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Artificial Intelligence for Hantavirus Outbreak Risk Prediction: A Multisource Early Warning Framework for Tourism, Hospitality, and Public Health Systems

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Abstract

Hantavirus infections remain relatively rare compared with many respiratory epidemics, yet their severe clinical outcomes, rodent-linked environmental exposure pathways, and occasional travel-associated clusters create a complex risk problem for tourism, hospitality, and public health systems. This article addresses the first research objective of a broader AI-driven business-continuity study: to examine how artificial intelligence can be used to predict hantavirus outbreak risks. Using a design-science and conceptual modeling approach, the paper proposes the Hantavirus Risk Prediction Artificial Intelligence (HRP-AI) framework, a multisource early warning model that integrates rodent and environmental signals, syndromic surveillance, laboratory data, travel and mobility indicators, digital weak signals, and business vulnerability indicators. The framework applies anomaly detection, spatiotemporal forecasting, natural language processing, ensemble learning, and explainable AI to produce dynamic risk scores for hotels, cruise operators, airlines, restaurants, event centers, tourism agencies, and public health authorities. The article contributes a publishable AI risk architecture, a feature taxonomy, model selection logic, validation metrics, and governance controls for privacy, data quality, and human oversight. The proposed model does not replace public health decision-makers; instead, it supports earlier detection, risk stratification, targeted prevention, transparent communication, and operational preparedness in high-contact travel and hospitality environments. The paper concludes that AI-based hantavirus risk prediction is most credible when it combines epidemiological evidence with environmental exposure data, operational business indicators, and explainable human-in-the-loop decision processes.

Keywords: Artificial intelligence, business continuity, epidemic intelligence, hantavirus, hospitality, outbreak prediction, public health surveillance, risk management, tourism

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Highlights

- AI integrates environmental, clinical, travel, and business data for hantavirus risk prediction.
- HRP-AI provides an explainable early warning framework for outbreak detection.
- Multi-source AI model supports risk stratification in tourism and hospitality settings.
- Human-in-the-loop governance improves transparency, preparedness, and decision-making.

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Ethics Statement

Not applicable. This study did not involve human participants, animals, patient data, clinical interventions, or identifiable personal information. The research is based on conceptual modeling, literature review, and framework development.

I. INTRODUCTION

Hantaviruses are zoonotic viruses mainly associated with rodent reservoirs and contaminated urine, droppings, saliva, or nesting materials. Human infection can occur when contaminated particles become airborne and are inhaled, when contaminated material reaches mucous membranes or broken skin, or rarely after rodent bites or scratches [1], [2]. In the Western Hemisphere, some hantaviruses can cause hantavirus pulmonary syndrome (HPS), a severe disease affecting the lungs. Public health guidance emphasizes that rodent infestation and direct exposure to contaminated materials are major exposure risks, while Andes virus is notable because limited person-to-person transmission has been documented under close and prolonged contact conditions [1], [2].

For tourism and hospitality systems, hantavirus risk has a dual character. First, the biological exposure pathway is environmental and operational: rodent control, sanitation, storage practices, employee safety, destination activities, and facility maintenance influence exposure probability.

Second, the business impact pathway is social and economic: public fear, cancellations, medical evacuation, event disruption, reputational damage, regulatory scrutiny, and cross-border contact tracing can produce large losses even when the number of clinical cases is small. The 2026 WHO Disease Outbreak News report on a cruise-ship-associated Andes hantavirus cluster illustrates the importance of rapid case identification, international contact tracing, laboratory

confirmation, isolation, risk communication, and coordinated public health response in a travel setting [3].

Artificial intelligence (AI) offers a practical opportunity to improve hantavirus preparedness because outbreak risk is rarely visible from one data source. A hotel may detect increased rodent complaints before health authorities receive confirmed case reports. A cruise operator may observe illness symptoms among passengers, but the signal may remain ambiguous without travel history and laboratory data. A public health agency may have confirmed infections, but insufficient operational insight into tourist itineraries, ship

cabins, excursion sites, or event-contact networks. AI can integrate these fragmented signals into probabilistic risk scores and trigger graded alerts before a small exposure event becomes an uncontrolled operational crisis.

This article focuses on the first objective of the broader research project: to examine how AI can be used to predict hantavirus outbreak risks. The article does not claim that AI can predict every zoonotic spillover event. Instead, it proposes a decision-support framework that combines epidemiological knowledge, environmental monitoring, travel and hospitality data, and explainable modeling. The central argument is that hantavirus risk prediction should be treated as a multisource, low-frequency, high-impact detection problem requiring conservative thresholds, transparent validation, and human oversight.

