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Infectious morbidity; military epidemiology; epidemiological surveillance; risk assessment; short-term forecasting; syndromic surveillance; laboratory monitoring; person-days.

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Modern approaches to the epidemiological, clinical, and laboratory assessment of infectious morbidity

Abstract
Background: Infectious morbidity in organized military units remains an important cause of medical losses and operational disruption. Stable daily contacts, shared accommodation, collective training, transport, catering facilities, and sanitary zones create conditions in which even mild infections may rapidly acquire group-level significance.
Objective: This study aimed to substantiate modern epidemiological, clinical, and laboratory approaches to the assessment of infectious morbidity in military units and to develop a short-term risk-based forecasting framework for differentiated preventive decision-making.
Methods: The proposed approach is based on weekly unit-level assessment using incidence per 1,000 person-days, outbreak activity, clinical severity, hospitalization patterns, laboratory verification, and lost duty days. Environmental, organizational, clinical, and laboratory risk indicators were considered, including ventilation, housing density, vaccination coverage, timeliness of medical consultation and isolation, hand hygiene, sanitary conditions, and evidence of repeated pathogen detection. Forecasting methods included syndromic surveillance, regression-based models, count-data approaches, gradient boosting comparison, calibration assessment, Brier score analysis, and decision curve evaluation.
Results: The article identifies a methodological gap between fragmented medical, laboratory, sanitary, and organizational data and the need for an integrated weekly surveillance system. A seven-day forecast horizon and risk-category-based reassessment model are proposed, allowing low-risk units to remain under routine weekly monitoring while moderate, high, and critical categories require accelerated reassessment and intensified preventive action.
Conclusion: A unit-week risk assessment model can strengthen early warning, improve the timing of preventive measures, and reduce the gap between epidemiological signals and practical military medical decisions.

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Introduction

Infectious morbidity remains a constant component of medical losses in organized military units. Repeated close contact in daily life and during service reduces the interval between the introduction of a pathogen and the emergence of related cases. Barracks accommodation, shared training facilities, transport, catering, and sanitary areas form a stable contact network. Even predominantly mild episodes can simultaneously incapacitate a significant portion of a unit and disrupt its training schedule. In practice, this means that preventive action must be taken before a major outbreak develops and must be based on a weekly assessment of the specific unit. [1–10]

A military collective is characterized by stable and recurring contacts; the same individuals live, eat, train, move, and perform their duties within a common routine. The contact network maintains its structure throughout the day and repeats from week to week. The introduction of a pathogen is rapidly transmitted from the individual to the unit level. In practice, this means that epidemiological surveillance must take into account the patient's movements, and not just the fact that they sought medical attention. [1–10, 41–46]

Barracks accommodation combines prolonged nighttime contact with a shared air environment; the number of individuals, room volume, arrangement of sleeping berths, and air exchange regime determine the accumulation of aerosol. Even with standard floor space, short-term overcrowding changes the actual number of close contacts; the risk is amplified by closed windows, high CO2 concentrations, and spending time together in the evening. With weekly observation, this relationship is viewed somewhat differently: the area per person and the number of people in the room are recorded simultaneously with ventilation indicators. [13–19, 32–38]

Daily training and service routines create additional points of intersection: classrooms, formations, transport, canteens, sports facilities, and sanitary zones connect separate sleeping quarters. While contacts between units may not occur at night, they regularly arise during classes and mass events. The daily training and service routine creates additional points of intersection, allowing a local outbreak to spread beyond its initial boundaries; classrooms, formations, transport, the canteen, sports facilities, and sanitary zones connect individual sleeping quarters. From a prevention management perspective, the inter-unit mixing is factored into the weekly risk profile. [1–10, 56–57]

The functional profile of a unit changes its exposure structure. Training, field, headquarters, barracks, and mixed modes differ in terms of mobility, time spent indoors, and frequency of external contacts. A field exercise reduces some indoor contacts but adds shared transport, tent accommodation, and limited sanitary infrastructure. A headquarters unit is less crowded but has stable inter-office connections. At the unit level, this concept takes a specific form: a comparison is made in man-days and is supplemented by a description of the service routine. [6–10, 16–17]

