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VISUALIZATION OF COMBAT INJURIES: TEMPORAL STRUCTURE AND DEMOGRAPHIC DETERMINANTS

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Background. Modern warfare with widespread use of body armour has shifted the spectrum of combat injuries. The study aims to describe the pattern of combat-related injuries from computed tomography (CT) imaging during the full-scale invasion of Ukraine and to assess the predictive value of age alone employing machine learning methods.

Materials and methods. Opportunistic retrospective cohort study of 606 consecutively evacuated adult males who underwent CT at a second-level medical centre from April 2022 to September 2025. Multiclass automated machine learning (H2O AutoML) was trained using age as the sole predictor of CT-diagnosed injury category.

Results and discussion. No acute pathology was found in 50.3 % of scans. The most common findings were metallic foreign bodies in soft tissues (25.5 %) and extremity fractures. Penetrating torso and severe traumatic brain injuries were rare (< 0.3 %). The age patterns strongly influenced injury pattern: soft-tissue shrapnel wounds predominated in patients < 40 years, whereas fractures and degenerative changes prevailed in older combatants. Over four years, the proportion of chronic and combined injuries increased 2–3-fold. The best-performing generalised linear model achieved R^2 = 0.9996, but log-loss remained high (5.04) in middle-aged groups, confirming limited predictive power of age alone.

Conclusion. CT remains a gold standard in stratifying combat injuries. Machine-learning models using demographic variables are promising as clinical decision-support tools in resource-constrained wartime settings.

Keywords: computed tomography; combat trauma; machine learning; Ukraine war.

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ВІЗУАЛІЗАЦІЯ БОЙОВИХ УШКОДЖЕНЬ: ТЕМПОРАЛЬНА СТРУКТУРА ТА ДЕМОГРАФІЧНІ ДЕТЕРМІНАНТИ
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Ретроспективне дослідження комп'ютерної томографії 606 поранених військових за 04.2022 – 09.2025: 50,3 % пацієнтів без гострої патології. Домінували металеві сторонні тіла в м'яких тканинах (25,5 %) та переломи кінцівок; тяжкі торакальні / черепно-мозкова травма – < 0,3 % через ефект бронезахисту. Визначено віковий профіль: < 40 років – уламкові контузії м'яких тканин; > 40 років – переломи, гемартрози, дегенеративні зміни опорно-рухового апарату. Лінійна модель лише за віком досягла R^2 = 0,9996, але log-loss 5,04 вказує на потребу додаткових предикторів. Комп'ютерна томографія залишається золотим стандартом стратифікації бойових ушкоджень. Машинне навчання на демографічних даних має потенціал як інструмент підтримки рішень в умовах війни.

Ключові слова: комп'ютерна томографія; бойова травма; машинне навчання; війна в Україні.

Introduction

Combat injuries differ from civilian trauma in being predominantly penetrating or blast-related, caused by fragmentation and firearms [1]. Protective equipment such as body armor and helmets mitigates risk to specific anatomical zones. The affected population primarily consists of young, healthy men, which influences their initial clinical status and rehabilitation potential.

Conflicts in Ukraine, Gaza, Iraq, and Afghanistan have refined imaging protocols and improved management of military and civilian patients [2; 3]. Computed tomography (CT) is the standard initial diagnostic modality for severe injuries, guiding clinical decisions through rapid assessment of injury extent and location [5–7]. In modern warfare with explosives and high-velocity weapons, CT enables precise injury evaluation and prognostic prediction [8].

Diagnostic complexity has driven integration of CT findings with quantitative analysis. Although machine learning (ML) predicts outcomes in traumatic brain injury, wartime application in the Ukrainian healthcare system demands infrastructural adaptation, external validation, and consideration of combat-specific injury patterns [9–11]. This study addresses the lack of regional analyses combining

CT data with combat injury demographics, including age, aligning with global ML trends for outcome prediction.

The aim of this research was to analyze the structure of combat injuries using CT data among veterans wounded during the full-scale invasion and to evaluate the role of demographic factors in predicting injury typology employing machine learning methods.

