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Chao Wu
Air Force Military Medical University
Ting Song
Air Force Military Medical University
Jiayi Zhang
Air Force Military Medical University
Jiaqi Yuan
Air Force Military Medical University
Yawei Lin
956th hospital
Zhen Sa
69245 Hospital
Nan Li
78th Group Army Hospital
Cong Ren
1771248450@qq.com
Air Force Military Medical University
Yanling Du
Air Force Military Medical University
Hong-juan Lang
Air Force Military Medical University

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Development and Weighting of a Task-Nurse-Nursing Robot Fit Indicator System and a Three-Dimensional Fit Calculation Framework for Biosafety Emergency Response: A Delphi and Fuzzy Analytic Hierarchy Process Study

Chao Wu[1], Ting Song[1], Jiayi Zhang[1], Jiaqi Yuan[1], Yawei Lin[2], Zhen Sa[3], Nan Li[4], Cong Ren[5*], Yanling Du[1*], Hongjuan Lang[1*]

1Department of Nursing, Air Force Military Medical University, Shaanxi, China, 2Anesthesiology Department, The 956th Hospital of the Chinese People's Liberation Army, Nyingchi, China, 3Medical First Section, The 69245 Hospital, Urumqi, Xinjiang, China, 4The 78th Group Army Hospital, Heilongjiang, China, 5Department of Infectious Diseases, Tangdu Hospital, China

Correspondence

Cong Ren, Department of Infectious Diseases, Tangdu Hospital, No.1 Xinsi Road, Baqiao District, Xi'an, 710038, Shaanxi, China.
Email: 1771248450@qq.com

Yanling Du, Nursing Department, Air Force Military Medical University, No.169 Changle West Road, Xi'an, 710032, Shaanxi, China.
Email: 450162073@qq.com

Hong-juan Lang, Nursing Department, Air Force Military Medical University, No.169 Changle West Road, Xi'an, 710032, Shaanxi, China.
Email: Langhj@fmmu.edu.cn

Abstract

Objective To develop a task-nurse-nursing robot fit indicator system for biosafety emergency response, determine the relative weights of indicators at each level, and propose an operational three-dimensional fit calculation framework as a basis for developing and validating a task-matching assessment tool.

Methods An initial indicator framework was developed through theoretical analysis, literature review, and qualitative interviews. A two-round Delphi survey of 15 experts was conducted to screen and revise the indicators, and Kendall's coefficient of concordance (W) was used to assess agreement among the experts. Fuzzy analytic hierarchy process was then used to construct aggregate judgment matrices, calculate indicator weights, and assess matrix compatibility. A conceptual fit calculation framework was further developed for three candidate execution modes: nurse-only, nursing robot-only, and nurse-robot collaborative execution. The framework was based on requirement-capability mapping, weighted capability deficits, and safety veto rules.

Results The initial framework comprised 3 first-level, 10 second-level, and 23 third-level indicators; after two Delphi rounds, the final system comprised 3 first-level, 9 second-level, and 36 third-level indicators. The valid response rate was 100% in both rounds, and the expert authority coefficient was 0.907. Kendall's W values for the first-, second-, and third-level indicators were 0.325, 0.313, and 0.338 in round 1 and 0.496, 0.386, and 0.386 in round 2, respectively (all $P < 0.01$), indicating good expert agreement. The initial weights of the first-level indicators were 0.3822 for nursing task characteristics, 0.3522 for nurse capabilities, and 0.2656 for nursing robot performance. The compatibility indices of all aggregate judgment matrices were <0.1. Based on the indicators and weights, a three-dimensional fit decision process comprising requirement-capability mapping, hard-constraint screening, capability-deficit calculation, and ranking of candidate execution modes was proposed.

Conclusion This study developed a preliminary task-nurse-nursing robot fit indicator system, relative indicator weights, and a conceptual fit calculation framework. The aggregate judgment matrices demonstrated acceptable internal compatibility. The framework provides a computable pathway for developing a task-matching assessment tool; however, the mapping relationships, rating anchors, thresholds, measurement properties, and practical scheduling utility require further calibration and validation through simulation exercises and multicenter studies.

Keywords: Biosafety incidents; emergency response; nursing robots; human-robot collaboration; task matching; Delphi method; fuzzy analytic hierarchy process

1 Background

Emerging biosafety incidents are typically characterized by high transmissibility, limited early detectability, rapid spread, and substantial occupational exposure risk. They can readily cause widespread infection and public health crises, posing major challenges to national public health emergency response systems (Saif-Ur-Rahman et al., 2025; Zhang et al., 2026). As a core frontline response workforce, nurses may be exposed for prolonged periods to environments with high infection risk, intense pressure, and heavy workloads. Their physical and psychological burden and occupational exposure risk are therefore substantially greater than in routine clinical settings (Islam et al., 2026; Liang et al., 2025). With the increasing application of artificial intelligence and intelligent robotics in healthcare, nursing robots can assume hazardous nursing tasks involving high exposure, heavy workloads, and frequent repetition. Their use may reduce occupational exposure among healthcare workers and alleviate staffing shortages during emergency response, thereby supporting a safer and more intelligent biosafety response system (Lee et al., 2024; Manley et al., 2022).

Current research on human-robot collaborative nursing and task allocation for intelligent devices has largely focused on routine clinical settings and cannot be transferred directly to high-risk, high-stress, and rapidly changing biosafety emergency response environments (Li et al., 2024; Vasquez et al., 2023). The two settings differ substantially in nursing task characteristics, the condition of the workforce, and the operating requirements placed on robots.

From the nursing-task perspective, routine clinical care is delivered in established wards with standardized workflows, relatively stable and controllable environments, and comparatively predictable risks (Kim et al., 2026). Tasks generally allow greater tolerance for error, and deviations in robot performance tend to affect efficiency rather than create systemic safety hazards (Liao et al., 2023; Song et al., 2025). In contrast, nursing tasks during biosafety emergencies are sudden, large-scale, and biologically hazardous. They include high-risk activities such as specimen collection in contaminated zones, monitoring in negative-pressure isolation units, terminal decontamination of affected areas, and transport of infectious waste (Bajjou et al., 2020). Even a single procedural omission may result in aerosol dispersion, cross-infection, or expansion of an outbreak. Error tolerance is therefore extremely low, and human-robot collaboration must be precise, standardized, and safe (Asokan et al., 2026; Zhou et al., 2025).