II. RESEARCH OBJECTIVE AND QUESTIONS

This specific research objective addressed in this

article is: to examine how AI can be used to predict hantavirus outbreak risks. This objective is translated into one primary research question and three operational subquestions.

Primary research question: How can AI detect early warning signs of hantavirus outbreak risks in tourism, hospitality, and public health systems?

Subquestion 1: What data streams should be integrated to predict environmental, clinical, travel, and business exposure risks?

Subquestion 2: Which AI methods are suitable for early detection, risk scoring, and forecasting under conditions of sparse outbreak data?

Subquestion 3: How can AI-generated predictions be translated into operational decisions without violating privacy, accountability, or public health governance standards?

The article is therefore structured as a design-oriented research contribution. It reviews relevant evidence on hantavirus transmission and AI-driven epidemic intelligence, identifies the predictive features needed for hantavirus risk modeling, proposes the HRP-AI architecture, and presents validation and governance requirements for implementation.

III. BACKGROUND AND LITERATURE REVIEW

A. Hantavirus Risk Characteristics

Hantaviruses create a prediction challenge because exposure is often ecological rather than purely interpersonal. The primary signal may originate from rodent abundance, weather patterns, building conditions, food-storage practices, or human activity in rural, forest, farm, ship, or ecotourism

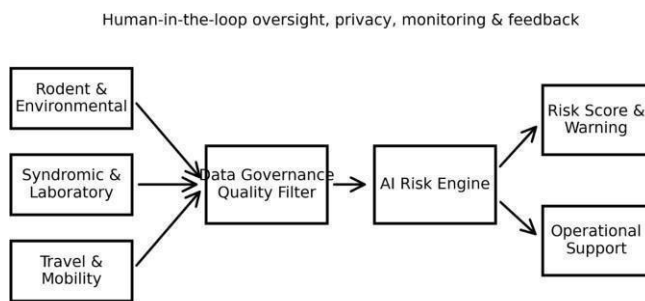
environments. CDC guidance notes that people are at risk when they contact virus-carrying rodents or contaminated urine, feces, saliva, or nesting materials, withinhalation of contaminated air during cleanup recognized as a key pathway [2]. These exposure conditions are highly relevant to hotels, lodges, camps, restaurants, event centers, cruise ships, and tourist sites where food storage, waste handling, enclosed spaces, maintenance routines, and excursions can shape risk.

The severity of HPS also makes early warning important. CDC describes HPS as initially flu-like and potentially progressing to severe respiratory illness; the agency notes that HPS is fatal in nearly four out of ten infected people [2]. WHO similarly emphasized in its 2026 event assessment that disease severity, age and comorbidities of exposed populations, close living quarters, shared indoor spaces, and the need for rapid clinical transfer influence risk management in shipboard settings [3]. Thus, AI prediction should not merely count suspected cases. It should estimate both probability of exposure and potential consequence for a given setting.

B. AI and Epidemic Intelligence

AI has increasingly been discussed as a tool for infectious-disease surveillance, outbreak detection, risk assessment, and response planning. Brownstein et al. describe AI and machine-learning tools as useful for identifying and tracking outbreaks and monitoring mitigation strategies [4]. More recent reviews argue that AI can support multiple outbreak stages, including early detection, risk assessment, diagnosis, control, and understanding of infection mechanisms, while warning that model performance depends on data

quality, interpretability, and privacy safeguards [5]. AI-driven epidemic intelligence extends traditional public health surveillance by combining structured data, unstructured text, digital signals, and operational information. Kaur and Butt argue that integrated AI-driven epidemic intelligence can improve early warning and forecasting by correlating cross-source data and supporting informed response [6]. Yan et al. further propose AI agents that aggregate multisource indicators



into composite risk scores, compare those scores against predefined thresholds, and communicate graded alerts in actionable formats [7]. These ideas are directly applicable to hantavirus risk prediction, especially in high-contact travel and hospitality settings where weak signals may appear across departments before formal case confirmation.

However, infectious-disease prediction also has a cautionary history. Digital trace models can overfit behavioral signals and produce misleading forecasts if they are not grounded in epidemiological data, validated against reliable outcomes, and monitored for drift. The failure of overly confident flu prediction systems showed that big-data models must be transparent, recalibrated, and combined with traditional surveillance rather than treated as replacements for

public health expertise. For hantavirus, where case counts are sparse and exposure settings vary widely, the strongest AI approach is therefore not a single black-box model, but a supervised, explainable, multisource decision-support framework.

