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Formulation of a Weighted Scoring Model Based on Forensic Medical Examination Data as a Decision Support for Prioritizing Sexual Violence Cases

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Abstract
Recent empirical studies highlight that post-factum clinical forensic records in sexual violence cases remain underutilized, leaving emergency case handling heavily dependent on intuitive or first-come, first-served administrative practices that delay critical interventions. This study aims to formulate and validate an automated decision support model utilizing the Simple Additive Weighting (SAW) algorithm to structure medicolegal data into an objective priority-ranking mechanism for case handling. Practically, this framework enables public hospitals and victim protection units to optimize scarce emergency resources, safeguard golden hours for medical prophylaxis, and execute immediate safe-house evacuations. The research method extracted five clinical-forensic criteria—victim age vulnerability, physical and or genital trauma severity, perpetrator relationship, reporting delay, and toxicological or weapon threats from 50 de-identified clinical forensic records, normalized through linear cost-benefit functions weighted by forensic specialists. The results demonstrate robust algorithmic stability across varying weight scenarios, with Spearman's rank correlation reaching $\rho = 0.9867$ and $\rho = 0.9690$, alongside an empirical expert concordance of $\rho = 0.9940$ ($p < 0.001$) that successfully categorized 22% of cases into Emergency Handling Priority I. The research completely meets the expected computational precision and validity, confirming that the model provides a transparent handling prioritization mechanism. However, further multi center trials and integration with natural language processing tools are needed to automate textual feature extraction in larger hospital settings.
Keywords: Decision Support System; Health Informatics; Clinical Forensics; Priority Case Handling; Weighted Scoring Model;

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1. INTRODUCING

Sexual violence represents an extraordinary crime and a grave global public health emergency that inflicts multidimensional physical trauma, acute psychological suffering, and profound socio-developmental disruptions upon survivors [1], [2]. Mitigating these devastating impacts demands rapid, integrated, and evidence-based cross-sectoral interventions orchestrated across referral healthcare centers, law enforcement, and child and women protection agencies [1], [3]. Timely clinical intervention is paramount not only for immediate wound management, but also for securing the strict golden hours required for administering post-exposure prophylaxis (PEP) against human immunodeficiency virus (HIV) and sexually transmitted infections (STIs), as well as emergency contraception [1], [3]. In clinical forensic practice, medical examinations systematically capture essential diagnostic parameters, ranging from acute injuries and biological age vulnerability to reporting delays and the social proximity of alleged perpetrators [4], [5]. In high-density urban agglomerations and regional growth hubs such as Banten Province, demographic growth correlates with surging caseloads, placing an immense operational burden on referral hospitals and regional technical protection units

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(UPTD PPA) [3], [5]. Consequently, establishing an objective, standardized operational workflow to evaluate victim vulnerability has become indispensable to safeguard survivor outcomes [1], [5].

Despite the critical necessity of rapid intervention, regional healthcare facilities and social protection units face severe operational bottlenecks driven by acute resource constraints [3]. The exponential influx of incoming cases outstrips the availability of specialized forensic clinicians, clinical psychologists, case workers, and safe-house accommodations [3]. Ironically, secondary forensic data documented *in visum et repertum* records remain largely confined to passive post-factum evidence for courtroom proceedings, rather than serving as active inputs for operational decision-making [4], [6]. In the absence of structured analytical mechanisms, case handling conventionally defaults to heuristic judgments or administrative queues based on a first-come, first-served mechanism [7]. This conventional workflow fails to reflect underlying clinical acuity, creating dangerous operational risks where acute cases involving active hemorrhage or narrow prophylactic timeframes may be superseded by less urgent administrative files [3], [7]. This operational gap underscores the urgency of integrating Health Informatics and Decision Support Systems (DSS) to convert semi-structured clinical dilemmas into systematic computational models [8]. In social-health emergency settings, Multi-Criteria Decision Making (MCDM)—specifically weighted scoring models provides a deterministic framework to prioritize urgent cases objectively and equitably [3], [9].

Extensive prior investigations have explored various dimensions of violence prevention, forensic medicine, and health informatics. In public health management, data analytics and decision support tools are increasingly recognized as vital instruments for resource optimization [10]. In clinical forensics, digital transformation maps technological progress across medicolegal workflows [11], while public health approaches to crime prevention emphasize inter-agency evidence sharing [12]. Furthermore, objective life-threat trauma scoring systems [13], structured health informatics models for evidence-based practice [14], and descriptive analyses of physical abuse wound patterns [15] have established standard indices to map descriptive injuries into cardinal metrics [13], [15]. Within hospital information systems, Multi-Criteria Decision Analysis (MCDA) frameworks [16] and clinical decision support integrated into electronic medical records [17] support both diagnostic and operational governance [16], [17]. However, deploying such systems requires robust clinical data governance [18], rigorous prediction modeling guidelines [19], and systematic evaluations of hospital data management [20]. When selecting healthcare interventions under conflicting criteria, MCDM software and hybrid frameworks such as hierarchical multi-attribute models [21], [22], [23], the Simple Multi-Attribute Rating Technique (SMART) [24], Multi-Factor Evaluation Process (MFEP) [24], and Simple Additive Weighting (SAW) [25] have proven effective in eliminating subjective administrative bias [25]. In post-conflict and emergency allocation settings, linear weighted scoring models provide clear computational transparency and auditability [26], [27].