Materials and Methods

In an opportunistic, retrospective, observational, descriptive study, a cohort of patients with combat-related injuries was assembled, who were admitted to a second-level medical center during the first four years of the full-scale invasion (April 2022–September 2025). Adult male patients (> 18 years) evacuated from the combat zone and had undergone CT for clinical indications were included; civilian patients were excluded. Data were obtained from electronic medical records by targeted search by age, date of examination, status, CT type, main radiological findings, and surgical outcomes. All records were anonymized and processed in accordance with the Declaration of Helsinki and applicable national legislation; the study was approved by the Ethics Committee of Odesa National Medical University (protocol No. 2, Feb 3, 2025).

In ~95 % of cases, brain CT was performed for suspected traumatic brain injury (TBI); chest CT was done only in the presence of external signs of injury or a specific request, whereas routine chest assessment was done by radiography. Imaging was performed using a NeuViz 64In multi-slice CT scanner (Neusoft Medical Systems Co., Ltd., China) with regular phantom calibration; quality control ensured image homogeneity, noise level, geometric accuracy, and Hounsfield unit consistency, thereby supporting reproducibility of results.

To quantify the effect of age on injury type, a multi-class H2O AutoML model [12] was developed, with age as the only predictor and diagnosis category as the outcome. For each patient, the model generated a set of relative probability scores for membership in each class; predictions were based on a linear combination of age with learned weights and normalization of outputs to a probability distribution. Automatic class balancing was applied to address class imbalance, and hyperparameter optimization was handled by the AutoML framework. To improve robustness, k-fold (k = 5) cross-validation was used; each fold produced a separate probability distribution, which was averaged by the final ensemble model to reduce random variation and increase prediction stability. Model performance was assessed using log loss, mean per-class error (MPCE), root mean square error (RMSE), and R^2 [13]. After training, a final prediction table containing the most probable diagnosis and the full probability spectrum for all diagnostic categories were generated. Computations were performed in R (ver. 4.3.2), and descriptive statistics are presented as means and SD.

Research results and their discussion

Over 36 months, CT was performed in 606 patients (mean age 37 ± 2 years): year 1 – 163(26.9 %); year 2 – 204(33.7 %); year 3 – 190(31.4 %); year 4 – 49(8.0 %). Primary mechanisms were mine-explosive injuries (59.9 %) and falls (40.1 %). Over half (50.3 %) showed no acute pathology, reflecting predominant use of CT to confirm or rule out clinically significant conditions [5–7].

The largest group of structural abnormalities comprised respiratory pathology (pleural and mediastinal changes), predominantly chronic inflammatory processes (sinusitis, pneumofibrosis), whereas specific infections such as tuberculosis were less common; isolated cases of emphysema, hydrothorax, or metastases (< 0.2 %) reflected age-related or somatic comorbidity. ENT pathology (ear, paranasal sinuses, orbit) was mostly chronic (sinusitis, mastoiditis > 4 %), with isolated polyps and developmental anomalies demonstrating CT diagnostic sensitivity. Musculoskeletal pathology (≈ 5 %) primarily involved degenerative-dystrophic spinal changes (osteochondrosis, spondyloarthrosis) consistent with the age and occupational profile of the combatant cohort, whereas isolated vascular lesions (haemangioma, aseptic necrosis), CNS findings (cysts, hygromas), and abdominal organ abnormalities (hepatosis, hydronephrosis) were incidental and clinically insignificant. Rare systemic diseases (sarcoidosis, metastases, < 0.3 %) carried prognostic weight warranting follow-up. Overall, non-combat pathology consisted of chronic inflammatory and degenerative processes affecting the respiratory system and musculoskeletal apparatus, with nearly a quarter of scans showing no CT evidence of pathology – confirming the rationale for CT use in early detection of subclinical changes.

The structure of combat injuries comprised soft-tissue injuries and isolated limb fractures (Fig. 1A), with a minor proportion of intracranial or thoracic injuries.

This injury pattern is typical of modern combat, where body armour and helmets substantially reduce lethality but increase the proportion of musculoskeletal injuries (Fig. 2, 3). It aligns with epidemiological trends in trauma patterns during military conflicts of the past decades [14].

Over 25 % cases involved metal-density foreign bodies in soft tissues, reflecting the predominance of contusion and fragmentation injuries (Fig. 1B, 4).

