mu\Delta X, 0.15^2)$. The coefficient values and the standard deviation were selected for model exploration rather than estimated from observed decisions. They create distinguishable stress-test conditions and cannot support prevalence or effect-size claims.

The prespecified mean shifts are shown in Table 2.

Simulated multidisciplinary committee condition

A five-role condition included an information-technology specialist, an infection-prevention specialist, a clinical-operations manager, a facilities-and-supply manager and a hospital administrator. The role assignments represented differentiated organizational attention domains rather than empirical profiles of those occupations. Each role received a limited set of risk-relevant mean shifts (Table 3); unlisted vectors were set to (0.00, 0.00, 0.00). Member shifts were sampled with a standard deviation of 0.12, and the five transformed estimates for each parameter were aggregated by the median. Arithmetic-mean aggregation was evaluated in sensitivity analysis.

This condition was not a balanced causal comparison with the individual profiles. It combined sparse, often zero-centered role assignments, smaller shift variability and an aggregation step, whereas the individual profiles were deliberately contrasting and applied across risks. Consequently, closeness to baseline may arise from parameterization and aggregation by construction. The analysis addresses how this specified simulated committee condition behaves; it does not test whether multidisciplinary committees are more accurate, less biased or more stable than individuals.

The role-specific shift assumptions are shown in Table 3.

Simulation procedure and outcomes

The primary analysis used 10,000 Monte Carlo iterations and random seed 20260723. In each iteration, baseline parameters and BTRS values were sampled; profile- and member-specific shifts were sampled and transformed; PARS values were calculated; committee parameters were aggregated; and the four risks were ranked from highest to lowest within each condition. Exact

ties were extremely rare because continuous distributions were used; average ranks were assigned if a tie occurred.

The primary outcome was any rank reversal relative to the corresponding iteration-specific baseline. Additional outcomes were mean, standard deviation, median, 2.5th to 97.5th percentile simulation interval (SI), absolute and relative score change, probability of receiving the highest rank, probability of moving upward or downward, mean absolute rank change, complete-ranking stability and Spearman rank correlation with baseline.

Sensitivity analyses repeated the simulation with 50,000 iterations; individual shift standard deviations of 0.10 and 0.20; all mean shifts reduced and increased by 25%; and arithmetic-mean rather than median committee aggregation. These analyses evaluate internal numerical robustness, not construct or external validity.

Software, reproducibility and ethics

The simulation was implemented in Python 3.13.5 with NumPy 2.3.5 and pandas 2.2.3. The manuscript reports the fixed seed, synthetic inputs, transformation, aggregation and outcome definitions. Complete code and detailed sensitivity outputs are available upon reasonable request.

The study used only synthetic data and involved no human participants, patient records, healthcare workers, identifiable institutions, biological material or confidential information. Ethics approval and informed consent were therefore not required. The scenario profiles must not be interpreted as psychological assessments of actual people or occupational groups.

Use of generative AI in manuscript preparation: ChatGPT (OpenAI) was used for language editing and journal-format adaptation. All scientific content, model assumptions, analyses and interpretations were reviewed by the authors, who take full responsibility for the final manuscript.

Results

The baseline distributions overlapped (Table 4; Figs. 1 and 2). Ransomware had the highest mean baseline score (0.157; 95% SI, 0.081-0.258) and ranked first in 53.1% of iterations. Capacity surge, infection outbreak and oxygen interruption had mean scores of 0.126, 0.123 and 0.106 and ranked first in 19.9%, 18.7% and 8.3% of iterations, respectively. These results confirm that the synthetic inputs did not force a single invariant ordering.

Under the recent cyber-incident condition, the mean ransomware score increased by 84.1% and ransomware ranked first in 97.2% of iterations. The complete ranking changed in 66.0% of iterations; mean absolute rank change was 0.513 and mean Spearman correlation with baseline was 0.704. Under institutional overconfidence, all four mean scores decreased by 21.4%-47.2%, but the nonuniform attenuation changed the complete ranking in 72.4% of iterations (mean absolute rank change, 0.557; correlation, 0.684). Under frontline clinical salience, infection, capacity and oxygen scores increased by 50.2%, 38.5% and 31.2%, while ransomware decreased by 4.5%. Rank reversal occurred in 77.7% of iterations (mean absolute rank change, 0.637; correlation, 0.619; Fig. 3).