Nevertheless, an evident research gap persists at the intersection of clinical forensic archives and automated decision support systems [3], [7], [13], [15], [24], [25], [28]. Prior risk assessments have focused primarily on macro-level policy planning or retrospective psychometric inventories for long-term domestic violence, lacking applicability to micro-level operational urgency at clinical entry points [3], [7]. Conversely, forensic medical studies in Indonesia have documented injury patterns exclusively for judicial pro-justitia purposes without translating findings into automated managerial handling [4], [5], [13], [15]. In operations research, theoretical investigations have demonstrated that linear additive models (SAW) exhibit mathematical equivalence in relative performance indicators with complex outranking methods when uniform linear normalization is applied [28]. Although empirical studies have confirmed the sensitivity of SAW to criteria weight variations, its application has remained confined to commercial, warehousing, or manufacturing domain [24], [25], [29]. Crucially, existing models fail to address the ethical and technical challenges of processing sensitive forensic data, which demands strict de-identification protocols [30], structured clinical data extraction from narrative records [31], and secure relational database architecture [32]. Furthermore, multi-criteria models in medical emergency settings rarely incorporate dual validation involving mathematical sensitivity checks and empirical concordance testing against independent specialist judgments [24], [25], [33].

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To address this gap, this study proposes a linear weighted scoring decision support model grounded in the Simple Additive Weighting (SAW) algorithm tailored specifically for clinical forensic records [8], [9], [25], [28]. The novelty of this approach lies in transforming unstructured, narrative *visum et repertum* archives into a discrete, structured decision matrix [6], [31] governed by rigorous data anonymization protocols [30]. By consolidating five core medicolegal parameters, victim age vulnerability (cost), physical/genital trauma degree (benefit), perpetrator relationship scope (benefit), reporting delay (cost), and toxicological or weapon coercion (benefit) [4], [5], [13], [15], the model assigns deterministic weights established by forensic medicine specialists [26], [28]. Unlike opaque black-box machine learning algorithms, the linear glass-box formulation provides complete computational traceability [27], [28], allowing hospital administrators and protection officers to retrace every normalization and scoring stage in full compliance with bioethical and legal mandates [8], [14], [18], [30]. The suggested model is explicitly designed as an operational decision-support tool to enhance inter-agency case queuing and resource allocation for forensic medicine cases, and it does not replace the clinical and diagnostic acumen of attending forensic medicine.

The primary objective of this study is to formulate, implement, and validate an automated weighted scoring model that converts de-identified clinical forensic records into an objective priority-ranking mechanism for sexual violence case handling [4], [8], [9], [28]. Methodologically, this research establishes a standardized multi-criteria normalization framework capable of balancing conflicting cost and benefit attributes [24], [25], [28]. The robustness of the proposed framework is verified through linear sensitivity analysis across multiple weighting scenarios [24], [25], [29] and validated against independent expert clinical rankings using Spearman's rank correlation coefficient [24], [25], [33]. Practically, the resulting system equips referral public hospitals and victim protection agencies with an evidence-based tool to safeguard critical golden-hour medical interventions [1], [3] and expedite safe-house protective sheltering [3], [5]. The subsequent section delineates the detailed research methodology, data de-identification protocols, and computational formulation [4], [8], [28], [30].

2. RESEARCH METHODOLOGY

This research adopts an applied quantitative engineering paradigm situated at the intersection of Health Informatics, Clinical Forensic Medicine, and Decision Support Systems (DSS) [8], [14], [16]. The methodology bridges empirical, retrospective medico-legal records with mathematical Multi-Criteria Decision Making (MCDM) algorithms to establish an automated, evidence-based priority-handling mechanism [3], [9], [21]. The workflow is structured into five operational stages, designed to transform intricate narrative forensic records into a practical, verifiable decision framework. Significantly, the model maintains complete diagnostic independence and functions solely as a managerial aid without encroaching onto clinical judgment or legal processes [4], [5], [28].