Soft-tissue defects, including wounds with loss of covering structures, were identified in 5.5 % patients (Fig. 5), consistent with the frequency of open injuries associated with blast mechanisms [2–3].

Mild traumatic brain injuries without visible CT abnormalities (concussion and subclinical disturbances) accounted for 3.3 %. Among fractures, lower-limb injuries (tibia, femur) predominated, whereas upper-limb fractures were less frequent; this pattern might reflect more effective torso armour and the characteristics of blast loading, although formal correlation analysis was beyond the scope of this study.

Thoracic injuries (haemothorax, hydropneumothorax, lung contusion) were rare (≤ 0.3 %), supporting the effectiveness of individual body armour. Isolated changes of the middle ear, nose, and paranasal sinuses related to blast acoustic trauma were also uncommon (< 0.2 %).

Lower-limb amputation states (0.7 %) and isolated upper-limb amputations reflected severe combined injuries and required staged reconstructive management. Postoperative changes (after laparotomy, splenectomy, vertebroplasty), including follow-up examinations, were recorded in fewer than 0.3 % of cases.

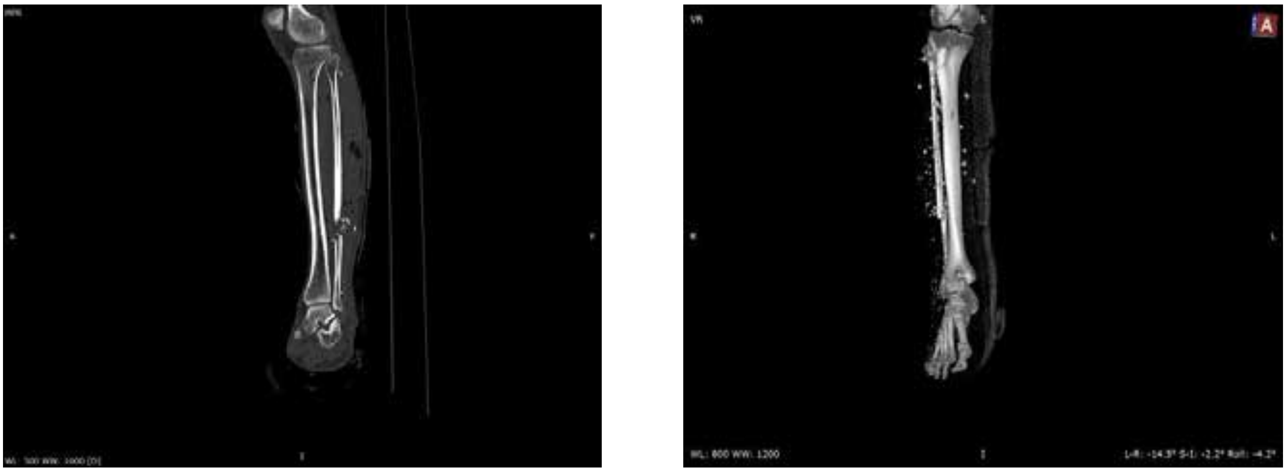

Fig. 1. Patient K., 28. Fracture of the fibula with multiple fragments; cast applied. A. MSCT image of the right lower leg (computed reconstruction). B. MSCT. Subtractive 3D reconstruction

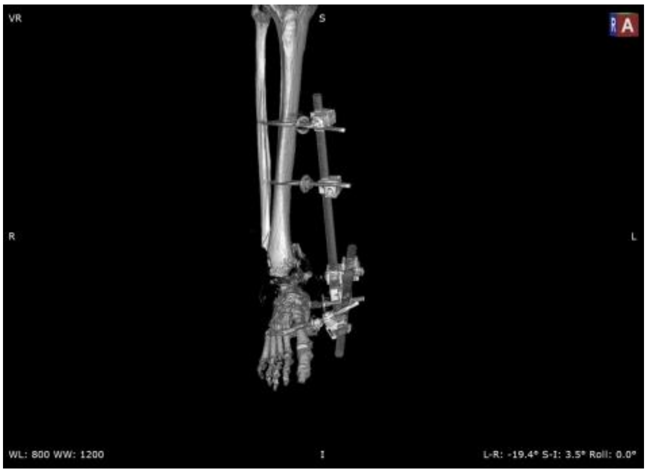

Fig. 2. Patient L., 35. MSCT. Subtractive 3D reconstruction of the right lower limb. Distal metaphyseal fractures. External fixation apparatus