Median aggregation across the five simulated roles produced smaller changes: mean scores increased by 4.9% for ransomware, 7.6% for infection, 6.1% for oxygen interruption and 2.6% for capacity surge. The complete ranking was unchanged in 68.6% of iterations, equivalent to 31.4% with at least one rank reversal; mean absolute rank change was 0.183 and mean correlation with baseline was 0.917. This numerical proximity is descriptive of the specified sparse shifts, lower member-level variance and aggregation rule. Because these design features differed from the individual conditions, the result does not isolate an effect of multidisciplinarity.

At 50,000 iterations, rank-reversal frequencies were 65.4%, 71.8%, 78.1% and 31.6% for the cyber-incident, overconfidence, clinical-salience and simulated committee conditions, respectively. Varying individual shift uncertainty produced ranges of 60.9%-69.3%, 69.4%-74.9% and 76.6%-79.9% for the three individual profiles. Reducing or increasing mean shifts by 25% changed the committee condition from 30.9% to 33.4%. Mean rather than median aggregation yielded 26.6%. The qualitative result - profile-specific sensitivity and an aggregation condition closer to baseline - was internally stable, but these tests do not establish empirical validity or committee superiority.

Full simulation summaries are presented in Table 4.

Discussion

The central contribution of the simulation is not the absolute frequency of rank reversals, which is conditional on synthetic inputs, but the demonstration that strategic risk rankings can be treated as organizationally contingent outputs rather than neutral technical facts. From an attention-based perspective, a risk score helps structure managerial attention: changes in the assumptions that feed the score may alter which threat receives priority, preparedness resources or escalation. PRISM-Risk makes this contingency reviewable by separating a documented baseline from parameter-level interpretive shifts and by reporting whether those shifts change the ordering of risks.

The framework also extends a sensemaking perspective on health organization and management by operationalizing interpretation at the point where a risk score is constructed. Sensemaking research emphasizes that organizational actors transform ambiguous cues into actionable understandings [4]. PRISM-Risk does not label these interpretations as bias by default. Instead, it asks which parameter changes under a given informational frame, how strongly the ranking

depends on that change and whether additional evidence or broader participation is warranted. This moves perceptual disagreement from an implicit feature of committee deliberation to an explicit object of sensitivity analysis.

Strategic unobservability is a provisional construct intended to connect organizational attention with risk governance. It represents the extent to which a threat may be insufficiently detected, monitored, communicated, escalated or represented in organizational decisions. The construct is broader than technical detectability and should not be interpreted as a validated dimension of risk. Its value at this stage is conceptual: it directs attention to the possibility that a hazard can be technically known yet organizationally under-represented. Its equal multiplicative role in the present model remains an unvalidated modeling choice and requires empirical and structural testing.

The three individual conditions represent deliberately contrasting informational frames rather than types of healthcare professionals. A recent incident can reveal genuine vulnerability while concentrating attention on a salient threat. Confidence in controls can support coordination while attenuating warning signals. Frontline proximity can reveal patient-facing constraints that strategic dashboards miss while reducing attention to delayed technological hazards. These patterns are consistent with the proposition that attention and sensemaking are situated, but the simulation does not identify which frame is more accurate in real organizations.

The simulated committee contrast must be interpreted more narrowly than its raw numerical difference suggests. Its closeness to baseline is partly built into the simulation because many role-risk vectors were zero, member variability was smaller and estimates were aggregated. Mean aggregation produced even fewer reversals than median aggregation. These findings show that the composition of assumptions and the choice of aggregation rule affect stability; they do

not demonstrate a benefit of multidisciplinary participation. Real group performance depends on evidence sharing, facilitation, hierarchy, dissent, expertise and whether apparent stability reflects calibration or merely convergence.