From the nurse perspective, staff in routine clinical settings usually have stable roles, clearly defined responsibilities, and consistent working environments. Their day-to-day psychological burden is relatively moderate, and basic operational skills may be sufficient for stable human-robot collaboration (Kato et al., 2023; Shaw and Chen, 2025). Biosafety emergency response teams, however, are often assembled temporarily across institutions and departments, resulting in heterogeneous team composition and substantial variation in response experience (Li et al., 2024). Responders must also wear cumbersome personal protective equipment throughout operations, which can restrict vision, hearing, and movement. When these constraints are compounded by mass-casualty care, threats from unknown pathogens, and sustained high-pressure operations, decision fatigue and deterioration in task performance may occur. These conditions place greater demands on dynamic and precise human-robot task coordination (Wu et al., 2025; Zhou et al., 2025).

From the nursing-robot perspective, robots used in routine clinical settings mainly undertake low-risk activities such as material delivery and basic supportive care. They are not usually required to withstand corrosive decontamination environments; their functions are relatively generic, and failures generally cause only temporary task interruption (Graf, 2020; Kim et al., 2022). Biosafety emergencies impose specific hard requirements for environmental adaptability, biological protection, and specialized task performance. Nursing robots may need resistance to disinfectant corrosion, autonomous surface decontamination, sealed transport of contaminated materials, and reliable operation in negative-pressure environments (Gao et al., 2021). Equipment failure or execution errors may facilitate pathogen spread, environmental contamination, or loss of operational control. The associated risks and safety constraints are therefore substantially greater than those in routine clinical settings (Yang et al., 2020).

Accordingly, this study focused on biosafety emergency response and aimed to develop a task-nurse-nursing robot fit indicator system. Indicators were screened, revised, and refined through literature review, semistructured interviews, and expert consultation, and their relative weights were determined using the fuzzy analytic hierarchy process. A conceptual fit calculation framework based on requirement-capability mapping, measurement of capability deficits, and safety veto rules was then proposed to provide an operational pathway for developing and validating a human-robot task-matching assessment tool. Because no data from actual tasks, personnel, or

equipment operations were included, the calculation framework is intended solely to define methods for the next stage of tool development; no empirical inference is made regarding its matching accuracy or scheduling utility.

2 Development of the Preliminary Task-Nurse-Nursing Robot Fit Indicator System for Biosafety Emergency Response

2.1 Theoretical Framework for Task-Nurse-Nursing Robot Fit

A theoretical framework for task-nurse-nursing robot fit was developed using systems theory, synergetics, and human factors engineering. Systems theory was used to define an emergency nursing system comprising tasks, nurses, and robots (Tiwari, 2023); synergetics emphasized interdependence and collaboration among these components (Haken, 2017); and human factors engineering was used to identify constraints affecting personnel and equipment in high-pressure, high-risk, and complex environments, including limitations imposed by personal protective equipment (Drews et al., 2019). Task requirements, nurse capabilities, and nursing robot performance were therefore specified as the three first-level dimensions of the indicator system (Figure 1). In this study, three-dimensional fit was operationally defined as the extent to which the capability supply of nurse-only, nursing robot-only, or nurse-robot collaborative execution covers the requirements of a specific nursing task while satisfying biosafety hard constraints. Thus, fit is not the simple sum of scores across the three dimensions; it is the correspondence and comparison between task requirements and execution capabilities on shared evaluation dimensions.

2.2 Literature Review

PubMed, Web of Science, and China National Knowledge Infrastructure (CNKI) were systematically searched for literature published from 2016 to 2026 on nursing tasks in biosafety emergencies, nurses' capability to respond to biosafety incidents, and the technical performance of nursing robots. Controlled terms and free-text terms were combined using the following general search expression: ("biosafety" OR "biological hazard" OR "biosafety emergency" OR "emergency response" OR "infectious disease outbreak" OR "public health emergency") AND ("nursing robot" OR "care robot" OR "medical robot" OR "service robot" OR "humanoid robot") AND ("human-robot interaction" OR "human-robot collaboration" OR "task allocation" OR "task matching" OR "adaptation evaluation" OR "index system"). Reference lists of included articles were also screened to identify additional studies and improve search sensitivity. Studies were eligible if they (1) examined emergency nursing in sudden

biosafety incidents or infectious disease emergencies; (2) addressed nursing task characteristics, nurses' emergency response capabilities, nursing robot performance, human-robot task matching, or fit indicators; (3) were original articles, systematic reviews, or studies developing indicator systems; and (4) had full text available. Studies were excluded if they (1) focused on nonemergency care in routine wards or outpatient settings; (2) examined general-purpose industrial or domestic robots unrelated to clinical nursing; or (3) were conference abstracts, popular science articles, duplicate publications, or reports with incomplete data. Of 629 records retrieved, 127 were included after deduplication, title and abstract screening, and full-text screening. These studies yielded 3 first-level, 9 second-level, and 18 third-level indicators.

2.3 Semistructured Interviews

Based on the literature review, purposive sampling was used to recruit 17 participants with experience in biosafety emergency response for semistructured interviews. Participants included nurse leaders responsible for emergency management in tertiary hospitals, infection prevention and control experts, public health emergency managers, and clinical operations and maintenance staff for nursing robots. Interviews explored factors involved in matching task requirements, nurse capabilities, and nursing robot performance during biosafety emergency response. All interviews were audio-recorded and transcribed. Thematic analysis was used to derive and revise indicators (Drews et al., 2019), resulting in an initial framework of 3 first-level, 10 second-level, and 23 third-level indicators (Figure 2).

3 Establishment of the Task-Nurse-Nursing Robot Fit Indicator System for Biosafety Emergency Response

The indicators in the preliminary system were screened and revised through a Delphi survey (Sist et al., 2026). Questionnaires were distributed by email, with a 14-day interval between rounds. In round 2, experts received feedback on the group statistics and indicator revisions from round 1. After the indicator content had been finalized, the experts performed pairwise comparisons of indicators, and initial relative weights were calculated using the fuzzy analytic hierarchy process (Atijosan and Atijosan, 2026).

3.1 Delphi Survey

3.1.1 Characteristics of the Expert Panel

Fifteen experts in nursing management, frontline clinical nursing, infectious disease prevention and control, intelligent healthcare, and public health emergency

management participated in two Delphi rounds. Eligibility criteria were (1) an associate senior or higher professional title; (2) a master's degree or higher; (3) at least 10 years of experience in a relevant field; and (4) provision of informed consent and voluntary participation. Expert characteristics are presented in Table 1.

3.1.2 Panelist Participation and Authority

All questionnaires were returned in both Delphi rounds, giving a valid response rate of 100% in each round. The judgment coefficient, calculated from the frequency distribution of the experts' bases for judgment, was 0.953 (Table 2). Twelve experts rated themselves as very familiar with the subject and three as moderately familiar, yielding a familiarity coefficient of 0.860. The expert authority coefficient, calculated as the arithmetic mean of the judgment and familiarity coefficients, was 0.907, indicating a high level of panel authority (Roche et al., 2025).

