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ArtificialIntelligenceforHantavirusOutbreakRiskPrediction:AMultisourceEarlyWarning Framework for Tourism, Hospitality, and Public Health Systems

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Abstract

Hantavirusinfectionsremainrelativelyrarecomparedwithmanyrespiratoryepidemics, 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 objectiveof 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, cruiseoperators, airlines, restaurants, eventcenters, tourism agencies, and public health authorities. The article contributes a publishable AI risk architecture, a feature taxonomy,modelselectionlogic,validationmetrics,andgovernancecontrolsforprivacy, 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 predictionismostcrediblewhenitcombinesepidemiologicalevidencewithenvironmental 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

IndexTerms-Artificialintelligence,businesscontinuity,epidemicintelligence,hantavirus,hospitality, outbreak prediction, public health surveillance, risk management, tourism.

Highlights

- AIintegratesenvironmental,clinical,travel,andbusinessdataforhantavirusriskprediction.
- HRP-AIprovidesanexplainableearlywarningframeworkforoutbreakdetection.
- MultisourceAImodelssupportriskstratificationintourismandhospitalitysettings.
- Human-in-the-loopgovernanceimprovestransparency,preparedness,anddecision-making.

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EthicsStatement

Notapplicable.Thisstudydidnotinvolvehumanparticipants,animals,patientdata,clinicalinterventions, or identifiable personal information. Theresearch isbased on conceptual modeling, literature review, and framework development.

I. INTRODUCTION

Hantavirusesarezoonoticvirusesmainlyassociated 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].IntheWesternHemisphere,some hantaviruses can cause hantavirus pulmonary syndrome (HPS), a severe disease affecting the lungs.Publichealthguidanceemphasizesthatrodent 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].

Fortourismand hospitalitysystems, 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 maintenanceinfluenceexposureprobability.

Second,thebusinessimpactpathwayissocialand economic: public fear, cancellations, medical evacuation,eventdisruption,reputationaldamage, regulatory scrutiny, and cross-border contact tracing can produce large losses even when the numberof clinical cases is small. The2026 WHO Disease Outbreak News report on a cruise-ship-associated Andes hantavirus cluster illustrates the importance of rapid case identification, internationalcontacttracing,laboratory confirmation, isolation, risk communication, and coordinatedpublichealthresponseinatravelsetting [3].

Artificial intelligence (AI) offers a practical opportunity to improve hantavirus preparedness becauseoutbreakriskisrarelyvisiblefromonedata source. A hotel may detect increased rodent complaints before health authorities receive confirmed case reports. A cruise operator may observeillnesssymptomsamongpassengers,butthe signalmayremainambiguouswithouttravelhistory and laboratory data. A public health agency may have confirmed infections, but insufficient operationalinsightintotouristitineraries,ship cabins, excursionsites, orevent-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.

Thisarticlefocusesonthefirstobjectiveofthebroader research project: to examine how AI can be used to predicthantavirusoutbreakrisks.Thearticle does not claim that AI can predict every zoonotic spillover event. Instead, it proposes a decision-support frameworkthatcombinesepidemiologicalknowledge, environmentalmonitoring,travelandhospitalitydata, 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. RESEARCHOBJECTIVEAND QUESTIONS

Thespecificresearchobjectiveaddressedinthis article is: to examine how AIcan 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?

Subquestion2: WhichAImethodsaresuitablefor earlydetection,riskscoring,andforecastingunder conditions of sparse outbreak data?

Subquestion3: HowcanAI-generatedpredictions 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 evidenceonhantavirustransmissionandAI-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. BACKGROUNDANDLITERATURE REVIEW

A. HantavirusRiskCharacteristics

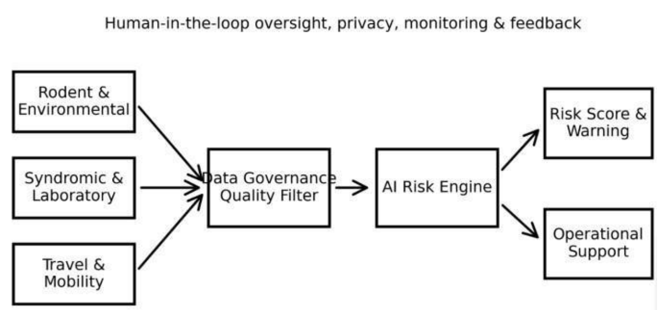
Hantavirusescreateapredictionchallengebecause exposure is often ecological rather than purely interpersonal. The primary signal may originate fromrodentabundance,weatherpatterns,building conditions,food-storagepractices,orhuman activityinrural,forest,farm,ship,orecotourism environments. CDC guidance notes that people are at risk when they contact virus-carrying rodents or contaminated urine, feces, saliva, or nesting materials,withinhalationofcontaminatedairduring cleanup recognized as a key pathway [2]. These exposure conditions are highly relevant to hotels, lodges, camps, restaurants, event centers, cruise ships,andtouristsiteswherefoodstorage,waste handling, enclosed spaces, maintenance routines, and excursions can shape risk.