IV. CONCEPTUAL MODEL: HANTAVIRUS RISK PREDICTION AI

The proposed Hantavirus Risk Prediction Artificial Intelligence (HRP-AI) framework is designed as a modular early warning system. It generates a risk score for a location, business facility, conveyance, or travel itinerary at a given time. The model combines environmental exposure likelihood, clinical signal strength, travel-contact patterns, digital weak signals, business vulnerability, and control capacity.

Fig. 1. HRP-AI multisource early warning pipeline for hantavirus risk prediction.

A. Risk Equation

The conceptual risk score can be represented as follows:

$$Risk(l, t) = \text{sigmoid}(E(l, t) + S(l, t) + T(l, t) + D(l, t) + B(l, t) - C(l, t))$$

where l represents the location, facility, ship, route, or destination; t represents time; E represents environmental and rodent exposure; S represents syndromic and laboratory surveillance; T represents travel, mobility, and contact patterns; D represents digital weak signals; B represents business vulnerability; and C represents control capacity such as sanitation readiness, rodent-control strength, medical referral capacity, and public health response readiness. The sigmoid function converts the

weighted input into a probability-like risk score between 0 and 1.

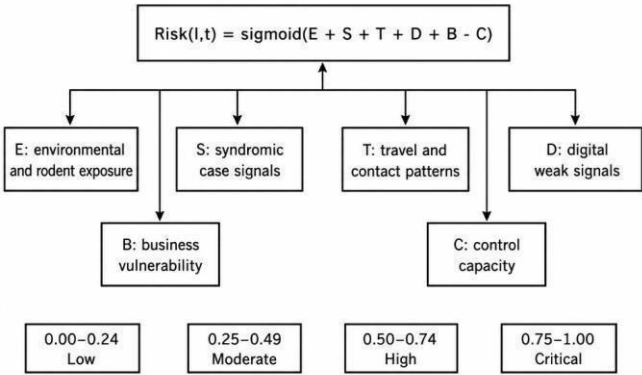


Fig.2.Compositerisk-scorearchitectureandalerttiers.

B. DataSourcesandPredictiveFeatures

A hantavirus prediction system should not rely on a single dataset. The strongest framework uses triangulation, where weak signals from different sources reinforce or contradict one another. Table I summarizescoredatacategoriesandtheirrelevance.

TABLE I: DATA STREAMS FOR AI-BASED HANTAVIRUS RISK PREDICTION

Datastream	Example features	Prediction value
Rodent and environmental	Rodent complaints, trap counts, nesting evidence, waste conditions, rainfall, vegetation, temperature, building age	Estimate ecological exposure probability
Syndromic and clinical	Fever, myalgia, cough, shortness of breath, gastrointestinal	Detect early human illness clusters

	symptoms, clinic visits, absenteeism	
Laboratory and case reports	RT-PCR confirmation, serology, sequencing, confirmed/probable/suspected case definitions	Validate signals and trains supervised labels
Travel and mobility	Itineraries, ship cabin zones, hotel guest origins, excursion logs, airliner route links, event attendance	Map exposure networks and importation risk
Digital weak signals	Search trends, news reports, social media posts, customer reviews, call-center complaints	Add early unstructured warning signals
Business operations	Occupancy, cancellations, cleaning logs, pest-control reports, staff shortages, supply availability	Link health risk to operational vulnerability

C. Model Layers

Layer 1 is data ingestion. It connects public health data, environmental monitoring, pest-control records, travel databases, hospitality management systems, and digital text streams. In tourism and hospitality settings, this layer may include hotel maintenance tickets, cruise sanitation logs, restaurant waste-management records, guest illness reports, event attendance data, and excursion itineraries. Because these data are heterogeneous, the ingestion layer must standardize time stamps, locations, identifiers, and source reliability.

Layer 2 is data governance and preprocessing. It removes duplicates, flags missingness, anonymizes or pseudonymizes personal data, and assigns

confidence scores to each source. This layer is essential because outbreak prediction is vulnerable to noise. For example, a spike in online searches may reflect media attention rather than true exposure, while a single hotel complaint may reflect maintenance issues rather than rodent infestation. Governance rules prevent such signals from generating disproportionate alerts.