3.1.3 Agreement Among Experts

Kendall's W values for the first-, second-, and third-level indicators were 0.325, 0.313, and 0.338 in round 1 and 0.496, 0.386, and 0.386 in round 2, respectively; all P values were <0.01 (Table 3). The generally higher W values in round 2 indicated improved agreement and a high level of consistency in the experts' judgments of indicator importance.

3.1.4 Finalization of the Indicator System

The importance of each indicator was rated on a 5-point Likert scale. Indicators were retained when the mean importance score was >=3.5 and the coefficient of variation was <0.25; qualitative comments from the experts were also considered when refining indicator wording (Vandooren et al., 2026). Revisions across the two rounds are summarized below.

Round 1: Mean importance scores across all indicator levels ranged from 3.467 to 4.867, and coefficients of variation ranged from 0.066 to 0.197. Three third-level indicators had mean scores <3.5 and did not meet the retention criterion. The experts submitted 18 revision suggestions. At the second level, the original dimensions of time criticality of emergency tasks and emergency nursing workload were merged into emergency nursing service characteristics, reducing the number of second-level indicators from 10 to 9. At the third level, three indicators with limited relevance to biosafety emergencies (fit for routine nurse-patient communication, convenience of routine maintenance, and compatibility with general nursing procedures) were removed. Sixteen indicators addressing biosafety-specific requirements were added,

including need for contactless task execution, tolerance to high-concentration disinfectants, autonomous decontamination and self-protection capability, and emergency response capability for robot failures. The wording of 12 indicators was refined to improve contextual specificity and conceptual precision; for example, robot operating capability was revised to operational stability in isolation environments, and personnel operating capability was specified as ability to use protective equipment.

Round 2: Mean importance scores ranged from 3.533 to 4.867, and coefficients of variation ranged from 0.064 to 0.176. Agreement among experts improved relative to round 1. The experts proposed no substantive additions or deletions; wording was adjusted slightly for two third-level indicators without changing their meaning or hierarchical placement.

After two Delphi rounds, the final task-nurse-nursing robot fit indicator system for biosafety emergency response comprised 3 first-level, 9 second-level, and 36 third-level indicators. Its hierarchical structure is shown in Figure 3.

3.2 Determination of Indicator Weights Using the Fuzzy Analytic Hierarchy Process

After the indicator content had been finalized through the two Delphi rounds, the experts conducted pairwise comparisons of indicators within the same hierarchical level. Fuzzy analytic hierarchy process was used to convert judgments of relative importance into weights, thereby providing a more structured basis for weight allocation (Cui et al., 2025).

3.2.1 Construction of the Fuzzy Complementary Judgment Matrix

A 0.1-0.9 scale was used to express the relative importance of two indicators at the same level with respect to the indicator at the next higher level, producing the fuzzy complementary judgment matrix A = (aij)n x n (i, j = 1, 2, ..., n). When aij = 0.5, factors ai and aj are equally important. When aij is in [0.1, 0.5), aj is more important than ai; when aij is in (0.5, 0.9], ai is more important than aj (Soltanzadeh et al., 2026; Table 4).

Table 4. Interpretation of the Quantitative Scale for the Fuzzy Complementary Judgment

3.2.2 Weight Calculation

Let A = (aij)n x n denote a fuzzy complementary judgment matrix and W = (W1, W2, ..., Wn)T its weight vector. The weights of the fuzzy complementary judgment matrix were calculated using Equation (1) (Mousavi et al., 2026):

$$W_i = \frac{\sum_{r,j=1}^{n} a_{ij} + \frac{n}{2} - 1}{n(n-1)} \quad (1)$$

where wi denotes the weight of factor ai (i = 1, 2, ..., n).

3.2.3 Compatibility Assessment of the Fuzzy Complementary Judgment Matrix

To evaluate the internal compatibility between the weight vector obtained from Equation (1) and the judgment matrix, the characteristic matrix W* was constructed from the weight vector and the compatibility index I(A, W*) was calculated (Moslem et al., 2022), as follows:

Characteristic matrix W*:

$$W* = (b_{ij})_{n*n} = \frac{w_i}{w_i + w_j} \quad (2)$$

Compatibility index I(A, W*):

$$I(A, W*) = \frac{1}{n^2} \sum_{i,j=1}^{n} |a_{ij} + b_{ji} - 1| \quad (3)$$

where A and W* are n x n fuzzy complementary judgment matrices. An aggregate judgment matrix was considered to meet the prespecified compatibility criterion when I(A, W*) < 0.1. A smaller I value indicates greater compatibility between the judgment matrix and the characteristic matrix derived from the weights (Toly Chen et al., 2022).

3.2.4 Calculation of Weights at Each Indicator Level

The pairwise comparisons of the three first-level indicators provided by the 15 experts were aggregated to obtain the fuzzy complementary judgment matrix shown in Table 5. The data in Table 5 yielded the following aggregate fuzzy complementary judgment matrix for the first-level indicators:

Pairwise judgment matrix A

$$A = \begin{bmatrix} 0.5 & 0.5267 & 0.7667 \\ 0.4733 & 0.5 & 0.64 \\ 0.2333 & 0.36 & 0.5 \end{bmatrix}$$

Using Equation (1), the weights of the first-level indicators were calculated as follows:

$$A = \frac{\sum_{r,j=1}^{n} a_{ij} + \frac{n}{2} - 1}{n(n-1)} = \frac{(0.5+0.5267+0.7667) + \frac{3}{2} - 1}{3(3-1)} = 0.3822$$

$$B = \frac{\sum_{r,j=1}^{n} a_{ij} + \frac{n}{2} - 1}{n(n-1)} = \frac{(0.4733+0.5+0.64) + \frac{3}{2} - 1}{3(3-1)} = 0.3522$$

$$C = \frac{\sum_{r,j=1}^{n} a_{ij} + \frac{n}{2} - 1}{n(n-1)} = \frac{(0.2333+0.36+0.5) + \frac{3}{2} - 1}{3(3-1)} = 0.2656$$

Using Equation (2), the characteristic matrix W* for the first-level indicators was calculated as follows:

$$Wx = \begin{bmatrix} 0.5 & 0.5204 & 0.59 \\ 0.4796 & 0.5 & 0.5701 \\ 0.41 & 0.4299 & 0.5 \end{bmatrix}$$

The weights for the first-level fuzzy complementary judgment matrix were calculated using Equation (1), as follows:

$$W = [0.3822 \quad 0.3522 \quad 0.2656]$$

Using Equation (3), the compatibility index of the aggregate judgment matrix for the first-level indicators was I = 0.0562, which was <0.1 and therefore met the prespecified criterion. The global weight of each indicator was calculated as the weight of its parent indicator multiplied by its local weight.