The severity of HPS also makes early warning important.CDCdescribesHPSasinitiallyflu-likeand potentially progressing to severe respiratory illness; theagencynotesthatHPSisfatalinnearlyfourinten infected people [2]. WHO similarly emphasizedinits 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 shipboardsettings[3]. Thus, AIprediction should not merely count suspected cases. It should estimate both probabilityofexposureandpotentialconsequencefor a given setting.

B. AIandEpidemicIntelligence

AI has increasingly been discussed as a tool for infectious-disease surveillance, outbreak detection, riskassessment,andresponseplanning.Brownsteinet al. describe AI and machine-learning tools as useful foridentifyingandtrackingoutbreaksandmonitoring mitigation strategies [4]. More recent reviews argue thatAIcansupportmultipleoutbreakstages,including early detection, risk assessment, diagnosis, control, andunderstandingofinfectionmechanisms,while warningthatmodelperformancedependsondata quality,interpretability,andprivacy safeguards [5]. AI-driven epidemic intelligence extends traditional public health surveillance by combining structured data, unstructured text, digital signals, and operationalinformation.KaurandButtarguethat

integrated AI-driven epidemic intelligence can improve early warning and forecasting by correlating cross-source data and supporting informedresponse[6].Yangetal.furtherpropose AIagentsthataggregatemultisourceindicators



into composite risk scores, compare those scores against predefined thresholds, and communicate gradedalertsinactionableformats[7].Theseideas are directly applicable to hantavirus risk prediction, especially in high-contact travel and hospitalitysettingswhereweaksignalsmayappear across departments before formal case confirmation.

However, infectious-disease prediction also has a cautionaryhistory.Digitaltracemodelscanoverfit 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 surveillanceratherthantreatedasreplacementsfor public health expertise. For hantavirus, where case countsaresparseandexposuresettingsvarywidely, the strongest AI approach is therefore not a single black-box model, but a supervised, explainable, multisource decision-support framework.

IV. CONCEPTUALMODEL: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 scoreforalocation,businessfacility,conveyance,or travelitineraryatagiventime.Themodelcombines environmental exposure likelihood, clinical signal strength, travel-contact patterns, digital weak signals,businessvulnerability,andcontrolcapacity.

Fig.1.HRP-AImultisourceearlywarningpipeline for hantavirus risk prediction.

A. RiskEquation

Theconceptualriskscorecanberepresentedas follows:

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

wherelrepresentsthelocation,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;andCrepresentscontrolcapacitysuch as sanitation readiness, rodent-control strength, medicalreferralcapacity,andpublichealthresponse readiness.Thesigmoidfunctionconvertsthe weightedinputintoaprobability-likeriskscore between 0 and 1.

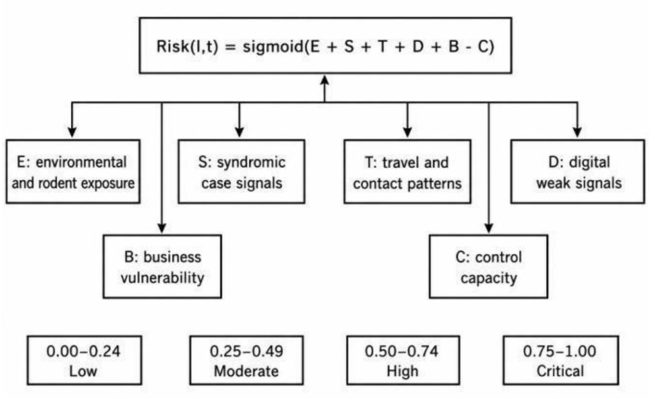


Fig.2.Compositerisk-scorearchitectureandalerttiers.