For health services research and management, the value of PRISM-Risk lies in treating prioritization as a governed decision process. Health management requires choices that balance organizational performance and public value [18], and adaptive planning benefits from explicit review of assumptions as conditions change [19]. The proposed analysis can complement, rather than replace, simulation-based planning tools used for hospital resources [21]. It may be most useful before major preparedness investments, when managers need to know whether a priority is robust to plausible alternative readings of the same evidence.

Strategic unobservability further links scoring with organizational monitoring and escalation. Healthcare resilience depends on information moving across clinical, technical, administrative and infrastructure boundaries [24, 26]. Warning information can exist but remain fragmented or absent from formal decision structures. Cognitive hazards in technology-supported decisions reinforce the need for reviewable assumptions and human oversight [27], while approaches that integrate rational and emotional dimensions of risk management support treating perception as information to examine rather than noise to delete [28].

Accordingly, PRISM-Risk should operate as a challenge tool. A stable ranking may justify continued attention but does not prove correctness; repeated reversals indicate a need for better evidence, alternative scenarios or broader deliberation. Baseline and perception-sensitive scores should therefore be reported together with parameter dispersion and the rationale for shifts, because a single aggregate can conceal minority information that may be strategically important.

A cautious organizational workflow has five steps: define the decision horizon and evidence standard; obtain independent baseline parameter estimates; document plausible cognitive, organizational and role-related influences; test score and ranking stability without hiding individual dispersion; and record the final decision together with assumptions that could change it. A rank reversal should trigger review, not automatic reprioritization.

Hospitals could use this workflow during risk-register reviews, preparedness exercises and planning for cyber resilience, infection control, critical supplies, infrastructure or surge capacity. The managerial benefit is not a supposedly more accurate score, but a clearer audit trail showing which assumptions drive priority and where additional evidence or cross-functional deliberation is most valuable. Local definitions and thresholds require calibration, and outputs should remain advisory. The approach must not be embedded in automated personnel assessment or used to adjust scores on the basis of demographic characteristics.

Limitations and future research

All numerical inputs, profiles, uncertainty distributions and committee roles were synthetic. The four scenarios were selected for heterogeneity and do not represent a complete hospital risk register. The baseline is an analytical benchmark, not a perception-free truth, and the framework does not distinguish bias from complementary information or genuine uncertainty. Because input distributions overlapped by design, the reported rank-reversal frequencies are conditional on that construction.

Strategic unobservability is a proposed construct, and its equal multiplicative role has not been validated. Alternative additive, multiplicative, Bayesian or hierarchical formulations may behave differently. Baseline parameters and risks were sampled independently, so cascading failures, common causes, feedback and time dependence were omitted. The analysis also excluded

intervention costs, resource constraints, risk appetite, equity, regulation, utility and mitigation effectiveness; ranking is therefore not a complete allocation model.

The simulated committee condition did not model discussion, unequal expertise, authority, conformity, information withholding, polarization or opinion change. Its comparison with individual profiles was structurally unequal, so no inference about real committee accuracy or stability is warranted. Internal sensitivity analyses establish only computational consistency. They do not establish construct validity, predictive validity, usability, calibration or improved decisions.

Future work should use structured elicitation and scenario experiments with clinical, administrative, technical, facilities and safety professionals. Repeated-measures or multilevel models could estimate how much variation is attributable to risks, assessors, roles, institutions and evidence conditions. Studies should compare aggregation and facilitation procedures, represent correlated and dynamic risks and evaluate calibration, recognition of neglected threats, transparency, decision time, preparedness action, equity implications and unintended effects. Any elicitation instrument requires separate validation before institutional use.

Conclusions

PRISM-Risk offers a theory-informed way to examine how organizational attention, sensemaking and documented interpretive assumptions enter judgment-dependent healthcare risk scores and alter strategic priorities. In this synthetic simulation, deliberately contrasting conditions generated frequent rank reversals, while a sparsely parameterized simulated committee condition remained closer to baseline. That contrast reflects the modeled assumptions and does not show that real committees are superior. The framework should be treated as an

exploratory organizational challenge process until its constructs, parameters, decision effects and governance safeguards are empirically validated.