Layer 3 is feature engineering. The model converts raw inputs into epidemiologically meaningful variables: rodent exposure density, recent sanitation failures, high-risk cleanup events, symptoms compatible with HPS, travel overlap with confirmed cases, cabin or room proximity, duration of close contact, local healthcare capacity, and business

vulnerability. Feature engineering must reflect known hantavirus exposure pathways rather than generic respiratory disease assumptions.

Layer 4 is AI modeling. The framework uses several complementary algorithms. Anomaly detection identifies unusual deviations in rodent complaints or symptom reports. Spatiotemporal forecasting estimates how risk changes across locations and time. Natural language processing extracts relevant signals from maintenance reports, news, reviews, and social media. Ensemble learning combines multiple weak predictors into a calibrated score. Explainable AI identifies which features drive the alert so managers and public health officials can understand the decision logic.

Layer 5 is alerting and decision support. Instead of issuing a single binary warning, HRP-AI classifies

risk into low, moderate, high, and critical tiers. A low score triggers routine monitoring; moderate risk triggers enhanced cleaning, pest inspection, and targeted staff awareness; high risk triggers public health consultation, intensified contact review, and operational adjustments; critical risk triggers formal outbreak response, isolation protocols, medical referral, regulatory notification, and crisis communication.

V. AI METHOD SUITABLE FOR HANTAVIRUS PREDICTION

Because hantavirus outbreaks are relatively rare, a robust prediction system should combine methods rather than depend on one algorithm. Table II summarizes the AI methods most relevant to the research objective.

TABLE II: CANDIDATE AI METHODS AND THEIR USE IN HRP-AI

AI method	Main task	Application to hantavirus risk
Anomaly detection	Detect unusual changes	Flags sudden increases in rodent sightings, illness reports, or guest complaints
Spatiotemporal models	Forecast risk across place and time	Estimates hotspots by destination, facility zone, cabin group, or travel route
NLP and LLM-assisted extraction	Analyze unstructured text	Extract exposure clues from reviews, maintenance logs, news, and field reports
Graph analytics	Map exposure networks	Link travelers, rooms, ship zones, excursions, events, and contacts

Randomforest/gradient boosting	Classifyrisk	Combinesnonlinearpredictors andranksfeatureimportance
Bayesianmodels	Updateuncertainty	Supportslow-datapredictionand probabilisticrevisionasevidence arrives
ExplainableAI	Interpretdecisions	Showswhyallocation or businessunitreceivedarisk score

A. Anomaly Detection

Anomaly detection is useful when confirmed case labels are sparse. Unsupervised methods such as isolation forests, one-class support vector machines, robust z-score detection, and autoencoders can establish normal baselines for rodent complaints, pest-control incidents, cleaning events, clinic visits, or guest illness reports. When values move outside the expected baseline, the system can trigger human review. This approach is especially relevant for hotels, cruise ships, and event venues because small operational anomalies may precede official disease reports.

However, anomaly detection must be conservative. Not every unusual pattern is a public health threat. The model should therefore require cross-source confirmation before escalation. For example, rodent sightings plus sanitation failure plus compatible symptoms is stronger evidence than a single viral social media post. The HRP-AI design assigns source reliability weights and requires threshold logic to reduce false positives.

B. Spatiotemporal Forecasting

Spatiotemporal forecasting is needed because hantavirus risk varies by location, season, environmental conditions, and human movement. A destination with increased rainfall, vegetation shifts, rodent population growth, rural tourist activity, and poor waste controls may have higher risk than a similar business in a controlled urban environment. Forecasting models can estimate near-term risk at daily, weekly, or monthly intervals, depending on data availability.

Useful approaches include Bayesian hierarchical models, generalized additive models, recurrent neural networks, temporal convolutional networks, and gradient boosting models with lagged variables. In practice, simpler interpretable models may be preferred during initial deployment because the cost of an unexplained false alarm can be high for businesses and public health agencies. Advanced models should be used when validated data and technical capacity are available.

C. Natural Language Processing

Many early outbreak signals are textual. Hotel maintenance staff may write notes such as rodent droppings found near storage. Customers may post

reviews about pests, unusual illness after a lodge stay, or poor sanitation. Local news may report unexplained respiratory illness. NLP can convert these unstructured signals into features through entity recognition, topic classification, sentiment analysis, and event extraction.

LLM-assisted extraction should be used with safeguards. It can summarize reports and classify risk cues, but its outputs should be verified against source documents and rules. In the HRP-AI framework, LLMs are restricted to extraction and summarization support, not autonomous public health decision-making. Human review remains required for high-risk alerts.