Initial weights for the second- and third-level indicators were calculated in the same manner and are summarized in Table 6 and Figure 4. All aggregate judgment matrices had compatibility indices <0.1. At the second level, the indices were 0.0733 for group A, 0.0618 for group B, and 0.0350 for group C. At the third level, the indices were 0.0748 for A1, 0.0900 for A2, 0.0604 for A3, 0.0709 for A4, 0.0824 for B1, 0.0866 for B2, 0.0416 for B3, 0.0683 for C1, and 0.0826 for C2. All matrices therefore met the prespecified compatibility criterion.

3.3 Three-Dimensional Fit Calculation Framework (Theoretical Formulation)

To translate the indicator system from a weighting structure into an operational task-matching method, a three-dimensional fit calculation framework was proposed using the indicators and initial weights in Table 6. The unit of assessment is a specific nursing task, and three execution modes are considered: nurse-only execution (N), nursing robot-only execution (R), and nurse-robot collaborative execution (NR). The framework sequentially performs requirement-capability mapping, hard-constraint screening, capability-deficit calculation, and ranking of candidate execution modes. No data from actual tasks, personnel, or equipment were used to estimate model parameters. The equations below therefore constitute an operational framework requiring validation and are not empirical findings of this study.

3.3.1 Requirement-Capability Mapping and Standardization

For nursing task k, let t_{kj} denote the standardized requirement on shared evaluation dimension j, and let c_{kpj} denote the capability supplied by candidate execution mode p on the same dimension. Both range from 0 to 1; higher values indicate greater task requirements and stronger capability supply, respectively. Shared evaluation dimensions are derived from the existing indicators through requirement-

capability mapping matrix *M*. Category A indicators form the task-requirement vector, whereas categories B and C form the nurse-capability and nursing-robot-capability vectors, respectively. For the collaborative execution mode, capability supply is combined using either a complementary-maximum rule or a collaborative-bottleneck rule, depending on the indicator. Observable rating anchors must be established for each indicator and further calibrated using an independent expert panel, simulated tasks, and actual equipment parameters so that requirements and capabilities can be compared on the same scale.

A preliminary mapping may link infection prevention and control requirements (A12 and A41-A43) to nurses' protective and biosafety capabilities (B11-B12) and nursing robots' adaptability to biosafety incidents (C11-C13). Operational complexity and error-tolerance requirements (A21 and A23-A25) may be mapped to nurses' emergency practical skills, on-site decision-making, and risk-based judgment (B13-B15 and B32) and to nursing robots' task execution and abnormal-event warning capabilities (C22-C25). Time-criticality and workload requirements (A14 and A31-A33) may be mapped to nurses' adaptability to high-stress environments (B31) and nursing robots' continuous operation and autonomous task completion capabilities (C21-C22). This mapping is only a theoretical draft derived from the meanings of the current indicators and requires a separate content-validity evaluation.

3.3.2 Capability-Deficit and Fit-Score Calculation

To represent the bottleneck effect in high-risk tasks, the framework uses a one-sided capability deficit: only the portion by which capability falls below the requirement is penalized, whereas capability exceeding the requirement does not reduce fit. For task k and candidate execution mode p, the capability deficit on evaluation dimension j is defined as:

$$g_{kpj}^{-} = \max(0, t_{kj} - c_{kpj}) \tag{4}$$

The weighted capability deficit D_{kp} is then calculated as:

$$D_{kp} = \frac{\sum_{j \in J_k} \omega_j g_{kpj}^{-}}{\sum_{j \in J_k} \omega_j} \tag{5}$$

where J_k is the set of shared evaluation dimensions involved in task k and ω_j is the normalized weight of mapped evaluation dimension j. In an initial tool, the third-level global weights of related indicators in Table 6 may be combined according to

the mapping rules and renormalized. The specific aggregation method and its robustness must nevertheless be established through independent expert calibration and sensitivity analysis. D_{kp} ranges from 0 to 1, with lower values indicating smaller capability deficits.

The fit score F_{kp} for a candidate execution mode is calculated as:

$$F_{kp} = V_{kp}(1 - D_{kp}) \tag{6}$$

3.3.3 Safety Veto Rules and Selection of the Execution Mode

V_{kp} is a binary safety-feasibility indicator that takes a value of 0 or 1. Hard constraints, including infection protection, task error tolerance, authority for clinical decision-making, equipment resistance to decontamination, and adaptability to isolation environments, cannot be compensated for by strengths on other indicators. If any hard constraint fails to meet the minimum requirement for the task, V_{kp} = 0 and the fit score for that candidate mode is set to 0. If all hard constraints are satisfied, V_{kp} = 1 and the weighted capability deficit is then calculated. Hard-constraint items and minimum standards should be defined according to applicable regulations, equipment certification, scope-of-practice requirements, and context-specific expert consensus.

Among candidate modes that pass safety screening, the mode with the highest fit score is selected as the recommended mode:

$$p_k^* = \underset{p \in P_k}{\operatorname{argmax}} F_{kp}, F_{kp} \geq \tau \tag{7}$$

where P_k is the set of candidate execution modes that pass hard-constraint screening and τ is the minimum acceptable fit threshold. If no candidate mode reaches τ, the task should undergo manual review, personnel or equipment should be reconfigured, or the task should be deferred. If the difference in fit scores between two modes is smaller than the prespecified switching margin δ, a nurse-robot collaborative option should be assessed preferentially or the clinical lead should make the final determination.

3.3.4 Parameter Calibration and Validation Pathway

This study does not prespecify numerical values for τ or δ. Future research should first use an independent expert panel to evaluate the content validity of the requirement-capability mapping matrix, rating anchors, and hard-constraint list. Simulated cases covering different risk levels, task types, and equipment states should then be used to compare model recommendations with reference decisions from a multidisciplinary expert panel and to assess unsafe assignments that are incorrectly

classified as feasible. Multicenter simulation exercises should subsequently examine test-retest reliability, discriminative ability, calibration, and threshold stability. Finally, prospective implementation studies should evaluate effects on task completion time, occupational exposure among nurses, patient safety, equipment failures, and the manual takeover rate. Until these validation steps are complete, model outputs should be used only as decision-support information and not as automated scheduling instructions.