Fig. 3. Patient M., 27. Metal plate system osteosynthesis (MOS) of the orbital floor and anterior wall of the maxillary sinus with metal plates: A. 3D reconstruction of the CT skull bone sequence. B. MSCT, axial projection

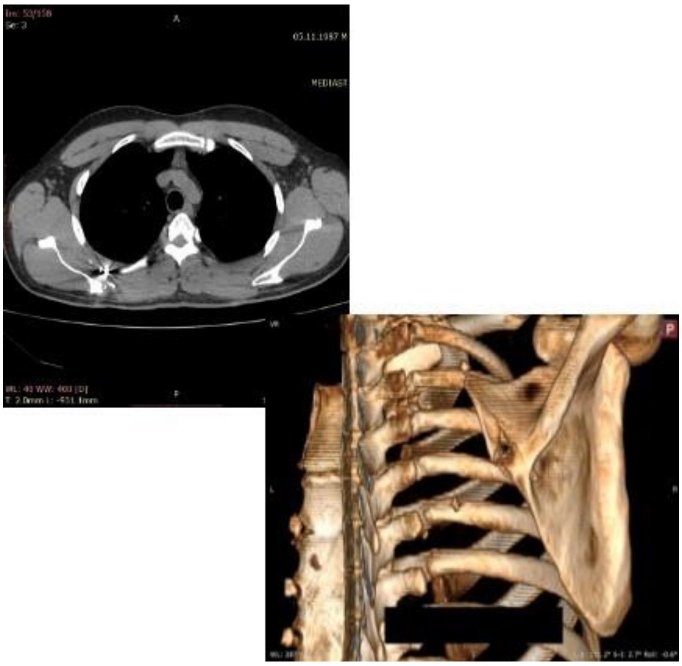

Fig. 4. Patient N., 35. Gunshot fracture of the right scapula:
A. MSCT, axial chest projection. B. Subtractive 3D reconstruction

Fig. 5. Patient O., 28. MSCT chest, axial projection. Penetrating wound of soft tissues of the left anterior chest wall

The low proportion of metal-density foreign bodies in bone, together with a relative increase in haemarthroses and degenerative or post-traumatic changes, suggests a chronic component of cumulative trauma (Fig. 6).

Degenerative-dystrophic processes (spondylosis, arthrosis, retrolisthesis) were predominantly recorded in patients older than 35 years and accounted for a minor proportion of the total sample (< 1 %).

Role of age in injury frequency and severity

Analysis of clinical data from 2022–2025 revealed distinct age-stratified patterns of combat injuries (Fig. 7).

In younger groups (< 40 years), superficial injuries were more common, including infiltrates and metal-density foreign bodies in soft tissues, whereas in older age categories fractures and secondary degenerative changes were observed more frequently.

For the 25–39 years age range, maximum density of soft-tissue injuries, tibia fractures, and knee joint injuries was noted. The increased frequency of loading-type injuries – tibia fractures, haemarthroses, and soft-tissue haematomas – is consistent with previous observations in combat personnel of this age [14].

In middle-aged patients (40–59 years), the injury profile shifted towards chronic and combined processes: osteochondrosis, scapula, clavicle, and pelvic bone fractures were more frequent, along with metatuberculous lung changes as secondary post-traumatic or reactive manifestations. This spectrum reflects the cumulative effect of repeated mechanical loading with degenerative tissue remodelling; some cases involved polytrauma combining fractures, soft-tissue injuries, haematomas, intra-articular haemorrhages, and vertebral compression deformities. Such clinical heterogeneity produced the greatest variability in this age group, complicating differentiation and prognostication, driven by high physical activity, prolonged overloading, and secondary degenerative processes against a background of microtrauma and post-stress musculoskeletal changes [10; 12; 14].