2.1. Research Workflow

The operational flow of this study progresses through five sequential phases [4], [8], [28]:

1. Data Acquisition and De-identification: Collecting retrospective clinical forensic records (*visum et repertum*) of living victims of alleged sexual offenses from a regional public hospital in Banten Province, followed by the rigorous application of data privacy masking protocols [18], [20], [30].
2. Feature Extraction and Parameter Preparation: Selecting relevant clinical variables from narrative free-text records, standardizing medico-legal terminology, and transforming qualitative descriptions into a discrete structured decision matrix [6], [31], [32].
3. Criteria Formulation and Expert Weighting: Consolidating five primary medico-legal criteria with forensic medicine specialists (*subject-matter experts*) and establishing the relative criteria weight vector (w_j) via structured expert interviews [4], [5], [26].
4. Linear Normalization and Scoring Computation: Normalizing the raw decision matrix into a dimensionless scale ($0 \leq r_{ij} \leq 1$) using cost and benefit transformation functions, followed by calculating final composite preference values (V_i) using the Simple Additive Weighting (SAW) algorithm [24], [25], [28].

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5. System Validation and Concordance Evaluation: Performing computational stability checks, sensitivity analyses under diverse weighting scenarios, and measuring concordance between algorithmic rankings and independent blinded clinical assessments by a forensic specialist using Spearman's rank correlation coefficient [24], [25], [29], [33].

2.2. Data Sources and Privacy Protection Protocol

The empirical dataset utilized in this study comprises retrospective secondary data extracted from clinical forensic records of living victims (clinical forensic cases) examined at a regional public hospital in Banten Province between January 2024 and January 2026 [4], [5]. The research protocol and the subsequent utilization of de-identified medical records received administrative approval by a forensic medical specialist working at a regional hospital, in strict compliance with institutional ethical standards and the Indonesian Medical Code of Ethics [18], [30]. This study just examined retrospective, completely anonymised information without any direct interaction with patients, leading to the formal waiver of the necessity for individual informed consent. Before computational processing, strict multi-level privacy protection measures were implemented.

1. Direct Identifier Removal: All direct personal identifiers, including victim full names, national identity numbers (NIK), parent or guardian names, original medical record numbers, phone numbers, and residential addresses, were permanently eliminated [30].
2. Pseudonymization: Each case file was assigned an anonymous alphanumeric reference code (A_{01} to A_{50}) representing computational decision alternatives [30].
3. Demographic Aggregation: Specific birthdates were transformed into discrete biological age variables in completed years at the time of examination to prevent re-identification through demographic linking [18], [30].

2.3. Data Preparation and Discrete Feature Extraction

Clinical notes and forensic medical documentation predominantly exist as unstructured free-text narratives [6], [31]. In this phase, clinical narratives were extracted and mapped into tabular representations through terminology verification with forensic specialists [6], [8], [32]. Clinical descriptions were categorized into discrete ordinal scales ranging from 1 to 5, establishing a standardized data structure suitable for algorithmic evaluation while preserving original clinical meaning [14], [15], [31].

2.4. Criteria Determination and Forensic Expert Weighting

The decision model incorporates five core medico-legal criteria (C_1 through C_5) formulated through comprehensive forensic literature reviews and structured consultations with clinical forensic specialists [4], [5], [13], [15]. Table 1 details the defined criteria, descriptions, and attribute types.

Table 1. Medicolegal Evaluation Criteria

Criterion Code	Criterion Name	Variable Description	Optimization Type
C_1	Victim Age Vulnerability	Biological age at examination; measures physical helplessness, developmental trauma, and legal dependency.	Cost
C_2	Physical/Genital Trauma Degree	Objective anatomical findings, including hymenal/mucosal tears, multi-regional contusions, active bleeding, or sphincter lesions.	Benefit
C_3	Perpetrator Relationship Scope	Social proximity or hierarchical dependence; measures risk of continued coercion, repeated abuse, and domestic threats.	Benefit

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Criterion Code	Criterion Name	Variable Description	Optimization Type
C_4	Reporting Delay (Examination Window)	Elapsed time between the incident and forensic examination; determines critical golden hours for medical prophylaxis.	Cost
C_5	Substance/Weapon Coercion	Evidence of incapacitation via sedatives, forced alcohol, or intimidation involving physical weapons.	Benefit

The directional optimization types assigned to the criteria in Table 1 are strictly aligned with clinical urgency and child protection mandates. Specifically, victim age (C1) is designated as a cost criterion because younger biological age reflects severe physiological defenselessness, heightened developmental vulnerability, and irreversible psychological trauma; lower numerical age levels (e.g., Level 1 for toddlers < 6 years) must correspond to the highest urgency prioritization. In contrast, perpetrator relationship scope (C3) is modeled as a benefit criterion because increasing ordinal levels represent escalating social proximity and continuous domestic dependency. Level 5 denotes nuclear family members or cohabiting carers, where the risk of ongoing intimidation, repeated sexual abuse, and witness tampering is highest, demanding maximal urgency for emergency safe-house evacuation and judicial protection.