List of abbreviations

BTRS: Baseline technical risk score

PARS: Perception-adjusted risk score

PIV: Perceptual influence vector

PRISM-Risk: Perception-sensitive Risk Integration in Strategic Management

SI: Simulation interval

Declarations

Ethics approval and consent to participate

Not applicable. The study used only synthetic scenario data and involved no human participants, human data, identifiable institutional records, biological material or patient information.

Consent for publication

Not applicable.

Availability of data and materials

All synthetic input values, the fixed random seed and the summary results generated during the current study are included in this article and its tables. The simulation code and detailed sensitivity outputs are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

MK conceptualized the study and supervised the work. MK and MS developed the methodology. MS and MK performed the formal analysis. MK and MS drafted the manuscript and contributed to review and editing. MS and MK prepared the visualizations. Both authors read and approved the final manuscript.

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Tables

Table 1. Synthetic baseline parameter assumptions for the healthcare risk scenarios

Risk scenario	**Probability, mean (SD)**	**Impact, mean (SD)**	**Strategic unobservability, mean (SD)**
Ransomware-related digital disruption	0.35 (0.08)	0.82 (0.06)	0.55 (0.09)
Healthcare-associated infection outbreak	0.45 (0.09)	0.78 (0.07)	0.35 (0.08)
Medical oxygen supply interruption	0.18 (0.05)	0.95 (0.03)	0.62 (0.08)
Emergency department and intensive-care capacity surge	0.58 (0.09)	0.72 (0.07)	0.30 (0.07)

Table 2. Mean log-odds shifts assigned to individual perceptual conditions

Perceptual condition	**Risk scenario**	**ΔP**	**ΔI**	**ΔU**
Recent cyber incident	Ransomware-related disruption	0.85	0.35	0.20
Recent cyber incident	Infection outbreak	-0.10	-0.05	0.00
Recent cyber incident	Oxygen interruption	-0.15	-0.05	0.00
Recent cyber incident	Capacity surge	-0.10	-0.05	-0.05

Perceptual condition	Risk scenario	ΔP	ΔI	ΔU
Institutional overconfidence	Ransomware-related disruption	-0.55	-0.15	-0.45
Institutional overconfidence	Infection outbreak	-0.25	-0.10	-0.25
Institutional overconfidence	Oxygen interruption	-0.35	-0.10	-0.40
Institutional overconfidence	Capacity surge	-0.20	-0.05	-0.20
Frontline clinical salience	Ransomware-related disruption	-0.10	0.00	0.05
Frontline clinical salience	Infection outbreak	0.45	0.30	0.20
Frontline clinical salience	Oxygen interruption	0.20	0.45	0.25
Frontline clinical salience	Capacity surge	0.50	0.30	0.10

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492 Table 3. Mean log-odds shifts for the simulated multidisciplinary committee

Committee role	Principal risk scenario	Shift vector (ΔP, ΔI, ΔU)
Information-technology specialist	Ransomware-related disruption	(0.65, 0.25, 0.25)
Infection-prevention specialist	Infection outbreak	(0.55, 0.35, 0.25)
Infection-prevention specialist	Capacity surge	(0.10, 0.05, 0.00)
Clinical-operations manager	Infection outbreak	(0.25, 0.20, 0.10)
Clinical-operations manager	Oxygen interruption	(0.15, 0.25, 0.10)
Clinical-operations manager	Capacity surge	(0.55, 0.35, 0.15)
Facilities-and-supply manager	Ransomware-related disruption	(0.10, 0.10, 0.10)
Facilities-and-supply manager	Oxygen interruption	(0.50, 0.45, 0.35)
Hospital administrator	All four risks	(-0.15, -0.05, -0.15)

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494 Table 4. Simulation findings across assessment conditions