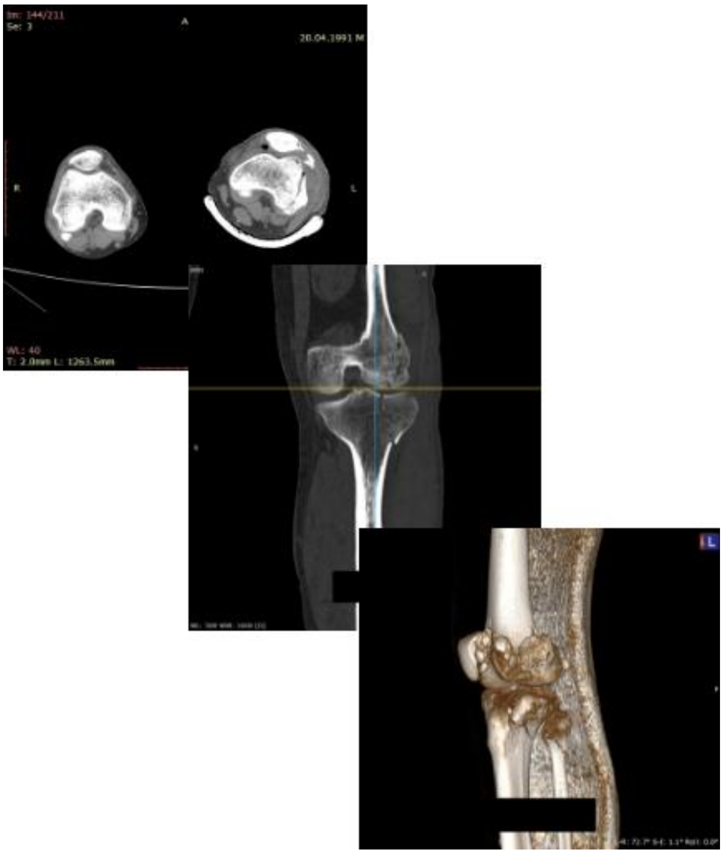

Fig. 6. Patient P., 31. Intra-articular comminuted fracture of the left knee joint involving the lateral condyles of the femur, tibia, and patella. Pneumohemarthrosis. MSCT of the left knee joint: A. Axial projection of both joints. B. Vertical reconstruction of the left joint (posterior). C. Subtractive 3D reconstruction of the left knee joint