B. DataSourcesandPredictiveFeatures

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

TABLEI:DATASTREAMSFORAI-BASEDHANTAVIRUSRISKPREDICTION

Datastream	**Examplefeatures**	**Predictionvalue**
Rodentandenvironmental	Rodentcomplaints,trapcounts, nesting evidence, waste conditions,rainfall,vegetation, temperature,buildingage	Estimatesecologicalexposure probability
Syndromicandclinical	Fever,myalgia,cough,shortness ofbreath,gastrointestinal	Detectsearlyhuman illness clusters

	symptoms,clinicvisits, absenteeism	
Laboratoryandcase reports	RT-PCRconfirmation,serology, sequencing, confirmed/probable/suspected casedefinitions	Validatessignalsandtrains supervised labels
Travelandmobility	Itineraries, ship cabin zones, hotelguestorigins,excursion logs,airlineroutelinks, event attendance	Mapsexposurenetworksand importation risk
Digitalweaksignals	Searchtrends,newsreports, social media posts, customer reviews,call-centercomplaints	Addsearlyunstructuredwarning signals
Businessoperations	Occupancy, cancellations, cleaning logs, pest-control reports,staffshortages,supply availability	Linkshealthrisktooperational vulnerability

C. ModelLayers

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 orpseudonymizespersonaldata,andassigns confidence scores to each source. This layer is essential because outbreak prediction is vulnerable tonoise.Forexample,aspikeinonlinesearchesmay 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 exposuredensity,recent sanitation failures, high-risk cleanup events, symptoms compatiblewithHPS,traveloverlapwithconfirmed cases, cabin or room proximity, duration of close contact,localhealthcarecapacity,andbusiness vulnerability. Feature engineering must reflect known hantavirus exposure pathways rather than generic respiratory disease assumptions.

Layer4isAImodeling.Theframeworkusesseveral complementary algorithms. Anomaly detection identifiesunusualdeviationsinrodentcomplaintsor 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 lowscoretriggersroutinemonitoring;moderaterisk triggers enhanced cleaning, pest inspection, and targeted staff awareness; high risk triggers public health consultation, intensified contact review, and operationaladjustments;criticalrisktriggers formal outbreak response, isolation protocols, medical referral, regulatory notification, and crisis communication.

V. AIMETHODSSUITABLEFOR 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.

TABLEII:CANDIDATEAIMETHODSANDTHEIRUSEINHRP-AI

AImethod	Maintask	Applicationtohantavirusrisk
Anomalydetection	Detectunusualchanges	Flags sudden increases in rodent sightings,illnessreports,orguest complaints
Spatiotemporalmodels	Forecastriskacrossplaceand time	Estimates hotspots by destination,facilityzone,cabin group, or travel route
NLPandLLM-assisted extraction	Analyzeunstructuredtext	Extractsexposurecluesfrom reviews,maintenancelogs,news, and field reports
Graphanalytics	Mapexposurenetworks	Linkstravelers,rooms,ship zones,excursions,events,and contacts

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

A. AnomalyDetection

Anomaly detection is useful when confirmed case labels are sparse. Unsupervised methods such as isolationforests,one-classsupportvectormachines, 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 theexpectedbaseline, thesystemcantrigger human review. This approach is especially relevant for hotels,cruiseships,andevent venuesbecausesmall 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 confirmationbeforeescalation. Forexample,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. SpatiotemporalForecasting

Spatiotemporal forecasting is needed because hantavirus risk varies by location, season, environmentalconditions,andhumanmovement.A destinationwithincreasedrainfall,vegetationshifts, 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, andgradientboostingmodelswithlaggedvariables. In practice, simpler interpretable models may be preferredduringinitialdeployment becausethecost 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. NaturalLanguageProcessing

Many early outbreak signals are textual. Hotel maintenance staff may write notes such as rodent droppingsfoundnearstorage.Customersmaypost 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

Hantaviruspredictionintravelandhospitality environmentsrequiresnetworkthinking.Cruise ships,airlines,hotels,restaurants,eventcenters,and touragenciesconnectpeoplethroughcabins,rooms, excursions,transportroutes,diningareas,staff shifts,andsharedindoorspaces.Graphanalyticscan represent these relationships and identify exposure clusters, bridge contacts, and high-centrality locations.

A graph-based layer is especially useful when a confirmedorprobablecaseappears.Thesystemcan rapidlyidentifywhosharedacabinzone,excursion, meal period, transport segment, or event with the case. This approach supports risk-based contact tracing and reduces unnecessarydisruption for low-risk individuals.

VI. APPLICATION TO TOURISM, HOSPITALITY,ANDPUBLICHEALTH

A. HotelsandLodges

Hotelsand lodgescanuseHRP-AItointegratepest-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.Forrurallodgesandecotourismsites, AI can also connect guest excursion data with known rodent exposure conditions and local health alerts.

B. CruiseCompanies

Cruise ships are complex closed or semi-closed environments where close quarters, shared indoor spaces, international travel, and medical evacuation logisticscancomplicateresponse.HRP-AIcanhelp 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, contacttracing, isolation, testing, medical evacuation, and transparent communication, all of whichcanbesupportedbystructuredAIdashboards [3].