Individual susceptibility and unit vulnerability are different levels of analysis. Age, immunity, and comorbidities pertain to an individual service member, while ventilation and contact structure pertain to the collective; individual risk cannot be directly extrapolated to the probability of a group-wide increase in cases. A unit with a small number of susceptible individuals may remain vulnerable due to delayed isolation of the source. The organizational significance is related not only to the frequency of events: the prognostic tool is constructed at the unit-week level. [31–41, 46–47]

A seven-day interval is a compromise between the speed and stability of observation. In a small group, daily numbers fluctuate significantly and are often zero, while monthly aggregation smooths out short-term spikes and delays intervention. A week corresponds to the organizational reporting cycle and preserves the ability to respond before a major outbreak develops. In daily practice, a physician faces a more complex picture: with high or critical risk, the reassessment period is reduced to twenty-four hours. [31–39, 50–57]

Man-days are the preferred denominator for comparing units and periods. They simultaneously account for population size and observation duration. Changes in personnel composition due to transfers, leaves, or field exercises distort calculations based on a constant staff number. An equal number of cases acquires a different intensity with unequal exposure. Another aspect is important for the medical service: all final frequency indicators are calculated per 1,000 man-days. [24–25]

The operational significance of infectious morbidity extends beyond clinical severity; numerous mild diseases can create a greater total volume of losses than a few severe cases. Isolation and temporary relief from duty restrict participation in training and operational activities. The medical support system must account for recovery times and the distribution of losses within units. With weekly observation, this relationship is viewed somewhat differently: lost duty days are considered an independent outcome. [53, 26–40]

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Table 1.1. Epidemiological features of a military collective

Component	Characteristic	Measurable indicator	Management decision
Contact network	Recurring daily and service contacts	Number of persons, joint activities, mixing	Segregation and changing routes
Accommodation	Prolonged stay in a shared air environment	Area per person, CO2, ventilation	Adjusting capacity and air exchange
Reinforcements	Introduction and change in the susceptible contingent	Proportion of new personnel over 14 days	Medical screening and separate observation
Service regimen	Night duty, field conditions, transport	Sleep, field days, mass events	Changes to schedule and contacts
Medical response	Seeking care, examination, isolation	Delay in hours	Active detection and early isolation
Medical casualties	Removal from duty	Days lost per case	Planning of reserves and resources

In the working protocol, the largest number of measured parameters relates to the environmental and organizational blocks. Clinical and laboratory signals occupy fewer positions but have a high priority when a related event occurs.

Respiratory infections form the main component of group morbidity in most military contingents. Airborne droplet and aerosol mechanisms are combined with direct contact and re-contamination of common surfaces. Prolonged stays indoors increase the total inhalation dose and the number of secondary contacts. An upsurge can develop over several days and precede laboratory verification. In practice, this means that syndromic surveillance of respiratory cases is included in the early warning circuit. [11–19, 32–38]

Influenza remains a significant concern due to its seasonality, high rate of transmission, and potential complications; its initial symptoms overlap with those of other respiratory infections. Vaccine effectiveness varies by season, but high coverage reduces the risk of mass absenteeism. At the unit level, this approach takes a specific form: prevention combines vaccination, seeking early medical attention, ventilation, and temporarily limiting contact. Without laboratory sampling of the first linked cases, the etiological structure remains uncertain. [27, 37–45]

Adenovirus infections hold particular historical significance for military training centers. Periods when specific vaccinations were discontinued were accompanied by a resurgence of severe respiratory illness. The young age of recruits, the simultaneous formation of units, and intensive training create conditions for major epidemics. The organizational significance is related not only to the frequency of events: adenovirus infection is distinguished as a separate nosological group and by a laboratory signal. These observations underscore the dependence of the epidemic process on the preventive measures in place. [1–5, 46–55]

The coronavirus infection has added to our understanding of covert transmission in closed communities. Asymptomatic and mildly symptomatic individuals maintained contact until a group outbreak was detected. The experience on ships and at training bases has revealed the limitations of relying on entry quarantine alone. Control requires a sequential combination of testing, ventilation, isolation, and post-arrival observation. An important limitation arises here: the coronavirus signal is evaluated alongside other respiratory pathogens. [8–10, 16–19]

Acute intestinal infections and foodborne toxic-infections have a different mechanism of group spread; the interval between a common exposure and multiple cases can be short. A shared food product or water source can simultaneously expose a significant portion of a unit. In daily practice, a physician faces a more complex picture: two related cases following a common exposure are considered a critical signal. In this context, the timing of meals, the list of exposed individuals, and the condition of the mess hall and water supply are particularly important. [42–45]