4 Discussion

4.1 Methodological Rigor of the Task-Nurse-Nursing Robot Fit Indicator System for Biosafety Emergency Response

Guided by systems theory, synergetics, and human factors engineering, this study incorporated task requirements, nurse capabilities, and nursing robot performance into a single indicator framework. Indicators were generated and revised through literature review, semistructured interviews, and consultation with experts from multiple disciplines. The expert authority coefficient was 0.907, and the indicator structure stabilized after two Delphi rounds, indicating a high level of expert acceptance (Dimeff et al., 2023). Pairwise comparisons quantified the experts' judgments of relative importance and may have reduced subjectivity associated with direct weighting. Compatibility indices for all judgment matrices were <0.1, supporting the internal compatibility of the matrices and the reliability of the resulting weights (Varshney et al., 2024).

4.2 Interpretation of the Indicator Weights

The fuzzy analytic hierarchy process results describe the experts' judgments of the relative importance of the indicators. The weights quantify how a multidisciplinary panel prioritized factors relevant to task-nurse-nursing robot fit in biosafety emergency response. Unlike patterns of human-robot fit in routine clinical care, the ranking observed in this study reflects an operating environment characterized by high infection exposure, low tolerance for error, intense psychological stress, and rapid change (Lee et al., 2023; Zheng and Lowe, 2025). The pattern also illustrates the underlying logic linking tasks, nurses, and nursing robots in collaborative operations.

4.2.1 Nursing Task Characteristics: The Risk-Oriented Core of Fit

Nursing task characteristics had the highest first-level weight (0.3822), followed by nurse capabilities (0.3522) and nursing robot performance (0.2656). This ranking

indicates that task characteristics received the greatest relative importance. Biosafety emergency tasks often involve exposure risk, time pressure, procedural complexity, and little tolerance for error (Wu et al., 2024); therefore, using task requirements as the starting point for subsequent matching assessments is theoretically appropriate. Direct comparisons of three-dimensional fit weights between routine clinical settings and biosafety emergencies are currently lacking, and the context specificity of these findings requires confirmation in comparative studies.

Within nursing task characteristics, the second-level weights were 0.2950 for biosafety incident characteristics, 0.2744 for operational characteristics of nursing tasks, 0.2344 for infection prevention and control requirements, and 0.1961 for emergency nursing service characteristics. Third-level indicators with relatively high global weights included required level of personal protection, biosafety incident classification and response level, and infection exposure risk level. These findings suggest that infection risk and response requirements should be prioritized when validating task-entry and matching rules (Ijarotimi et al., 2026). Task risk directly determines the safety boundary and division of labor in human-robot collaboration. High-exposure, highly repetitive, and low-complexity tasks may preferentially be assigned to nursing robots to reduce occupational exposure among nurses, whereas clinically critical tasks that are complex, allow little error, and depend on clinical judgment should remain under human responsibility to protect the quality and safety of the response (Huang et al., 2026).

4.2.2 Nurse Capabilities: Multidimensional Competence for Operationalizing Fit

Nurse capabilities had a first-level weight of 0.3522. In competency frameworks for routine clinical nursing, technical skills and nurse-patient communication are usually core dimensions, whereas psychological adjustment is often secondary. In this study, the second-level weights were 0.3867 for biosafety incident response capability, 0.3489 for human-robot collaboration capability, and 0.2644 for psychological stress tolerance capability. This distribution reflects the multidimensional capabilities required of nurses in emergency settings and is consistent with the findings of Shi et al. (2026). At the third level, adaptability to high-stress environments had a local weight of 0.5834, the highest within psychological stress tolerance capability. In public health emergencies, prolonged work under intense pressure and protective-equipment constraints may impair efficiency and decision accuracy and contribute to operational errors and burnout. Psychological stress tolerance is therefore

fundamental to sustained performance (Shin and Yun, 2026). Ability to use protective equipment, practical critical care and emergency nursing capability, and human-robot collaborative task performance capability also had relatively high weights, consistent with Agurto Cordova et al. (2024). Future assessment tools should therefore evaluate sustained performance under protective conditions and the ability to collaborate with robots in addition to professional emergency response skills.

4.2.3 Nursing Robot Performance: Scenario Suitability as a Prerequisite for Effective Support

Nursing robot performance had a first-level weight of 0.2656. Its weight distribution differed from the performance-first emphasis commonly found in assessments of nursing robots for routine clinical care, indicating context-specific priorities. Conventional assessment systems often assign substantial weight to general operational capabilities such as navigation and obstacle avoidance, execution accuracy, and endurance, while treating environmental adaptability as supplementary (2021; Mistry, 2025). In this study, adaptability to biosafety incidents had a second-level weight of 0.5700, exceeding the 0.4300 weight for task execution capability and establishing scenario suitability as a prerequisite for functional expansion. This pattern reflects the high infection risk of biosafety environments: before entering contaminated areas, nursing robots must withstand corrosive decontamination and maintain their own biosafety protection; otherwise, they may become vectors of pathogen transmission and cause cross-infection or other secondary harm (Ke et al., 2025). Tolerance to high-concentration disinfectants and autonomous decontamination and self-protection capability had the two highest global weights within this dimension, exceeding general capabilities such as navigation, obstacle avoidance, and emergency fault recovery. These findings further support scenario suitability as an entry requirement for deploying robots in emergency response. Continuous operational stability and autonomous task completion then extend performance once this prerequisite has been met. The weights may inform future equipment selection, entry assessment, and research and development validation.

4.3 Practical Implications of the Task-Nurse-Nursing Robot Fit Indicator System for Biosafety Emergency Response

Building on the indicator weights, this study proposed an operational pathway of requirement identification, capability mapping, safety screening, deficit calculation, and mode ranking. This pathway provides a computational interface for translating

the three-dimensional indicator system into a task-matching tool. In practice, a standardized requirement vector should first be generated for a specific nursing task. Capability supply should then be calculated for nurse-only, nursing robot-only, and nurse-robot collaborative execution. Noncompensatory conditions, including infection protection, task error tolerance, clinical decision-making, and equipment-environment fit, should undergo safety veto screening before weighted capability deficits and fit scores are calculated for feasible modes. This approach prevents a high total score from masking critical safety deficiencies and provides a unified logic for nursing robot selection, allocation of nurse capabilities, and human-robot task division. Once validated, the indicators, mapping matrix, and decision rules could be embedded in an intelligent scheduling platform for public health emergency nursing. Candidate execution modes could be generated using real-time task workload, personnel status, and equipment operating data, while final decisions remain subject to clinical review and dynamic human takeover (Guo and Li, 2022). The requirement-capability mapping coefficients, fit threshold, and switching margin have not yet been calibrated; therefore, the current framework represents a decision model requiring validation and must not be used directly for actual emergency scheduling.