C. AirlinesandTourismAgencies

Airlines and tourism agencies may not directly manage rodent exposure, but they can support risk prediction through itinerary reconstruction, passengernotification,route-levelexposure mapping,andintegrationwithpublichealthtraveladvisories.AIcanidentifyoverlappingitineraries,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. RestaurantsandEventCenters

Restaurantsandeventcentersfaceriskthroughfoodstorage,wastedisposal,back-of-housesanitation,facility maintenance, and crowd concentration. HRP-AI can combine pest-control logs, sanitation audits,staffillness reports,supplierdisruptions,and event attendance data. The goal is not tolabel restaurants asdisease sources without evidence, but to detect operational vulnerabilities that could increase exposure risk and trigger preventive action before illness occurs.

E. PublicHealthSystems

Publichealthagenciescanusethemodeltoprioritizeinvestigations,coordinatecontacttracing,identify

environmentalexposuresites,monitordigitalweaksignals,andcommunicatewithbusinesses.AIprediction ismost usefulwhenitimproves 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. MODELVALIDATIONANDEVALUATION

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-modedeploymentmeanstheAIsystemgeneratesriskscoreswithouttriggeringoperational decisionsuntilpublichealthexpertscompareitsalertsagainstrealoutcomesTABLEIII:RECOMMENDED EVALUATION METRICS

Metric	**Purpose**	**Interpretation**
Sensitivity/recall	Detecttrueriskevents	Highvalueisimportantbecause missedoutbreaksarecostly
Specificity	Avoidfalsealarms	Protectsbusinesses from unnecessarydisruption
Precision	Measurealertusefulness	Showshowoftenalertsare meaningful
Leadtime	Assessearlywarningvalue	Measuresdaysgainedbefore officialconfirmation
Calibration	Checkprobabilityaccuracy	Ensurespredictedriskmatches observedrisk

Explainabilityscore	Assessinterpretability	Determineswhetherusers can understanddrivers
Operationalutility	Measuredecisionimpact	Trackswhetheractionsreduce exposureandlosses

A. *ValidationData*

Potential validation data include official case reports, laboratory-confirmed cases, outbreak investigation reports, environmental inspection records, weather and land-use data, historical tourismactivity, 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. *FalsePositivesandFalseNegatives*

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 thereforeusesgradedalertsratherthan automaticshutdowndecisions.Amoderatealert 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-LoopGovernance*

AI predictions must remain advisory. Public health professionals, facility managers, clinicians, and legal or complianceofficersshouldreviewhigh-riskalertsbeforepublicaction.The modelshouldmaintainauditlogs showingdatasources,timestamps,risk

drivers, threshold decisions, and human approvals. This auditability supports accountability and allows retrospective learning after each alert.

VIII. ETHICAL,LEGAL,ANDGOVERNANCECONSIDERATIONS

Although this article focuses on prediction, ethical safeguards are inseparable from AI implementation. Hantavirusriskmodelsmayusesensitivemobility,health,employee,customer,andlocationdata.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, smallrestaurants,andlower-resourcedtourism operatorsmayhavelessdigitaldatathanlargehotelsorcruisecompanies.Amodeltrainedmainlyon high-resourcesettingscouldunder-detectriskinsmallerbusinesses or over-penalizelocations with more transparent reporting. To prevent this, HRP-AI should includeuncertainty estimates, source-coverageindicators,andhumancontextualreview.Transparencyis essentialfortrust. Businessleadersandpublichealthofficialsshouldbeabletoseewhythe modelproducedascore. ExplainableAIoutputs

may include top risk drivers, recent signal changes, geographic clusters, similar historical scenarios, and recommendedverificationsteps.Communicationtothepublicshouldavoidtechnicalexaggerationandpresent 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 AIcancontribute most effectivelyby integratingenvironmentalexposuredata,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 atthe intersectionofhuman mobility, shared spaces, food and waste systems, sanitation, and customer trust. Their data can enrich public health surveillance, whilepublic healthdatacanguidesaferbusiness decisions. HRP-AIthereforecreatesa bridgebetween 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 notbeused.Amodelthatviolatesprivacywillcreate 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 empiricaldeployment.FutureresearchshouldtesttheHRP-AImodelusinghistoricaloutbreakdata,tourism case studies, simulated facility data, and pilot programs with hospitality and public health partners. Comparativestudiescouldevaluatewhether AI-assistedinspection,contacttracing,andriskcommunication 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,andbusiness datato generateexplainableriskscoresfortourism,hospitality,andpublichealthsettings. 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 improvingreadinessbeforecasesescalate.Themost 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 studiesshouldcompareAI-assisted detection with traditional reporting timelines and measureleadtime,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. TABLEIV.PUBLICATIONINFORMATION

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