Skin infections do not usually cause a sharp weekly spike in cases, but they do create a steady loss of time. A small proportion of cases may be associated with prolonged restrictions on physical activity. Contact-based transmission is linked to bathing and laundry routines, uniforms, footwear, sports equipment, and living conditions. In practice, this means that assessing non-battle casualties complements the usual nosological structure. [26–24]

Parasitic and natural-focal infections require specific consideration in the context of service conditions. For these infections, factors such as territory, season, contact with vectors, field exercises, and living conditions are important. The

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overall density of personnel in barracks is not always the leading factor. Rare episodes can have high clinical significance and require specialized diagnostics. At the unit level, this principle takes a specific form: the analysis preserves individual nosological categories without mechanical aggregation. [26–24]

Clinical severity and hospitalization frequency characterize different aspects of morbidity. An identical proportion of severe forms may be accompanied by a different duration of absence from duty. Hospitalization depends on the diagnosis, severity, availability of an isolation ward, and the established patient routing protocol. In the context of weekly observation, this relationship is viewed somewhat differently: the number of days lost per case is calculated for each group. The structural analysis includes mild, moderate, and severe cases, as well as hospitalizations by nosology. [26–24]

The laboratory structure requires a mandatory denominator. A positive test acquires focal significance when there is an epidemiological link to other cases. The number of positive results without the total number of tests performed does not reflect diagnostic yield. This presents an important limitation: the analysis provides the number of tests, the proportion of positive results, and the distribution of pathogens. [31–45]

Lost duty days link the clinical and organizational levels. Total losses depend on both the number of cases and the average duration of absence. This indicator includes isolation, hospitalization, and temporary relief from duty. In practice, this means that the effectiveness of prevention is assessed by both components. A decrease in morbidity is not necessarily accompanied by a reduction in days per case. [53, 56–57]

Table 1.2. Main nosological blocks and epidemiological patterns

Block	Primary mechanism	Early signal	Key measures
Respiratory	Aerosol, droplet, contact	Increase in similar cases, repeated pathogen detection	Ventilation, separation, vaccination, early isolation
Intestinal and foodborne	Fecal-oral, common food or water factor	Two or more cases after a common exposure	Inspection of food, water, the canteen, and contacts
Dermal	Contact-household	Repeated cases in the same room or group	Bathing and laundry regimen, equipment, treatment, and disinfection
Parasitic	Contact, household, foodborne	Grouping of cases by premises or household factor	Screening, sanitation, treatment of contacts
Natural-focal	Vector-borne, zoonotic, field	Link to a territory and field deployment	Protection against vectors, route monitoring, diagnostics

Table 1.3. Indicators of infectious morbidity and sanitary losses

Indicator	Formula or unit	Interpretation	Limitation
Incidence rate	cases / person-days × 1000	Frequency, considering the scope of observation	Does not describe severity
Proportion of a nosology	cases in a group / all cases × 100%	Morbidity structure	Depends on diagnostics
Hospitalizations	hospitalizations / cases × 100%	Need for inpatient care	Depends on patient pathways
Positive tests	positive / performed × 100%	Diagnostic yield	Depends on selection
Outbreak activity	number and size of outbreaks	Clustered spread	Requires a single definition
Days lost	total days and days per case	Workload burden	Does not equal economic damage

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Occupancy density is a complex characteristic of contacts and air volume. The number of people in a room should be considered together with the area, height of the room, and duration of their shared time. The same area per person does not preclude differences in the arrangement of sleeping places and the possibility of separation. The capacity threshold has sanitary significance, but continuous values retain additional information. In practice, this means that the weekly report should record the number of people, the area per person, and whether the capacity was exceeded. [13–19, 22–28]

Temperature and humidity modify the condition of mucous membranes and the stability of viruses. Excessively high temperatures do not compensate for insufficient air exchange. Low absolute humidity is associated with the longer preservation of infectivity for some respiratory viruses. The organizational significance is related not only to the frequency of events: these parameters are used as context and are checked for non-linear relationships. The microclimate rarely acts in isolation from population density. [18–19, 39–43]