Assessment condition	Risk scenario	Risk score, mean (SD); 95% SI	Relative change vs baseline, %	Highest priority, %	Mean rank
Baseline	Ransomware disruption	0.157 (0.046); 0.081–0.258	Reference	53.1	1.76
Baseline	Infection outbreak	0.123 (0.039); 0.058–0.211	Reference	18.7	2.62
Baseline	Oxygen interruption	0.106 (0.033); 0.052–0.180	Reference	8.3	3.10
Baseline	Capacity surge	0.126 (0.038); 0.062–0.210	Reference	19.9	2.52
Recent cyber incident	Ransomware disruption	0.284 (0.068); 0.161–0.424	+84.1	97.2	1.03
Recent cyber incident	Infection outbreak	0.116 (0.040); 0.050–0.207	-6.1	1.2	2.83
Recent cyber incident	Oxygen interruption	0.094 (0.032); 0.043–0.169	-11.7	0.3	3.32
Recent cyber incident	Capacity surge	0.116 (0.039); 0.053–0.202	-8.5	1.3	2.81
Institutional overconfidence	Ransomware disruption	0.084 (0.032); 0.036–0.158	-47.2	22.8	2.52
Institutional overconfidence	Infection outbreak	0.089 (0.033); 0.037–0.166	-28.1	27.2	2.36

Assessment condition	Risk scenario	Risk score, mean (SD); 95% SI	Relative change vs baseline, %	Highest priority, %	Mean rank
Institutional overconfidence	Oxygen interruption	0.067 (0.025); 0.029–0.125	-37.2	8.3	3.15
Institutional overconfidence	Capacity surge	0.099 (0.034); 0.044–0.178	-21.4	41.7	1.98
Frontline clinical salience	Ransomware disruption	0.150 (0.048); 0.071–0.257	-4.5	17.6	2.72
Frontline clinical salience	Infection outbreak	0.182 (0.054); 0.089–0.298	+50.2	40.4	2.04
Frontline clinical salience	Oxygen interruption	0.138 (0.043); 0.065–0.234	+31.2	10.8	3.01
Frontline clinical salience	Capacity surge	0.173 (0.050); 0.088–0.280	+38.5	31.2	2.22
Multidisciplinary committee	Ransomware disruption	0.165 (0.048); 0.084–0.271	+4.9	52.1	1.78
Multidisciplinary committee	Infection outbreak	0.132 (0.042); 0.061–0.226	+7.6	20.9	2.54
Multidisciplinary committee	Oxygen interruption	0.112 (0.035); 0.054–0.192	+6.1	9.0	3.07
Multidisciplinary committee	Capacity surge	0.129 (0.039); 0.064–0.216	+2.6	18.0	2.61

Figure legends

Figure 1. Mean risk scores and 95% simulation intervals across the five assessment conditions. Points indicate means and error bars indicate the 2.5th and 97.5th percentiles from 10,000 iterations. Values are based on synthetic assumptions and are not estimates of actual hospital incidence or severity.

Figure 2. Probability that each healthcare risk received the highest-priority rank under each assessment condition. Percentages were calculated across 10,000 iterations and sum to 100% within each condition apart from rounding.

Figure 3. Stability of the complete four-risk ranking relative to the iteration-specific baseline. Bars show the proportion of iterations with the full ranking unchanged or at least one rank reversal. Values at right are mean iteration-specific Spearman rank correlations (ρ). The committee comparison is descriptive of its specified sparse role shifts, smaller member-level variance and aggregation rule; it is not evidence that real committees outperform individuals.