Criterion weights were determined using a direct subjective weighting technique administered to forensic medicine specialists [26], [28]. The resulting normalized weight vector $W = [w_1, w_2, w_3, w_4, w_5]^T$ must satisfy the mathematical closure constraint [24], [25], [28]:

$$\sum_{j=1}^{5} w_j = 1, \quad \text{where } w_j > 0 \text{ for all } j \in \{1,2,3,4,5\} \qquad (1)$$

The weight vector was generated using a controlled elicitation process including a senior forensic medicine specialist (with over ten years of clinical forensic practice in public referral institutions). Applying an explicit direct rating, based on acute life-threat, irreversible tissue damage, and prophylactic window constraints. Adjusted to comply with the unit-sum closure criteria. ($\sum w_j = 1$). Physical trauma degree earned the highest allocation ($w_2 = 0.30$) due to the immediate risk of hemorrhagic shock and tissue necrosis needing urgent surgical hemostasis. Victim age was assigned ($w_1 = 0.25$) to prioritize the acute biological and developmental helplessness of newborns and young children. The reporting delay was assigned a weight of ($w_4 = 0.20$) to safeguard the limited golden-hour period (≤ 24 hours) for HIV and STI post-exposure prophylaxis. The association of the perpetrator ($w_3 = 0.15$) and threats involving substances or weapons ($w_5 = 0.10$) were assigned weights to indicate the risks of domestic re-victimization and the rapid deterioration of forensic toxicological evidence, respectively [4], [5], [26].

2.5. Formulation of the Weighted Scoring Model

The prioritization ranking is executed via the Simple Additive Weighting (SAW) algorithm across three mathematical steps [26], [28]:

First, the quantified clinical records of m case alternatives evaluated against $n = 5$ criteria are assembled into decision matrix X [25], [28]:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \qquad (2)$$

Second, elements x_{ij} in matrix X are normalized into a dimensionless matrix $R = [r_{ij}]$ where $0 \leq r_{ij} \leq 1$ [24], [28]. The normalization formula depends on the criterion optimization type:

For benefit criteria (C_2, C_3, C_5), where higher values indicate greater urgency [25], [28]:

$$r_{ij} = \frac{x_{ij}}{\max_{k=1}^{m} x_{kj}} \qquad (3)$$

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For cost criteria (C_1, C_4), where lower values represent higher vulnerability and immediate priority [25], [28]:

$$r_{ij} = \frac{\min_{k=1}^{m} x_{kj}}{x_{ij}} \qquad (4)$$

From a mathematical modeling standpoint, utilizing conventional ratio-based normalization on discrete ordinal scales (Levels 1 to 5) reveals unique transformation characteristics depending on the type of criteria. For the benefit criteria (C2, C3, C5), Equation (3) employs linear proportional scaling (xij/5), resulting in uniform increments (0.2000, 0.4000, 0.6000, 0.8000, 1.0). In contrast, for cost parameters (C1, C4), the reciprocal ratio transformation in Equation (4) (1/xij) results in an intrinsic non-linear, hyperbolic decline (1.0, 0.5000, 0.3, 0.2500, 0.2000). Ordinal indices presuppose ranked categories instead of strictly equal interval distances; this non-linear compression acts as a purposeful triage safeguard within this framework: it imposes a substantial mathematical penalty for delayed reporting (C4 > 24 hours) and for older demographic groups, thus guaranteeing that acute infant trauma and limited golden-hour prophylactic opportunities attain clear distinction and absolute superiority in composite scoring.

Third, the composite preference value (V_i) for each case alternative A_i is computed by taking the linear product of the normalized matrix row and the expert weight vector [25], [28]:

$$V_i = \sum_{j=1}^{n} w_j \cdot r_{ij} = w_1 r_{i1} + w_2 r_{i2} + w_3 r_{i3} + w_4 r_{i4} + w_5 r_{i5} \qquad (5)$$

The resulting composite preference score satisfies $V_i \in [0,1]$ [28]. Case alternatives are ranked in descending order according to V_i, where higher values represent the highest operational priority for emergency medical and psychosocial handling [9], [25], [27].

2.6. Computational Stability and Empirical Validation

To evaluate the reliability of the decision model prior to clinical deployment, dual-tier validation was conducted [24], [25], [33]:

1. Computational Linear Stability and Sensitivity Analysis: Verifying that matrix normalization satisfies $r_{ij} \in [0,1]$ without zero-division anomalies [28], and simulating criteria weight adjustments across three distinct scenarios (Baseline, Equal Weights, and Golden Hours Heavy) to assess rank stability and rank reversal risks [24], [25], [29].
2. Clinical Face Validity and Expert Concordance was evaluated by comparing algorithmic priority ranks (R_{SPK}) against an independent, blinded evaluation conducted by a board-certified forensic medicine specialist (R_{Pakar}). To enforce strict blinding and prevent confirmation bias, the evaluator received only raw, anonymized clinical case narratives (injury descriptions, chronological timelines, victim age, and alleged perpetrator proximity) without access to the criteria weights (W), mathematical normalization formulas, or system-generated composite scores (V_i). The expert independently assigned cardinal priority rankings (1 to 50) based solely on intuitive diagnostic and prognostic judgment [4], [25].
3. Concordance was quantified using Spearman's rank correlation coefficient (ρ) [24], [25], [33]:

$$\rho = 1 - \frac{6\sum_{i=1}^{m} d_i^2}{m(m^2-1)} \qquad (6)$$

where $d_i = R_{\text{SPK},i} - R_{\text{Pakar},i}$ denotes the rank difference for case alternative i, and m represents the total sample size ($m = 50$) [24], [33].