New arrivals create both a risk of introduction and an organizational burden. The mass arrival of personnel from several formations expands the number of possible sources. Medical screening, separate observation, and verification of vaccination status reduce the likelihood of early spread. In daily practice, a physician faces a more complex picture: the indicator is expressed as a percentage over the preceding fourteen days. The absolute number of arrivals is insufficient without calculating their proportion of the total personnel. [1–10, 26–27]

Lack of sleep and night duties affect susceptibility and behavior at the onset of symptoms. The average sleep duration may conceal extreme values in certain groups. Chronic sleep deprivation is associated with altered immune regulation and a higher probability of clinical respiratory infection. In practice, this means the assessment is supplemented by the proportion of night duties and the weekly regimen. [20–22, 34–42]

Field exercises and mass events alter the usual contact structure. Temporary co-location, shared transportation, and the intermingling of units create new connections. A short-term event can have consequences the following week. Field conditions can simultaneously reduce exposure to indoor air and worsen sanitary conditions. At the unit level, this situation takes a specific form: the number of events is analyzed together with inter-unit mixing. [1–10, 56–57]

Seeking medical care late prolongs an infected individual's presence in the contact network. The proportion of late consultations and the average delay in isolation measure different links in the process. The period of moderate symptoms, when a service member continues to participate in group activities, is particularly vulnerable. With weekly observation, this relationship is viewed somewhat differently: a high-risk category requires active identification of symptomatic individuals. Reducing this delay is an achievable organizational outcome, even with unchanged seasonal morbidity. [20–30, 23–45]

Early clinical and laboratory signals occupy an intermediate position between a factor and an outcome. If incorrectly timed, they become signs of an event that has already occurred. The current rate of healthcare visits, the proportion of similar symptoms, and repeated pathogen detection can precede an outbreak. In practice, this means that the temporal sequence is verified during database preparation. The predictive line includes only information available before the start of the following week. [31–39, 50–57]

Table 1.4. Operational thresholds for factors used in the prognostic analysis

Factor	Threshold	Coding	Rationale
Ventilation	Less than 3 times per day	1 – unfavorable; 0 – otherwise	Insufficient regular air exchange
Average CO2	at least 1000 ppm	1/0	Accumulation of exhaled air
Vaccination coverage	less than 70%	1/0	Insufficient preventive background
Late presentation for care	at least 20%	1/0	Prolonged contact before examination
Hand hygiene	less than 75 points	1/0	Insufficient compliance
Laboratory signal	score of at least 1	1/0	Repeated or related detection

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Note: Threshold coding was applied in the final regularized model after analyzing the initial continuous values.

Short-term forecasting and early warning methods

Syndromic surveillance uses clinical presentations before a final diagnosis is made; a rise in fever, cough, sore throat, or diarrhea appears earlier than laboratory confirmation. The sensitivity of such a circuit is higher, while its specificity is lower. A signal requires verification of nosological homogeneity and its connection to a specific unit. Time series control limits compare the current value to the historical background. A short history and a small number of events reduce the stability of estimates. Farrington algorithms and their modifications account for trend, seasonality, and the distribution of count data. Organizational significance is not only related to the frequency of events: a formal signal is verified by a physician, taking into account sanitary and organizational information. A change in population size requires an explicit denominator or an offset. [34–38, 50–57]

Spatiotemporal methods identify local clusters. Scan statistics compare the observed number of events within changing windows to the expected level. For de-identified military units, precise coordinates are not required, but the group code is retained. A small number of units limits the spatial detail. An important limitation arises here: in the present study, the primary unit remains the unit-week. [37, 46–47]

Regression models allow for the assessment of the combined influence of multiple features. Repeated observations require mixed-effects models, generalized estimating equations, or cluster-robust standard errors. The logistic model is suitable for a binary event, while Poisson and negative binomial regressions are applied to count data. In daily practice, a physician faces a more complex picture: regularization is applied to the primary model, and a rare outcome increases the risk of unstable coefficients. [32–35]

Machine learning algorithms can account for nonlinearity and complex interactions. However, their high computational complexity is not always justified in a clinical setting. Decision trees, random forest, and gradient boosting do not require a predefined linear form. In practice, this means that a gradient boosting model is used for comparison, while an interpretable regression model remains the primary one. [34–38]

Discriminative ability characterizes how observations are ranked by risk. The area under the ROC curve (AUC) is the probability that a randomly chosen positive case will be ranked higher than a randomly chosen negative case. The AUC does not report how accurate the absolute probabilities are. Two tools with the same AUC may have different utility at a given threshold. At the departmental level, this concept takes a specific form: the metric is accompanied by a confidence interval and a confusion matrix. [44–48]