5 Conclusion

Through theoretical analysis, literature review, semistructured interviews, two Delphi rounds, and fuzzy analytic hierarchy process, this study developed a preliminary task-nurse-nursing robot fit indicator system for biosafety emergency response comprising 3 first-level, 9 second-level, and 36 third-level indicators and determined their relative weights. The first-level weights were 0.3822 for nursing task characteristics, 0.3522 for nurse capabilities, and 0.2656 for nursing robot performance, and all aggregate judgment matrices met the prespecified compatibility criterion. A conceptual three-dimensional fit calculation framework comprising requirement-capability mapping, hard-constraint screening, weighted capability deficits, and ranking of candidate execution modes was also proposed. The framework provides a computable pathway for developing a task-matching assessment tool. Its parameters, thresholds, and decision utility have not yet been empirically validated; it cannot replace clinical judgment or be used directly for actual emergency scheduling.

6 Limitations

This study has several limitations. First, although the Delphi panel included 15

experts from nursing management, infectious disease prevention and control, intelligent healthcare, and other relevant fields, the geographic and institutional diversity of the panel was limited, which may affect generalizability. Second, the indicator system has not been tested in simulation exercises, multicenter practice, or actual equipment trials; its effects on task allocation, occupational exposure, patient safety, and response efficiency therefore remain uncertain. Third, the proposed three-dimensional fit calculation framework is a theoretical formulation based on the current indicators and weights. The requirement-capability mapping matrix, rating anchors, hard-constraint list, fit threshold, and switching margin have not undergone independent expert calibration or prospective validation, and no fit scores for actual tasks are reported. The findings should therefore be regarded as a preliminary foundation for subsequent development and validation of a fit assessment tool.

Declarations

Ethical Considerations

The study was conducted in accordance with the Declaration of Helsinki and applicable Chinese ethical standards for medical research. The study protocol and the interview and Delphi materials were approved by the Medical Ethics Committee of Air Force Medical University (approval no. KY20260826). All interview participants and Delphi experts provided informed consent. Research data were stored anonymously or in de-identified form and were used only for the analyses reported in this study.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and analyzed during the current study are available from thr corresponding author on reasonable request (906963251@qq.com).

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Chao Wu, Ting Song, Jiaqi Yuan and Jiayi Zhang contributed to the research design and paper writing; Nan Li and Cong Ren contributed to the distribution and collection of the questionnaire; Yanling Du and Hongjuan Lang contributed to the research design and the data analysis; Zhen Sa and Yawei Lin contributed to the proofreading and English version of the paper.

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Consent to Participate

All individual human-participant participants, including semi-structured interview interviewees and Delphi expert panel members, were fully informed of the study purpose, data usage and confidentiality rules. Written informed consent was obtained from every participant prior to data collection. Participants were permitted to withdraw from the study at any time without penalty. All collected data were anonymised to protect personal privacy.

Clinical trial number: not applicable.

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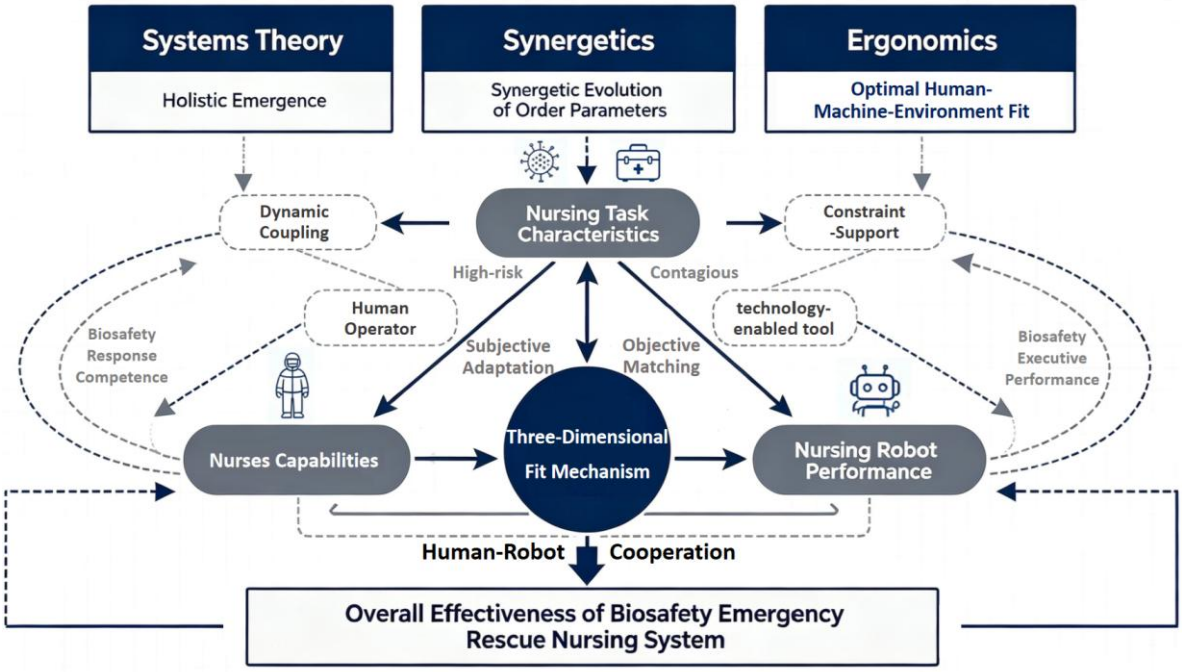


Figure 1. Theoretical framework for task-nurse-nursing robot fit in biosafety emergency response