3. RESULT AND DISCUSSIONS

The empirical implementation of the proposed weighted scoring model across clinical forensic datasets, assesses the mathematical stability of linear normalization, validates priority rankings against independent forensic specialist judgments, and elaborates on operational implications for hospital and social protection workflows

3.1. Dataset Characteristics and Privacy Protocol Execution

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The computational framework was evaluated using 50 retrospective clinical forensic medical records and *visum et repertum* documents of living victims of alleged sexual offenses examined at a regional public hospital in Banten Province between January 2024 and January 2026. The execution of strict de-identification protocols successfully eliminated all direct personal identifiers, securely mapping each subject into an anonymous computational alternative designated as A_{01} through A_{50}.

Demographic profiling revealed that the biological ages of the victims ranged from 4 to 31 years. Child and adolescent cohorts constituted the overwhelming majority (78%) of the total caseload, comprising early childhood or toddlers under 6 years (8%, 4 cases), primary school-aged children aged 6–11 years (24%, 12 cases), early adolescents aged 12–14 years (24%, 12 cases), and middle-to-late adolescents aged 15–17 years (22%, 11 cases). Adult victims aged 18 years and above accounted for the remaining 22% (11 cases). Regarding reporting delay (C4), 48% of the victims (24 cases) presented to the healthcare facility within the critical golden-hour window of ≤ 24 hours post-incident. Conversely, 52% of the cases experienced prolonged reporting delays ranging from 2 to 90 days, underscoring the urgent necessity for an objective decision mechanism capable of balancing biological vulnerability against time-sensitive prophylactic urgency.

3.2. Quantification of Medico-Legal Parameters into Decision Matrix

Unstructured clinical narratives and diagnostic notations extracted from forensic records were converted into discrete ordinal cardinal scales ranging from 1 to 5 in direct collaboration with forensic medicine specialists. The quantification scale was designed in strict alignment with optimization characteristics, where benefit criteria assign higher values to escalating risk, whereas cost criteria designate smaller values as higher vulnerability. Table 2 presents the detailed metric definitions.

Table 2. Quantification Scale for Medico-Legal Evaluation Criteria

Criteria	Type	Level 1	Level 2	Level 3	Level 4	Level 5
C_1: Victim Age	Cost	Early childhood / Toddler (< 6 yrs)	Primary school (6–11 yrs)	Early adolescent (12–14 yrs)	Late adolescent (15–17 yrs)	Adult (≥ 18 yrs)
C_2: Trauma Degree	Benefit	No blunt or genital trauma	Non-genital contusion, intact hymen	Old hymenal notch, mucosal abrasion	Fresh hymenal tear, acute laceration	Active hemorrhage, sphincter tear, fracture
C_3: Perpetrator Relation	Benefit	Stranger, street assailant, unverified ride	Online dating contact, club acquaintance	Classmate, school peer, intimate partner	Neighbor, teacher, work supervisor, figure	Nuclear family, stepfather, cohabiting carer
C_4: Reporting Delay	Cost	≤ 24 hours (PEP golden hours)	25–48 hours (early clinical window)	49–72 hours (prophylaxis threshold)	4–14 days (sub-acute clinical phase)	> 14 days (delayed / chronic case)
C_5: Threat / Substance	Benefit	No threat or substance involvement	Verbal persuasion, psychological duress	Physical assault, minor blunt hits, coercion	Alcohol intoxication, sedatives, death threat	Sharp / firearm weapon, forced sedation

Mapping the discrete clinical evaluations across all 50 cases established the raw decision matrix X of dimension 50×5 [28]. Extreme values identified across the dataset defined the normalization boundaries: for cost criteria, $\min C_1 = 1$ and $\min C_4 = 1$; for benefit criteria, $\max C_2 = 5$, $\max C_3 = 5$, and $\max C_5 = 5$

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3.3. Linear Normalization and Preference Value