Calibration assesses the correspondence between the predicted and observed probability. Grouping by quantiles facilitates graphical representation but does not replace numerical parameters. The intercept characterizes systematic over- or underestimation, while the slope is related to overfitting. With weekly observation, this relationship is considered somewhat differently: calibration is checked separately in each sample. The Brier score aggregates the error of the probabilistic forecast. [49, 50–53]

The choice of threshold depends on the cost of a miss and the resources available for prevention. A false positive signal increases the scope of verification and time constraints. A false negative result leaves a unit without enhanced measures when an event is beginning. From a prevention management perspective, a threshold of 0.10 is used for an active preventive level. In an early warning system, higher sensitivity is justified when re-evaluation is available. [50, 52–57]

Internal and external validation answer different questions. Bootstrapping assesses optimism on the original dataset, while a temporal sample validates transferability to a subsequent period. Sequential exclusion of units reveals dependence on individual groups. An independent site is necessary for rigorous external validation. In daily practice, a clinician faces a more complex picture: a later period involving the same units is not considered external validation. [46–52, 52–53]

Decision curve analysis (DCA) translates a probabilistic forecast into an expected clinical benefit. The net benefit weighs true and false positives, taking into account the threshold probability. This method compares the model to the strategies of treating all patients or treating none. A low prevalence of the event limits the absolute value of the metric. For a medical service, another aspect is important: DCA is used as an additional criterion for selecting the operating range. [50, 54–57]

Table 1.5. Early warning methods and their scope

Method	Input data	Advantage	Main limitation
Syndromic surveillance	Daily visits and symptoms	Early signal	Low specificity
Event-based surveillance	Unusual or related events	Immediate response	Depends on recognition
Control algorithms	Time series of count data	Formal threshold	Requires a stable baseline

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Logistic regression	Binary outcome and predictors	Interpretable probability	Logit linearity and rare events
Count data models	Cases and person-days	Accounts for the denominator	Overdispersion дисперсия
Gradient boosting	Large feature set	Nonlinearity	Overfitting and complexity
Decision curve	Probability and thresholds	Assessment of practical utility	Depends on the cost of errors

Table 1.6. Performance metrics for a prognostic model

Metric	Description	Preferred representation	Common misinterpretation
AUC	Discriminatory ability	Value and 95% CI	Mistaking for overall accuracy
Sensitivity	Proportion of detected events	Percentage at a given threshold	Ignores specificity
Specificity	Proportion of correctly excluded events	Percentage at a given threshold	Neglecting prevalence
PPV and NPV	Predictive values	Percentage and confusion matrix	Transfer to another population without recalculation
Brier	Mean squared error of probability	0–1, lower is better	Assessment without comparison to baseline risk
Calibration	Correspondence of probabilities	Intercept, slope, plot	One overall test instead of parameters
Net benefit	Balance of true and false positives	Curve by threshold	Use without a clinical threshold