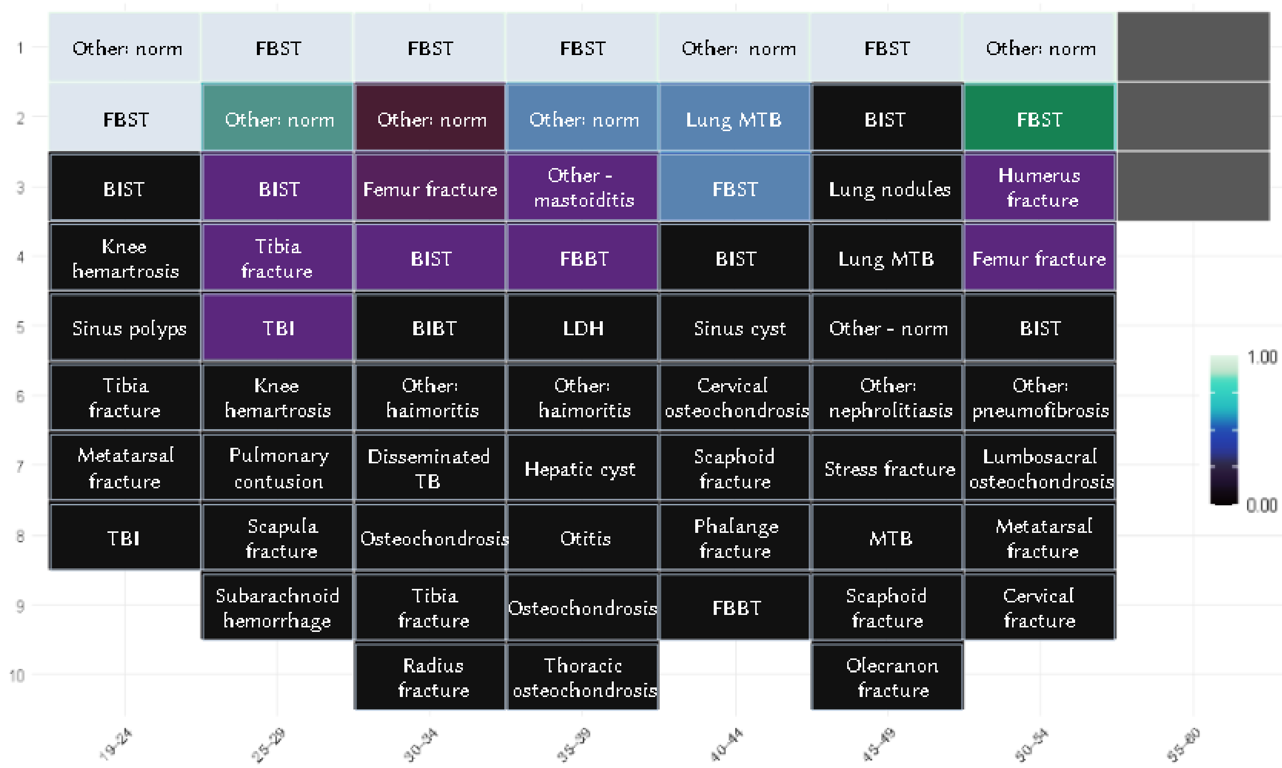

Fig. 7. Distribution of the most common diagnoses by age stratification (19–60 years). Axes: x – age groups; y – normalised ranking of diagnoses by prevalence. BIBT – blast injury of bone tissue; BIST – blast injury of soft tissue; FBBT – foreign bodies in bone tissue; FBST – foreign bodies in soft tissue; LDH – lumbar disc herniation; MTB – mycobacterium tuberculosis; TB – tuberculosis; TBI – traumatic brain injury

In older age groups (> 40 years), a decrease in incidence was noted alongside an increase in mean injury severity. Fractures of the radius, humerus, and femur predominated, reflecting age-related local reductions in bone mineral density and heightened risk of low-energy fractures.

A model of age impact

A multi-class generalized linear model (GLM) showed strong performance: log loss = 5.04, MPCE = 0.308, RMSE = 0.99, $R^2 = 0.9996$. The high R^2 value (with cautious interpretation) indicates model stability, whereas elevated log loss in middle-aged groups reflects increased data entropy due to class imbalance and the limited predictive power of age as the sole predictor [15; 16].

Comparison of model predictions with empirical data confirmed that age alone is an insufficient predictor: classification accuracy declined in the 30–59 years groups due to greater diversity of clinical scenarios. Normalized per-class accuracy varied substantially owing to uneven observation distribution [17], whereas younger and older cohorts showed more homogeneous classification patterns. Probabilities greater than 0.7 were presently considered as high model confidence, 0.3–0.7 as a zone of clinical uncertainty, and less than 0.1 as improbable outcomes.

Perfect classification accuracy (1.00) was achieved for soft-tissue defects, epidural haematoma, lung contusion, metatuberculous changes, and osteochondrosis, whereas lower values (0.02–0.17) were characteristic of metal-density foreign bodies in soft tissues, tibia fractures, and femur fractures – conditions with over-representation or complex morphology.

The full spectrum of predicted probabilities reflects model confidence and enables ranking of pathologies by reliability, rendering the approach suitable for initial prognostication of lesion localization in CT diagnostics. Combinations of high-probability comorbidities (eg, pelvic fractures with internal haemorrhage) could support automated generation of markers in clinical information systems, aligning with contemporary approaches to interpretable machine learning in clinical practice [6; 10; 11; 18–20].

Temporal evolution

Over 36 months, the temporal injury profile shifted from predominantly acute soft-tissue injuries early in the period to degenerative-dystrophic pathologies in 2024–2025. Soft-tissue injuries (metal-density foreign bodies) showed decreasing frequency – from ~ 27 % in 2022 to 18–20 % in 2025 – reflecting reduced isolated acute pathology amid stabilized combat loading and improved primary care. Traumatic brain injuries remained stable throughout (~ 45–52 % annually), underscoring the persistent nature of severe combined injuries (Fig. 8) and limited prevention opportunities in combat conditions [8].