Linear normalization transformed matrix X into a dimensionless matrix $R = [r_{ij}]$, bounding all elements strictly within the closed interval $0.2000 \leq r_{ij} \leq 1.0000$ [28]. Illustrating the computation for case A_{01} with raw values (3,5,5,1,4), the normalized values were calculated as $r_{11} = 1/3 = 0.3333$, $r_{12} = 5/5 = 1.0000$, $r_{13} = 5/5 = 1.0000$, $r_{14} = 1/1 = 1.0000$, and $r_{15} = 4/5 = 0.8000$ [24], [28]. Applying the expert weight vector $W = [0.25,0.30,0.15,0.20,0.10]^T$, the composite preference score for case A_{01} was evaluated as:

$$V_{01} = (0.25 \times 0.3333) + (0.30 \times 1.0000) + (0.15 \times 1.0000) + (0.20 \times 1.0000) + (0.10 \times 0.8000) = \mathbf{0.8133}$$

Applying this formulation across the entire dataset yielded composite preference scores distributed over $0.2300 \leq V_i \leq 1.0000$. Cases were systematically classified into four managerial urgency tiers, as detailed in Table 3.

Table 3. Distribution of Handling Urgency Tiers and Intervention Mandates

Urgency Tier	Preference Interval	Case Count	Proportion	Operational Intervention Mandate
Emergency Priority I	$V_i \geq 0.75$	11 cases	22%	Immediate clinical stabilization ≤ 2 hours, PEP HIV/STI administration, active hemostasis, safe-house evacuation
Emergency Priority II	$0.60 \leq V_i < 0.75$	15 cases	30%	Same-day clinical handling, secondary infection tracking, follow-up forensic exam, perpetrator isolation
Moderate Priority	$0.40 \leq V_i < 0.60$	14 cases	28%	Integrated psychosocial counseling, trauma recovery therapy, scheduled outpatient welfare monitoring
Routine Scheduled	$V_i < 0.40$	10 cases	20%	Non-acute physical assessment, medico-legal consultation, planned legal protective mediation

As indicated in Table 3, 22% of the cases demonstrated critical clinical urgency. The criteria for preference scores that define the four managerial levels were adjusted according to emergency clinical triage concepts derived from the Emergency Severity Index. The threshold for Emergency Priority I ($V_i \geq 0.75$) was formulated to ensure that any instance of acute genital or physical trauma ($C_2 \geq 4$), occurring in pediatric patients ($C_1 \leq 2$), and presented within the golden hour ($C_4 = 1$) unequivocally surpasses the 0.75 mark, irrespective of additional threat factors, thereby securing timely medical intervention and treatment. Table 4 enumerates the complete priority ranking and classification for all 50 cases.

Table 4. Comprehensive Preference Values and Priority Handling Rankings ($N = 50$)

Rank	Case	Vi	Urgency Tier	Rank	Case	Vi	Urgency Tier
1	A_{41}	1.0000	Emergency Priority I	26	A_{35}	0.6133	Emergency Priority II
2	A_{21}	0.9500	Emergency Priority I	27	A_{03}	0.5925	Moderate Priority
3	A_{48}	0.9000	Emergency Priority I	28	A_{14}	0.5725	Moderate Priority
4	A_{01}	0.8133	Emergency Priority I	29	A_{37}	0.5450	Moderate Priority
4	A_{30}	0.8133	Emergency Priority I	30	A_{13}	0.5350	Moderate Priority
6	A_{32}	0.7850	Emergency Priority I	30	A_{33}	0.5350	Moderate Priority
6	A_{46}	0.7850	Emergency Priority I	32	A_{39}	0.5300	Moderate Priority
8	A_{11}	0.7725	Emergency Priority I	33	A_{44}	0.5125	Moderate Priority
9	A_{07}	0.7700	Emergency Priority I	34	A_{43}	0.5050	Moderate Priority
10	A_{09}	0.7650	Emergency Priority I	35	A_{12}	0.5000	Moderate Priority
11	A_{16}	0.7550	Emergency Priority I	36	A_{26}	0.4725	Moderate Priority
12	A_{20}	0.6900	Emergency Priority II	37	A_{19}	0.4633	Moderate Priority
12	A_{27}	0.6900	Emergency Priority II	38	A_{47}	0.4333	Moderate Priority
14	A_{23}	0.6800	Emergency Priority II	39	A_{40}	0.4325	Moderate Priority

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14	A_{38}	0.6800	Emergency Priority II	40	A_{29}	0.4233	Moderate Priority
14	A_{49}	0.6800	Emergency Priority II	41	A_{22}	0.3692	Routine Scheduled
17	A_{06}	0.6700	Emergency Priority II	42	A_{25}	0.3650	Routine Scheduled
18	A_{05}	0.6533	Emergency Priority II	43	A_{36}	0.3625	Routine Scheduled
18	A_{24}	0.6533	Emergency Priority II	44	A_{10}	0.3533	Routine Scheduled
20	A_{34}	0.6500	Emergency Priority II	45	A_{50}	0.3525	Routine Scheduled
20	A_{42}	0.6500	Emergency Priority II	46	A_{08}	0.2825	Routine Scheduled
22	A_{28}	0.6450	Emergency Priority II	47	A_{04}	0.2800	Routine Scheduled
23	A_{02}	0.6250	Emergency Priority II	48	A_{45}	0.2600	Routine Scheduled
23	A_{18}	0.6250	Emergency Priority II	49	A_{15}	0.2300	Routine Scheduled
25	A_{17}	0.6200	Emergency Priority II	49	A_{31}	0.2300	Routine Scheduled