D. Graph Analytics and Contact Networks

Hantavirus prediction in travel and hospitality environments requires network thinking. Cruise ships, airlines, hotels, restaurants, event centers, and tour agencies connect people through cabins, rooms, excursions, transport routes, dining areas, staff shifts, and shared indoor spaces. Graph analytics can represent these relationships and identify exposure clusters, bridge contacts, and high-centrality locations.

A graph-based layer is especially useful when a confirmed or probable case appears. The system can rapidly identify who shared a cabin zone, excursion, meal period, transport segment, or event with the case. This approach supports risk-based contact tracing and reduces unnecessary disruption for low-risk individuals.

VI. APPLICATION TO TOURISM, HOSPITALITY, AND PUBLIC HEALTH

A. Hotels and Lodges

Hotels and lodges can use HRP-AI to integrate pest-control inspections, housekeeping notes, maintenance tickets, waste-management records, occupancy levels, guest illness reports, and local environmental conditions. The system can identify rooms, storage areas, kitchens, laundry rooms, basements, or outdoor facilities that require inspection. For rural lodges and eco-tourism sites, AI can also connect guest excursion data with known rodent exposure conditions and local health alerts.

B. Cruise Companies

Cruise ships are complex closed or semi-closed environments where close quarters, shared indoor spaces, international travel, and medical evacuation logistics can complicate response. HRP-AI can help by mapping cabin zones, passenger movement, symptom reports, medical visits, staff schedules, sanitation logs, and destination exposure histories. WHO reporting on the 2026 cruise-ship-associated Andes virus cluster emphasized coordinated response, contact tracing, isolation, testing, medical evacuation, and transparent communication, all of which can be supported by structured AI dashboards [3].

C. Airlines and Tourism Agencies

Airlines and tourism agencies may not directly manage rodent exposure, but they can support risk prediction through itinerary reconstruction, passenger notification, route-level exposure

mapping, and integration with public health travel advisories. AI can identify overlapping itineraries, high-risk destination clusters, and traveler groups requiring targeted communication. For tourism agencies, AI can also support safer scheduling of ecotourism activities and destination risk briefings.

D. Restaurants and Event Centers

Restaurants and event centers face risk through food storage, waste disposal, back-of-house sanitation, facility maintenance, and crowd concentration. HRP-AI can combine pest-control logs, sanitation audits, staff illness reports, supplier disruptions, and event attendance data. The goal is not to label restaurants as disease sources without evidence, but to detect operational vulnerabilities that could increase exposure risk and trigger preventive action before illness occurs.

E. Public Health Systems

Public health agencies can use the model to prioritize investigations, coordinate contact tracing, identify environmental exposure sites, monitor digital weak signals, and communicate with businesses. AI prediction is most useful when it improves speed and focus: which location should be inspected first, which contacts need active follow-up, which businesses need technical guidance, and which public messages will reduce panic without minimizing risk.

VII. MODEL VALIDATION AND EVALUATION

A publishable AI framework must include validation requirements. HRP-AI should be evaluated with historical outbreaks, simulated exposure events, expert-labeled case studies, and prospective shadow-mode testing. Shadow-mode deployment means the AI system generates risk scores without triggering operational decisions until public health experts compare its alerts against real outcomes

TABLE III: RECOMMENDED EVALUATION METRICS

Metric	Purpose	Interpretation
Sensitivity/recall	Detect true risk events	High value is important because missed outbreaks are costly
Specificity	Avoid false alarms	Protects businesses from unnecessary disruption
Precision	Measure alert usefulness	Show how often alerts are meaningful
Leadtime	Assess early warning value	Measures days gained before official confirmation
Calibration	Check probability accuracy	Ensures predicted risk matches observed risk

Explainability score	Assess interpretability	Determines whether users can understand drivers
Operational utility	Measure decision impact	Tracks whether actions reduce exposure and losses

A. Validation Data

Potential validation data include official case reports, laboratory-confirmed cases, outbreak investigation reports, environmental inspection records, weather and land-use data, historical tourism activity, pest-control records, and simulated facility scenarios. Because confirmed hantavirus cases are uncommon in many jurisdictions, the model should use transfer learning and Bayesian updating carefully, while avoiding overclaiming accuracy from limited data.

B. False Positives and False Negatives

False positives can harm businesses through unnecessary cancellations, reputational damage, and public anxiety. False negatives can harm public health by delaying exposure control and clinical care. HRP-AI therefore uses graded alerts rather than automatic shutdown decisions. A moderate alert can trigger inspection and monitoring; a high or critical alert requires public health review. This tiered design balances business continuity with safety.