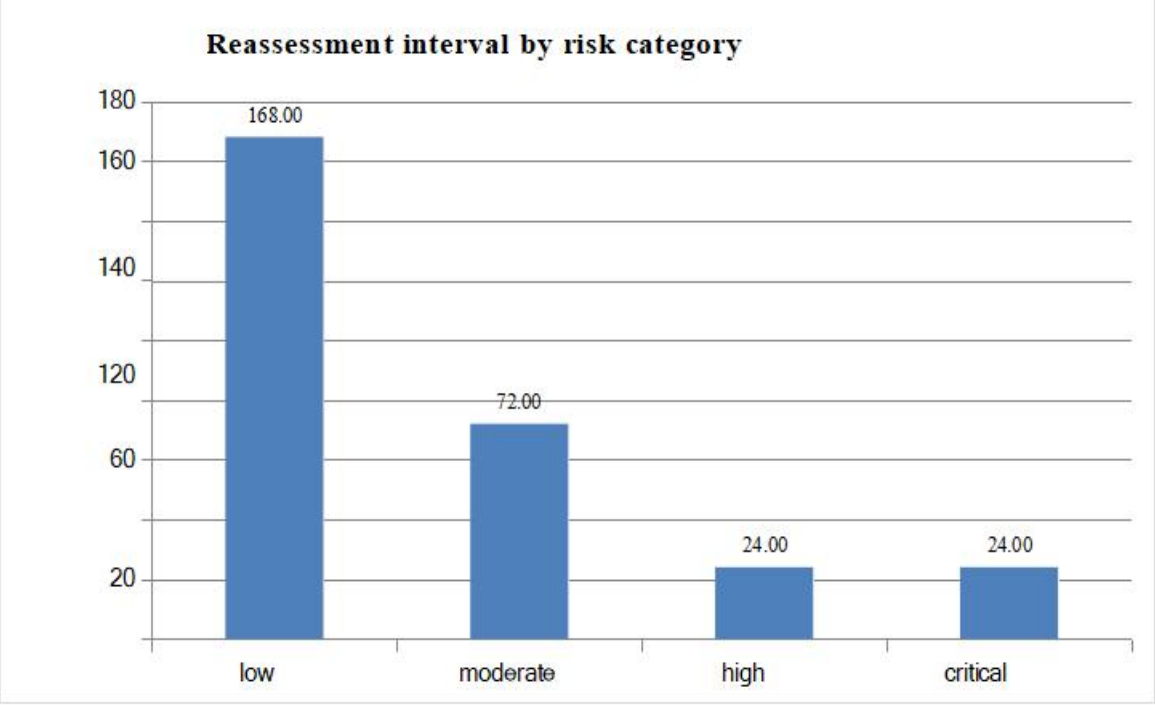

Figure 1.1. Reassessment interval by risk category

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A regular weekly cycle is maintained only at low risk. The moderate category requires a recheck after 72 hours, while high and critical levels switch monitoring to a daily regimen.

The main methodological gap is due to the disconnection of data sources. Medical records, laboratory results, sanitary surveys, and information on duty rosters are often analyzed separately. This kind of organization makes it impossible to verify the temporal sequence of factors and the outcome. A partial overlap of periods creates the risk of spurious correlation. In practice, this means that in our own study, five datasets were merged using anonymized codes and the calendar week. [31–41, 50–51]

Many studies lack a predetermined forecast horizon. A general assessment of "high risk" can refer to different time periods and may not specify the validity period of a decision. For a medical service, it is crucial to know whether a signal pertains to the next day, week, or month. An undefined horizon complicates accuracy verification. However, simply accounting for a feature is insufficient: the primary outcome is recorded for the subsequent seven days, and the secondary outcome for fourteen. [46–52, 52–53]

The comparison of units is often performed using absolute numbers or average annual headcount. Changes in cohort composition during the observation period and unequal exposure durations are not taken into account. The result depends on the size of the unit and cannot be directly compared. Person-days reduce this error and support count data models. This introduces an important limitation: all main intensity indicators share a common denominator. [34–35]

Operational scoring scales rarely undergo consistent verification of their calibration and thresholds. The point-based format must be derived from a probabilistic model or validated against a subsequent outcome. Equal weights are convenient but assume that all factors have equal significance. In practice, this means that the categories in this work are justified by the calculated probability and the cost of errors. [46–52, 56–57]

The evaluation of preventive interventions is vulnerable to seasonality and general time trends. Autumn and winter surges may coincide with the start or end of a program. A simple decrease after implementation does not separate the effect of the algorithm from natural dynamics. Control units and a difference-in-differences approach create a more rigorous basis. At the unit level, this principle takes a specific form: the transition period is identified separately and excluded from the main contrast. [46–55]

The absence of an independent site is often masked by the term "external validation." Later observations on the same units assess temporal generalizability but retain the common infrastructure and registration practices. Unit-level verification reveals another component of reproducibility. A strict distinction between types of validation increases the transparency of the results.