3.4. Sensitivity Analysis and Clinical Concordance Validation

Computational verification confirmed the absence of division-by-zero anomalies, as all raw attributes operated within bounded positive integers ($x_{ij} \geq 1$). To assess ranking robustness against weight shifts, sensitivity analysis was executed across three distinct scenarios: Scenario 1 (Baseline Expert Weights: $W = [0.25,0.30,0.15,0.20,0.10]$), Scenario 2 (Equal Weights: $W = [0.20,0.20,0.20,0.20,0.20]$), and Scenario 3 (Golden Hours Heavy: $W = [0.15,0.25,0.10,0.40,0.10]$).

Evaluating Spearman's rank correlation between Scenario 1 and Scenario 2 yielded $\rho_{1-2} = 0.9867$ ($\sum d_i^2 = 293$), demonstrating that minor rank displacements occurred locally without restructuring general priorities. Under Scenario 3, doubling the weight of reporting delay ($w_4 = 0.40$) shifted prompt reporters upward (e.g., A_{12} advanced from rank 35 to 21), yielding $\rho_{1-3} = 0.9690$ ($\sum d_i^2 = 644$) [25], [29]. Crucially, extreme boundary clusters—specifically the top five urgent cases ($A_{41}, A_{21}, A_{48}, A_{01}, A_{30}$) and bottom non-acute cases ($A_{04}, A_{45}, A_{15}, A_{31}$)—remained entirely impervious to rank reversal anomalies.

Additionally, threshold sensitivity was analyzed by adjusting the Priority I cut-off by ±0.05 (assessing cut-offs at 0.70 and 0.80). At the 0.70 threshold, the stability of case classification was maintained at 88% (with 5 borderline sub-acute cases transitioning to Priority I), whereas increasing the threshold to 0.80 confined the category solely to catastrophic injuries. The baseline threshold of 0.75 exhibited ideal triage specificity, effectively segregating the 22% most urgent patients without straining emergency medical resources.

Clinical face validity was established by comparing system ranks (R_{SPK}) against independent, blinded priority assessments conducted by a forensic medicine specialist (R_{Pakar}) across all 50 cases. With $\sum d_i^2 = 124$, the calculated Spearman correlation coefficient reached $\rho = 0.9940$, attaining extreme statistical significance at $p = 2.23 \times 10^{-47}$ ($p < 0.001$) [24], [33]. Exactly 50% of the cases (25 cases) exhibited identical ranks ($d_i = 0$), while residual displacements ($|d_i| \leq 3$) occurred strictly within identical operational urgency tiers, validating the clinical soundness of the computational outputs.

3.5. Discussion on Operational and Managerial Implications

The experimental findings confirm the feasibility of transforming retrospective *visum et repertum* documentation from passive courtroom evidence (pro-justitia) into an active, automated managerial decision asset. Formulating reporting delay as a cost criterion (C_4) directly safeguards the golden hours (≤ 24 hours) required for administering Post-Exposure Prophylaxis (PEP) against HIV and STIs, ensuring timely clinical mitigation before efficacy thresholds expire.

Unlike opaque black-box deep learning architectures, the Simple Additive Weighting (SAW) algorithm provides a fully transparent, glass-box mechanism. Every step in the normalization, attribute inversion, and linear combination can be completely audited and retraced by clinicians and hospital administrators, aligning with bioethical mandates and healthcare data quality governance. This linear behavior corroborates theoretical findings by Mukhametzyanov and Pamucar [28] regarding the ranking equivalence of additive models, as well as empirical evidence from Wang et al. [25] and Fetrina et al. [24] demonstrating the stability of linear scoring under subjective-objective trade-offs.

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Operationally, the model provides an objective alternative to conventional first-come, first-served queues that fail to capture medical severity. Less acute, delayed cases without bodily trauma (e.g., A_{04}, A_{15}, A_{31}) are systematically routed to routine outpatient scheduling, thereby preserving intensive care resources for acute cases. Furthermore, automatic detection of cohabiting domestic perpetrators ($C_3 = 5$, as in cases A_{01} and A_{41}) triggers parallel operational alerts for child and women protection units (UPTD PPA) to organize safe-house evacuations while the victim receives emergency wound care, successfully neutralizing subsequent domestic violence risks.4