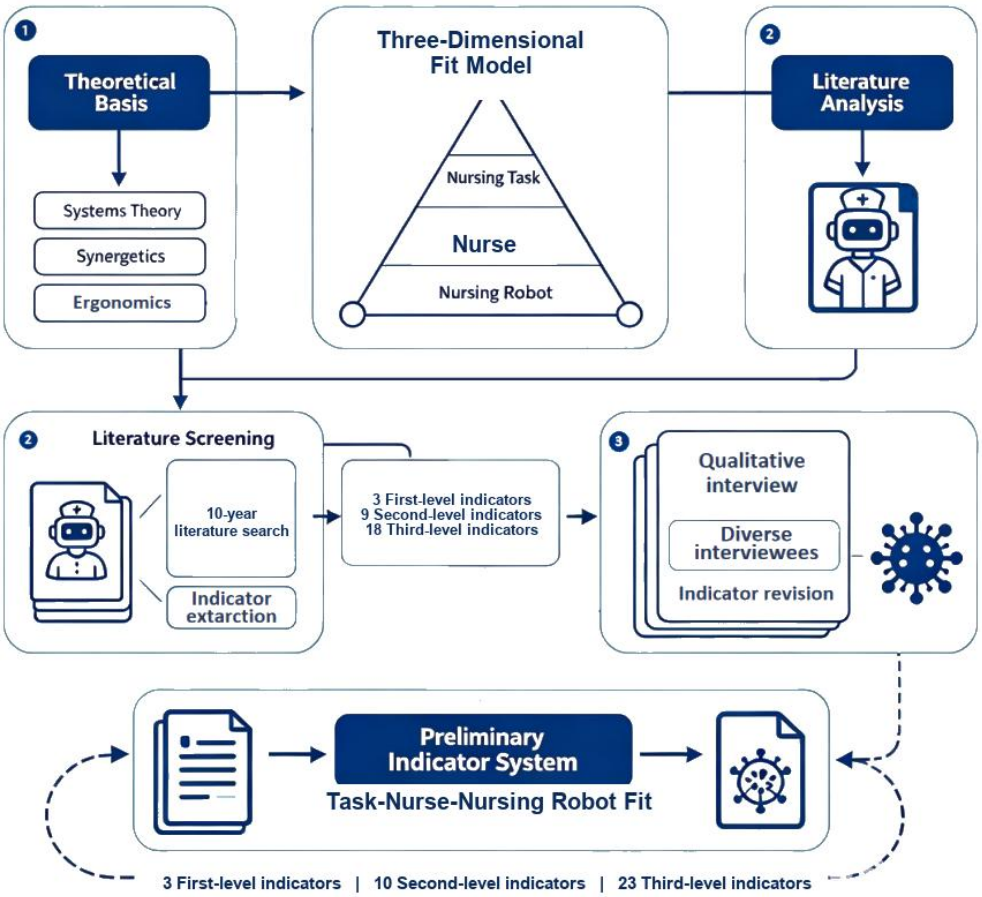


Figure 2. Flow diagram for development of the preliminary indicator system

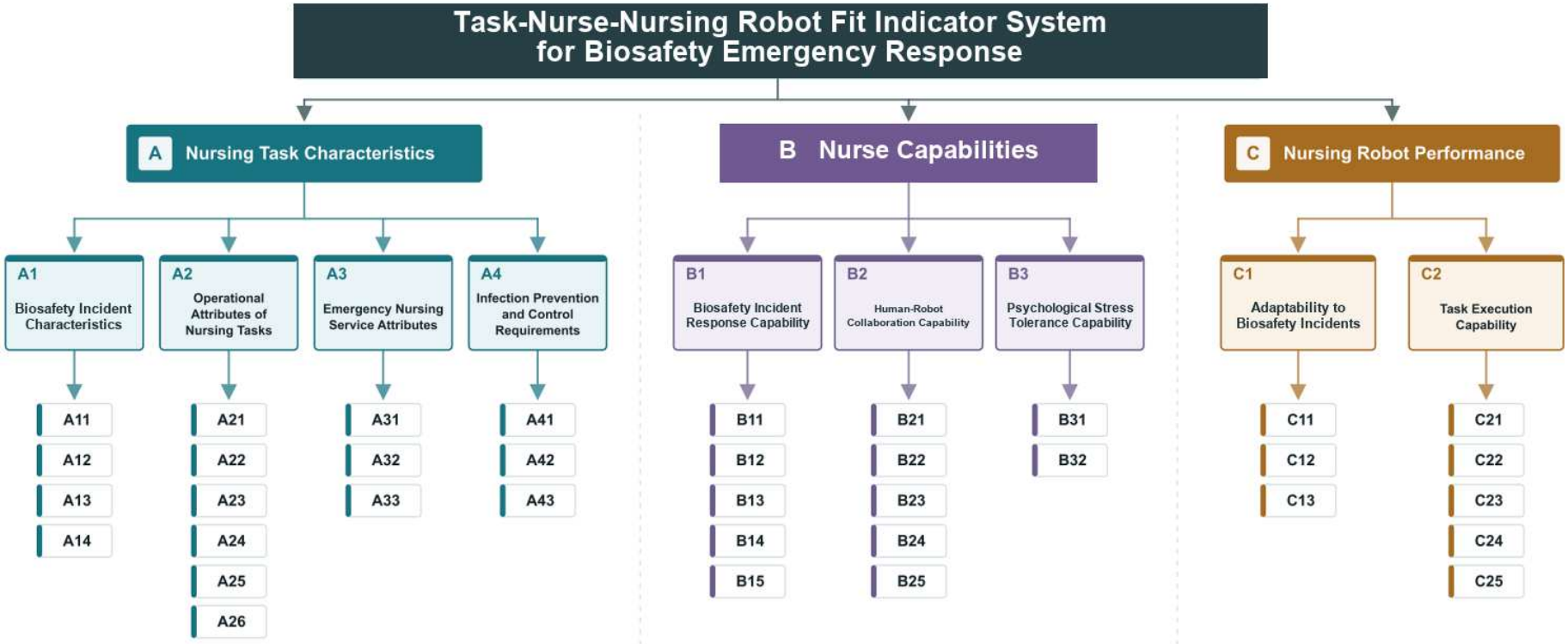


Figure 3. Hierarchical structure of the task-nurse-nursing robot fit indicator system for biosafety emergency response

Note. Codes and full names of the third-level indicators are provided in Table 6.

Characteristic	Category	n	Percentage (%)