A temporal shift was also noted in the morphological spectrum toward recurrent and combined injuries. Osteochondrosis, haemarthrosis, and bone fractures increased 2–3-fold compared with the initial period:

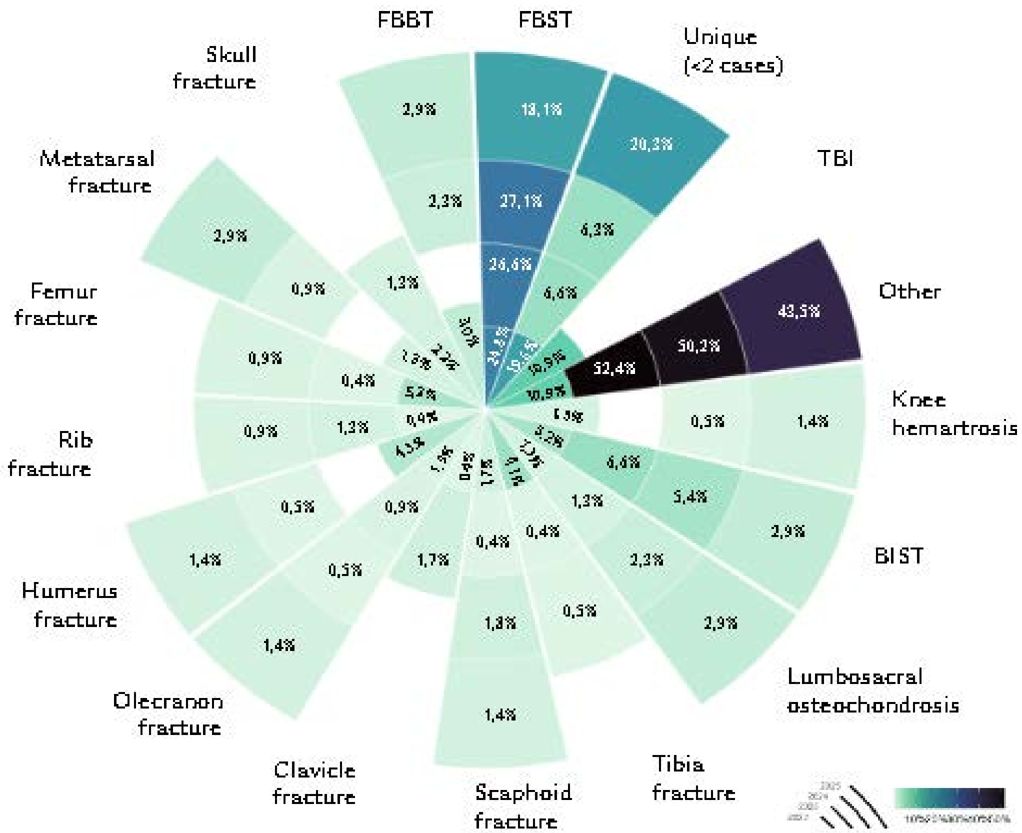

Fig. 8. Distribution of diagnoses, 2022–2025. BIST – blast injury in soft tissue; FBBT – foreign bodies in bone tissue; FBST – foreign bodies in soft tissue

their combined prevalence rose from 1–3 % in 2022 to over 6–8 % in 2025, with haemarthrosis of the knee joint showing peak frequency. The rise in degenerative-dystrophic processes relates to accumulation of post-traumatic sequelae, musculoskeletal overloading, and ageing of the patient cohort.

Rare nosologies, nearly absent at the start of observation, began to be recorded from 2024 onwards at moderate frequency, including metatuberculous changes, soft-tissue defects, and unique combined injuries. Overall, the traumatological profile evolved from acute to chronic and polytraumatic patterns, with implications for clinical prognostication, rehabilitation strategy development, and inpatient resource planning [20]. This study captured only a subset of wounded patients, as patient distribution depended on evacuation availability, receiving facility capacity, and need for specialized care.

Conclusions

1. Computed tomography enables rapid severity stratification of injuries and remains the cornerstone diagnostic tool at second-level hospital admission.
2. Statistical analysis revealed age-related differences in injury types: younger patients more frequently showed multiple fragmentation injuries, whereas older patients exhibited combined trauma dominated by cranio-cerebral components and degenerative-dystrophic pathology.
3. The multi-class machine learning model demonstrates potential for injury type prediction from demographic data, supporting its use as a clinical decision support tool.
4. These findings validate the rationale for implementing regional CT data analysis systems using machine learning methods to enhance diagnostic accuracy and outcome prediction for combat injuries.

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