Our own research combines epidemiological characterization, forecasting, and preventive management. Each task is associated with a separate method, table, figure, conclusion, and recommendation. The model is not considered in isolation from the quality of the database and the organizational process. Effectiveness is evaluated by medical and service-related endpoints. In daily work, a physician faces a more complex picture: a unified architecture reduces the gap between statistical signal and practical action. [1–24]

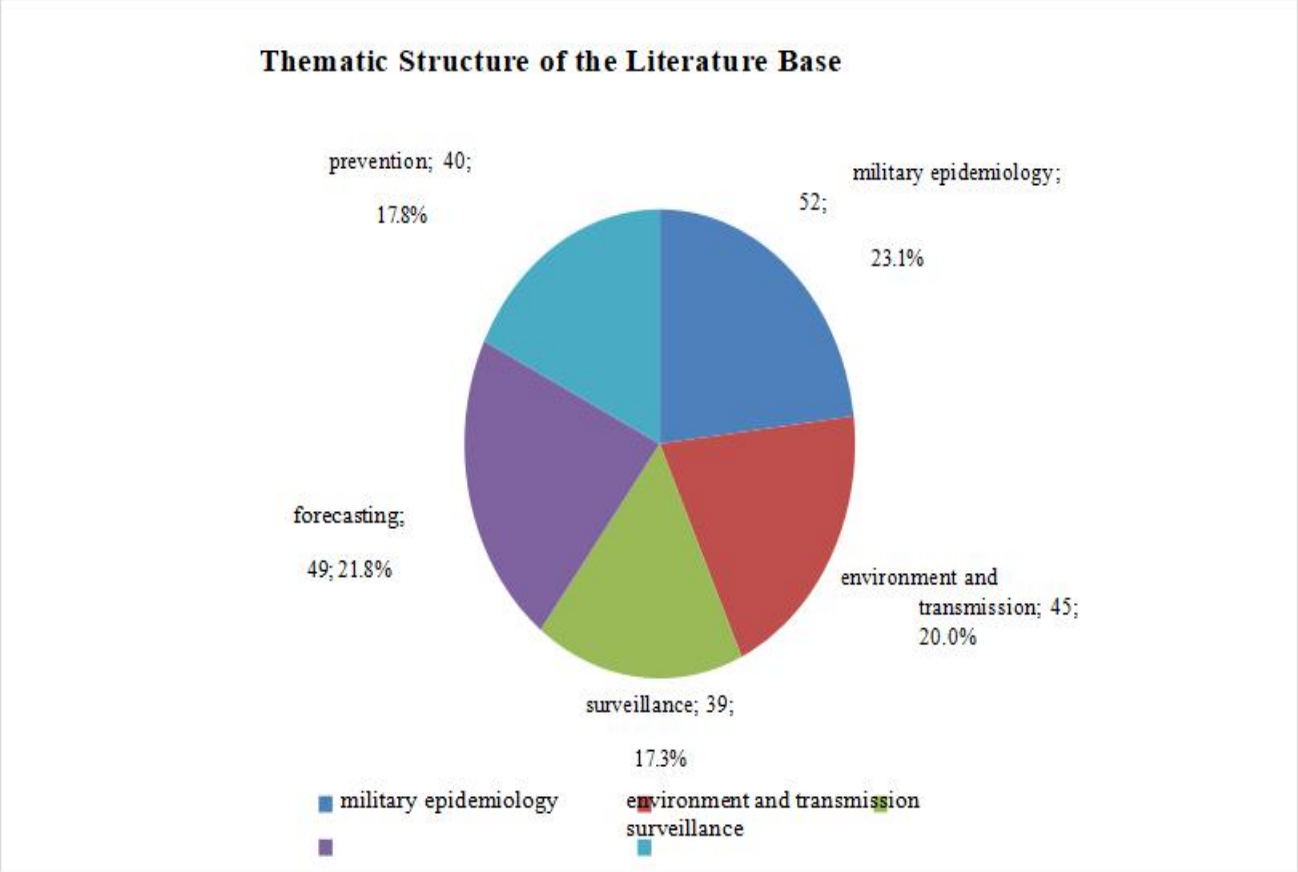

Figure 1.2. Thematic Structure of the Literature Database

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The list includes 236 sources. The largest sections are devoted to military epidemiology, transmission factors, surveillance methods, prognostic models, and the evaluation of preventive interventions.

Conclusion: A military unit is a self-contained epidemiological system with stable contacts, a variable composition, and a short timeframe for preventive decision-making. Incidence per 1000 person-days, outbreak activity, clinical and laboratory patterns, and lost duty days describe different aspects of the disease burden. The most manageable factors are air exchange, housing density, timeliness of seeking medical care and isolation, vaccination, sanitary conditions, and contact procedures. The literature data substantiate the list of factors but do not provide a ready-made, calibrated system for weekly application in the studied populations. This gap informed the design of a multi-level database, a seven-day forecast horizon, and the evaluation of a differentiated preventive algorithm.

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