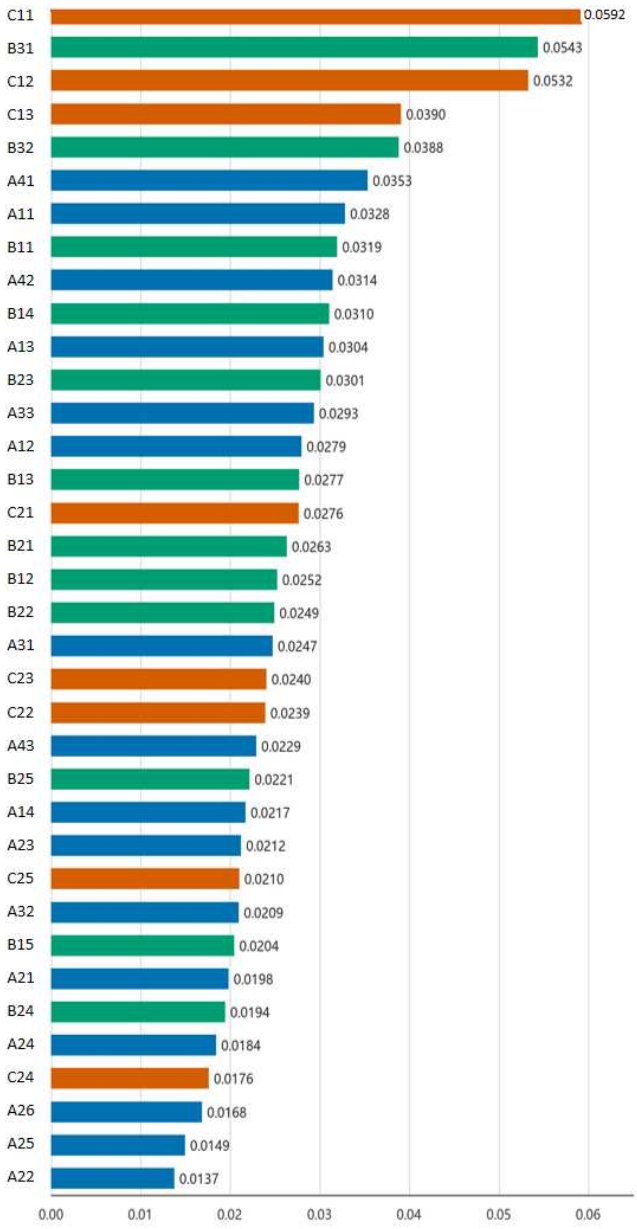


Figure 4. Ranking of the Global Weights of the Third-Level Indicators

Note. Codes and full names of the third-level indicators are provided in Table 6.

Table 1. Characteristics of the Delphi Panel (N = 15)

Sex	Male	4	26.67
	Female	11	73.33
Age (years)	<40	3	20.00
	≥40	12	80.00
Professional title	Senior	5	33.33
	Associate senior	10	66.67
Years of experience	<15	2	13.33
	≥15	13	86.67
Field of expertise	Nursing management	2	13.33
	Frontline clinical nursing	3	20.00
	Infectious disease prevention and control	3	20.00
	Intelligent healthcare	3	20.00
	Public health emergency management	4	26.67

Table 2. Frequency Distribution of the Experts' Bases for Judgment (N = 15)

Basis for judgment	High		Moderate		Low	
	n	%	n	%	n	%
Theoretical analysis	9	60.00	6	40.00	0	0.00
Practical experience	14	93.33	1	6.67	0	0.00
Domestic and international literature	6	40.00	8	53.33	1	6.67
Intuitive judgment	9	60.00	4	26.67	2	13.33

Table 3. Kendall's Coefficients of Concordance for the Two Delphi Rounds

Indicator level	Round 1			Round 2		
	W	χ^2	*P*	*W*	χ^2	*P*
First-level indicator	0.325	9.750	<0.01	0.496	14.889	<0.01
Second-level indicator	0.313	42.289	<0.01	0.386	46.303	<0.01

Indicator level	Round 1			Round 2		
Third-level indicator	0.338	111.396	<0.01	0.386	202.700	<0.01

Table 4. Interpretation of the Quantitative Scale for the Fuzzy Complementary Judgment Matrix

Scale	Meaning	Interpretation
0.5	Equal	The two factors are equally important
0.6	Slight	The row factor is slightly more important than the column factor
0.7	Moderate	The row factor is clearly more important than the column factor
0.8	Strong	The row factor is much more important than the column factor
0.9	Extreme	The row factor is extremely more important than the column factor
0.1-0.4	Reverse	If comparison of factors i and j gives aij = 0.6, then aji = 1 - 0.6 = 0.4

Table 5. Aggregate Fuzzy Complementary Judgment Matrix for the First-Level Indicators

	A Nursing task characteristics	B Nurse capabilities	C Nursing robot performance
A Nursing task characteristics	0.5	0.5267	0.7667
B Nurse capabilities	0.4733	0.5	0.64
C Nursing robot performance	0.2333	0.36	0.5

Table 6. Weights of the Task-Nurse-Nursing Robot Fit Indicators for Biosafety Emergency Response

First-level indicator	First-level weight	Second-level indicator	Second-level local weight	Second-level global weight	Third-level indicator	Third-level local weight	Third-level global weight
A Nursing task characteristics	0.3822	A1 Biosafety incident characteristics	0.2950	0.1127	A11 Biosafety incident classification and response level	0.2906	0.0328
					A12 Infection exposure risk level	0.2478	0.0279
					A13 Incident scope and task scale	0.2694	0.0304
					A14 Time criticality by response phase	0.1922	0.0217
		A2 Operational characteristics of nursing tasks	0.2744	0.1049	A21 Technical complexity of nursing procedures	0.1889	0.0198
					A22 Repetitiveness of nursing procedures	0.1309	0.0137
					A23 Nursing task error tolerance	0.2024	0.0212
					A24 Required operational precision	0.1756	0.0184
					A25 Degree of procedure standardization	0.1420	0.0149
					A26 Need for contactless task execution	0.1602	0.0168
		A3 Emergency nursing service characteristics	0.1961	0.0749	A31 Required response time	0.3300	0.0247
					A32 Emergency nursing task workload intensity	0.2789	0.0209
					A33 Task priority and urgency	0.3911	0.0293
		A4 Infection prevention and control requirements	0.2344	0.0896	A41 Required level of personal protection	0.3944	0.0353
					A42 Environmental decontamination requirements	0.3500	0.0314
					A43 Medical waste management requirements	0.2556	0.0229
B Nurse capabilities	0.3522	B1 Biosafety incident response capability	0.3867	0.1362	B11 Ability to use protective equipment	0.2340	0.0319
					B12 Biosafety knowledge	0.1853	0.0252
					B13 Emergency situation management capability	0.2037	0.0277
					B14 Practical critical care and emergency nursing capability	0.2273	0.0310
					B15 On-site decision-making, communication, and coordination capability	0.1497	0.0204
		B2 Human-robot collaboration capability	0.3489	0.1229	B21 Proficiency in robot operation	0.2140	0.0263
					B22 Trust in and acceptance of robots	0.2027	0.0249
					B23 Human-robot collaborative task performance capability	0.2453	0.0301
					B24 Adaptability to the user interface	0.1580	0.0194
					B25 Emergency response capability for robot failures	0.1800	0.0221
		B3 Psychological stress tolerance capability	0.2644	0.0931	B31 Adaptability to high-stress environments	0.5834	0.0543
					B32 Risk-based judgment and decision-making capability	0.4166	0.0388
C Nursing robot performance	0.2656	C1 Adaptability to biosafety incidents	0.5700	0.1514	C11 Tolerance to high-concentration disinfectants	0.3911	0.0592
					C12 Autonomous decontamination and self-protection capability	0.3511	0.0532
					C13 Operational stability in isolation environments	0.2578	0.0390
		C2 Task execution capability	0.4300	0.1142	C21 Continuous operational stability	0.2420	0.0276
					C22 Autonomous task completion capability	0.2093	0.0239
					C23 Navigation and obstacle avoidance in complex environments	0.2100	0.0240
					C24 Emergency fault recovery capability	0.1543	0.0176
					C25 Abnormal-event warning capability	0.1843	0.0210