Ransomware
Infection outbreak
Oxygen interruption
Capacity surge

Risk score

0.0
0.1
0.2
0.3
0.4

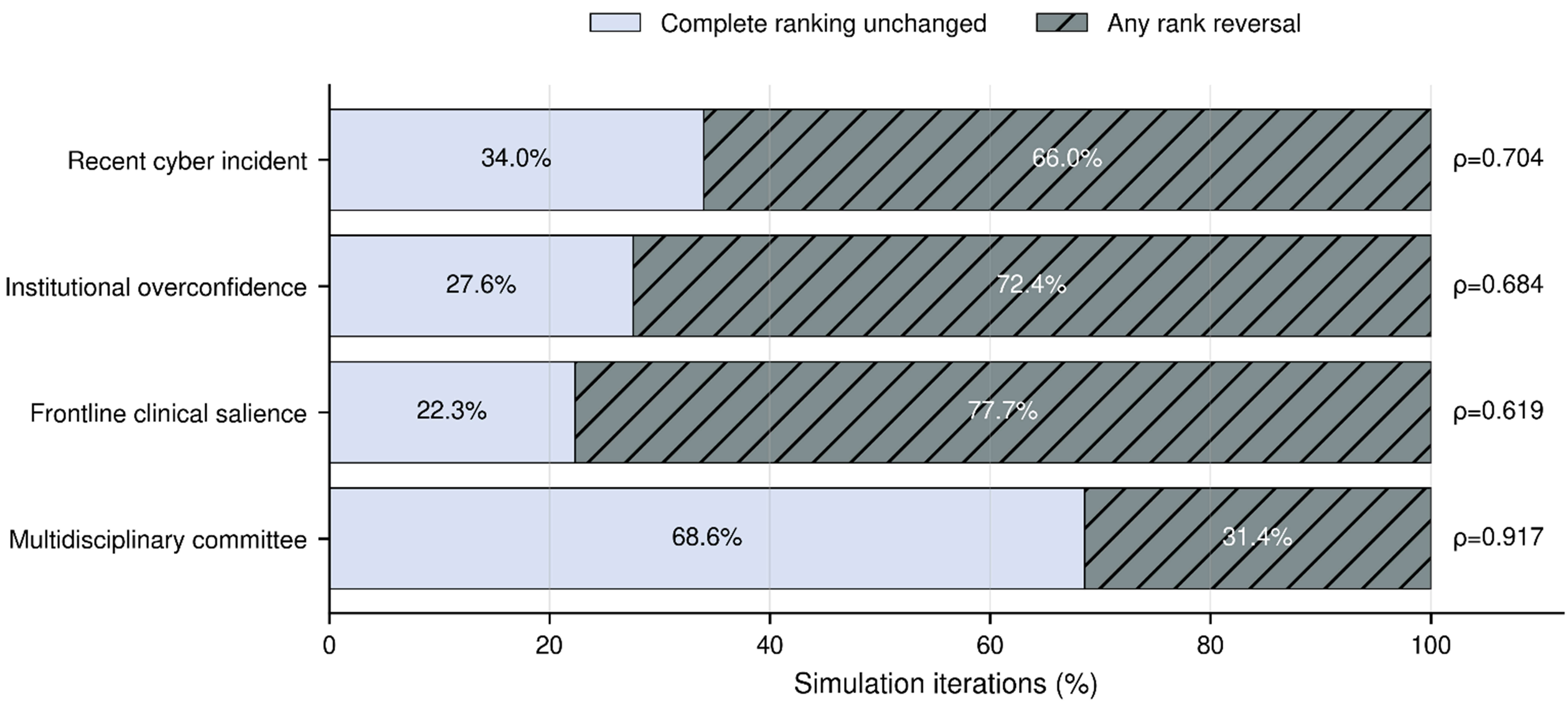
Baseline
Recent cyber incident
Institutional overconfidence
Frontline clinical salience
Multidisciplinary committee

Ransomware
Infection outbreak
Oxygen interruption
Capacity surge

Probability of highest priority (%)

100
80
60
40
20
0

Baseline
Recent cyber incident
Institutional overconfidence
Frontline clinical salience
Multidisciplinary committee


Complete ranking unchanged
Any rank reversal
Recent cyber incident
34.0%
66.0%
ρ=0.704
Institutional overconfidence
27.6%
72.4%
ρ=0.684
Frontline clinical salience
22.3%
77.7%
ρ=0.619
Multidisciplinary committee
68.6%
31.4%
ρ=0.917
0
20
40
60
80
100
Simulation iterations (%)