C. Human-in-the-Loop Governance

AI predictions must remain advisory. Public health professionals, facility managers, clinicians, and legal or compliance officers should review high-risk alerts before publication. The model should maintain audit logs showing data sources, timestamps, risk drivers, threshold decisions, and human approvals. This auditability supports accountability and allows retrospective learning after each alert.

VIII. ETHICAL, LEGAL, AND GOVERNANCE CONSIDERATIONS

Although this article focuses on prediction, ethical safeguards are inseparable from AI implementation. Hantavirus risk models may use sensitive mobility, health, employee, customer, and location data. Businesses must limit data collection to legitimate public health and safety purposes, use de-identification where possible, and comply with applicable privacy laws and public health reporting requirements. Data-sharing agreements should define ownership, retention, permitted uses, and emergency escalation rules.

Algorithmic fairness is also relevant. Rural lodges, small restaurants, and lower-resourced tourism operators may have less digital data than large hotels or cruise companies. A model trained mainly on

high-resource settings could under-detect risks in smaller businesses or over-penalize locations with more transparent reporting. To prevent this, HRP-AI should include uncertainty estimates, source-coverage indicators, and human contextual review. Transparency is essential for trust. Business leaders and public health officials should be able to see why the model produced a score. Explainable AI outputs

may include top risk drivers, recent signal changes, geographic clusters, similar historical scenarios, and recommended verification steps. Communication to the public should avoid technical exaggeration and present clear, actionable guidance.

IX. DISCUSSION

The first objective of this study asks how AI can be used to predict hantavirus outbreak risks. The answer is that AI can contribute most effectively by integrating environmental exposure data, syndromic signals, travel-contact patterns, operational business data, and digital weak signals into a transparent risk score. AI is not a substitute for laboratory confirmation or public health investigation, but it can reduce delay by identifying patterns that individual organizations may not see in isolation.

The tourism and hospitality context is particularly important. Hotels, cruise companies, restaurants, event venues, airlines, and tourism agencies operate at the intersection of human mobility, shared spaces, food and waste systems, sanitation, and customer trust. Their data can enrich public health surveillance, while public health data can guide safer business decisions. HRP-AI therefore creates a bridge between business continuity and disease prevention.

The proposed model also highlights that outbreak prediction is not only a technical task. A high-performing model that businesses do not trust will not be used. A model that violates privacy will create legal and ethical risk. A model that cannot explain its alerts may cause panic or resistance. Therefore, AI-based hantavirus prediction should be developed

as a sociotechnical system, combining algorithms with governance, communication, validation, and human expertise.

A limitation of this article is that it presents a conceptual and design-science framework rather than an empirical deployment. Future research should test the HRP-AI model using historical outbreak data, tourism case studies, simulated facility data, and pilot programs with hospitality and public health partners. Comparative studies could evaluate whether AI-assisted inspection, contact tracing, and risk communication reduce outbreak response time and financial losses.

X. CONCLUSION

AI can be used to predict hantavirus outbreak risks when prediction is understood as probabilistic early warning rather than certainty. The proposed HRP-AI framework integrates environmental, clinical, travel, digital, and business data to generate explainable risk scores for tourism, hospitality, and public health settings. The model supports earlier detection of weak signals, targeted prevention, risk-based contact tracing, and business-continuity planning.

For hotels, cruise companies, airlines, restaurants, event centers, tourism agencies, and public health authorities, the practical value of AI lies in improving readiness before cases escalate. The most responsible approach is human-in-the-loop, privacy-preserving, explainable, and validated against epidemiological evidence. With these safeguards, AI-driven hantavirus risk prediction can strengthen both public health protection and organizational resilience.

FUTURE RESEARCH

Future research should develop empirical datasets for hantavirus risk prediction by combining public health case data, environmental monitoring, pest-control records, travel itineraries, and hospitality operations. Pilot studies should compare AI-assisted detection with traditional reporting timelines and measure lead time, alert accuracy, response cost, and business continuity outcomes.

Additional work should examine how the model performs across different settings, including rural lodges, urban hotels, cruise ships, ecotourism excursions, restaurants, event centers, and airports. Researchers should also study how customers, employees, managers, and public health officials perceive AI-generated risk alerts and what communication strategies best support compliance without creating unnecessary fear.

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XII. TABLE IV. PUBLICATION INFORMATION

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