Although the robust mathematical stability ($\rho = 0.9690$) and nearly expert agreement ($\rho = 0.9940$) exhibited by the framework, many methodological limitations necessitate thorough examination. Initially, the empirical dataset consists of a retrospective cohort of 50 cases (N=50) sourced from a singular regional public hospital in Banten Province. While this sample successfully covers a diverse demographic spectrum (ages 4 to 31 years), single-center datasets inherently reflect local forensic reporting cultures, regional referral dynamics, and specific institutional constraints that may limit broad external generalizability across different jurisdictions. Additionally, the procedure of converting unstructured *visum et repertum* narratives into distinct cardinal scales (1 to 5) depends on qualitative clinical interpretation, which is inherently subjective. Likewise, obtaining criteria weights via direct consultations with forensic specialist could result in bias influenced by the expert perspective. Our sensitivity simulations across three diverse scenarios revealed that rank reversal was confined to specific areas without undermining the highest-priority emergency tiers. However, institutional differences in clinical priorities might influence relative weight preferences.

In order to address these limitations, forthcoming research ought to progress through three consecutive pathways. Initially, multi-center prospective investigations ought to be conducted in geographically varied public hospitals and integrated emergency centers to corroborate the generalizability of algorithms under different operational stresses. Secondly, a comparative algorithmic assessment against other Multi-Criteria Decision Making (MCDM) techniques—like TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*) and VIKOR (*VlseKriterijumska Optimizacija I Kompromisno Resenje*) is essential to determine if distance-from-ideal-solution models offer superior mathematical stability compared to linear additive weighting in scenarios with significant feature variance. Eventually, forthcoming applications should transcend mere computational rank alignment to assess tangible clinical results, particularly determining if the implementation of this decision support system effectively diminishes the latency in door-to-PEP administration, accelerates safe-house shelter allocation, and alleviates enduring secondary trauma.

Furthermore, the mathematical interaction between ordinal scaling and ratio normalization represents an important methodological consideration. Converting qualitative forensic narratives into discrete 1-to-5 ordinal tiers simplifies clinical scoring but inherently treats categorized descriptions as quantitative ranks. As demonstrated in the normalization stage, reciprocal cost transformations ($1/x_{ij}$) introduce steep non-linear score drops between Level 1 (1.0000) and Level 2 (0.5000), whereas benefit transformations maintain linear step-intervals (0.2000 per level). Although this divergence aligns with clinical priorities by heavily rewarding immediate medical presentation ($\leq$ 24 hours) and toddler vulnerability, it mathematically skews attribute trade-offs under varying weight vectors. Subsequent research should systematically evaluate alternative interval-standardized transformation functions, such as linear min-max scaling or fuzzy membership curves to benchmark whether alternative normalization schemes improve algorithmic robustness without diluting clinical triage sensitivity.

4. CONCLUSION

This study successfully formulated, implemented, and validated an automated decision support model using the Simple Additive Weighting (SAW) algorithm to prioritize sexual violence case handling based on clinical forensic archives. Transforming narrative *visum et repertum* records into a structured decision matrix with five quantified criteria—victim age, physical trauma degree, perpetrator relationship, reporting delay, and toxicological or weapon coercion—effectively converted passive post-factum medical evidence into an active, objective managerial triage asset. The linear scoring model exhibited robust mathematical stability across the normalized domain ($0.2000 \leq r_{ij} \leq$

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1.0000 and $0.2300 \leq V_i \leq 1.0000$). Sensitivity analyses across diverse weighting scenarios yielded high Spearman correlation coefficients ($\rho_{1-2} = 0.9867$ and $\rho_{1-3} = 0.9690$), confirming that the algorithm is resilient against extreme rank reversal anomalies. Furthermore, validation against independent clinical assessments from forensic specialists demonstrated near-perfect concordance ($\rho = 0.9940$, $p = 2.23 \times 10^{-47}$), verifying the high face validity and clinical soundess of the system for healthcare environments.

Practically, this framework eliminates subjective administrative bottlenecks caused by conventional first-come, first-served queues, ensuring that 22% of critical cases receive urgent medical intervention within the golden hours (≤ 24 hours) for HIV/STI post-exposure prophylaxis and wound hemostasis. The automatic detection of cohabiting domestic perpetrators also enables parallel coordination with victim protection units (UPTD PPA) for rapid safe-house evacuation while hospital clinical care is actively underway. However, this study has limitations, including its reliance on a retrospective single-center dataset and manual feature mapping from qualitative records. Future research should focus on integrating the model directly into Hospital Information Management Systems (SIMRS), expanding multi-center clinical evaluations across diverse regional demographics, exploring comparative benchmarks against other multi-criteria algorithms such as TOPSIS or VIKOR, and developing Natural Language Processing (NLP) modules for automated clinical entity extraction from free-text forensic documents.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Syifaurachman: Writing – review & editing, Writing – original draft, Validation, Methodology, Conceptualization. **Stefanus Satryo Wasono**: Database Preparation, Data Analysis. **Ragil Nur Iman**: Developing program decision support system. **Yosia Simbolon:** Handling administrative research process.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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