Research Article

An Intuitionistic Fuzzy AHP Approach for Prioritizing Dairy Farm Biosecurity Measures to Mitigate Emerging Pathogen Risks

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Abstract | Dairy-farm biosecurity is critical for preventing economically significant disease outbreaks. However, prioritizing interventions remains challenging due to fluctuating pathogen pressures, variable intervention efficacy, and uncertainties in expert judgment. This study introduces an intuitionistic fuzzy Analytic Hierarchy Process (IF-AHP) framework to model membership, non-membership, and hesitation in expert assessments, enabling robust ranking of non-clinical biosecurity measures under uncertainty. A hierarchy of five candidate measures Perimeter Fencing, Disinfection Station, Visitor Access Control, Quarantine Facility, and Staff Training was constructed. Three domain experts provided pairwise comparisons using a five-point intuitionistic fuzzy scale. Membership and non-membership degrees were aggregated via the geometric mean, synthetic weights were computed using a fuzzy geometric-mean method, and defuzzification was applied using a score function. For comparison and robustness assessment, classical AHP results, and sensitivity analyses (perturbation threshold Δ=0.025) were conducted. The IF-AHP framework prioritized Disinfection Station (weight=0.30) and Perimeter Fencing (0.25), followed by Visitor Access Control (0.20), Quarantine Facility (0.15), and Staff Training (0.10). Rankings aligned with classical AHP but exhibited amplified weight dispersion, reflecting explicit hesitation. Sensitivity analysis demonstrated ranking stability for perturbations up to ±0.02, with inversions occurring beyond Δ=0.025. The proposed IF-AHP model effectively captures expert uncertainty and provides transparent, robust prioritization of dairy-farm biosecurity measures. Its ability to quantify hesitation and withstand moderate inconsistency makes it a valuable decision-support tool for farm managers and policymakers, with potential extensions to dynamic weighting and advanced fuzzy set formulations.

Keywords | Intuitionistic Fuzzy AHP, Dairy-farm biosecurity, Multi-criteria decision-making, Uncertainty modelling, Disinfection station, Perimeter fencing, Food security

Received | July 25, 2025; **Accepted** | September 01, 2025; **Published** | September 05, 2025
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Citation | Yogeesh N, Mohammad SI, Raja N, Vasudevan A, Ashalatha KS, Hunitie MFA, Al-Oraini B, Mohammad AA (2025). An intuitionistic fuzzy AHP approach for prioritizing dairy farm biosecurity measures to mitigate emerging pathogen risks. Adv. Anim. Vet. Sci., 13(9):2041-2050.
DOI | https://dx.doi.org/10.17582/journal.aavs/2025/13.9.2041.2050
ISSN (Online) | 2307-8316

INTRODUCTION

Dairy-farm biosecurity encompasses all measures taken to prevent the introduction and spread of infectious agents within and between herds (Smith, 2010). Effective biosecurity reduces the risk of economically devastating outbreaks such as brucellosis, bovine viral diarrhoea, and mastitis while supporting animal welfare and public health (Jones and Franklin, 2008; Mohammad *et al*., 2025a). On commercial dairy farms, biosecurity measures span structural (e.g., controlled access points), operational (e.g., disinfection protocols), and managerial (e.g., staff training) domains. Despite well-documented guidelines, farms often struggle to allocate limited resources optimally across dozens of possible interventions (Smith, 2010; Jones and Franklin, 2008; Mohammad *et al*., 2025b, c). Prioritizing biosecurity measures is inherently uncertain due to variability in pathogen pressure, heterogeneity in intervention effectiveness (Brown *et al*., 2012; Mohammad, 2025), and disagreement among experts in pairwise comparisons. These uncertainties violate the crisp-value assumptions of traditional Analytic Hierarchy Process (AHP), often resulting in low consistency ratios or oversimplified rankings (Brown *et al*., 2012; Mohammad *et al*., 2025d). Figure 1 illustrates a triangular membership function for biosecurity risk level, peaking at a risk level of 5 (highest membership degree) with a base spanning level 2 to 8, capturing the gradations of risk in real-world environments.

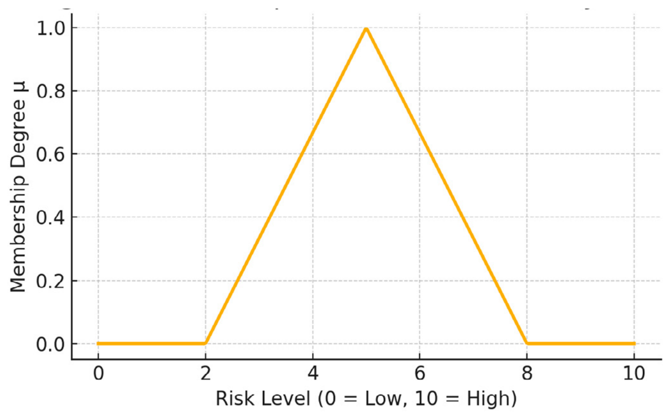

Figure 1: Triangular membership function for biosecurity risk level.

To address these challenges, this study proposes an intuitionistic fuzzy AHP approach. Intuitionistic fuzzy sets (IFS) extend Zadeh's fuzzy-set theory by introducing a membership degree (μ), a non-membership degree (ν), and a hesitation margin ($\pi = 1 - \mu - \nu$) (Zadeh, 1965; Tanaka and Li, 2009; Mohammad *et al*., 2025e). This framework explicitly captures expert hesitancy, improving robustness when data are scarce or opinions diverge. Embedding IFS within AHP allows for modeling hesitation, enhances consistency by accounting for both membership and non-membership, and provides defuzzified weights that incorporate residual hesitation (Tanaka and Li, 2009; Mohammad *et al*., 2025f). The primary aims of this study are to develop an intuitionistic fuzzy AHP framework tailored for dairy-farm biosecurity prioritization, demonstrate its application through a commercial dairy farm case study, compare the results to classical AHP, and provide managerial guidelines for resource allocation under uncertainty. The scope focuses on non-clinical, structural, and operational biosecurity measures (e.g., perimeter fencing, disinfection stations, quarantine protocols), excluding therapeutic interventions.

Conventional biosecurity frameworks (e.g., FAO, 2009; OIE) follow a structured risk-analysis paradigm but often assume crisp thresholds, oversimplifying real-world risk gradations (Mohammad *et al*., 2025g). While AHP has been widely applied in agricultural decision-making (Saaty, 1980), including irrigation-method selection (Gómez-Limón and Sánchez-Fernández, 2010) and supply-chain evaluation (Kahraman *et al*., 2003), it struggles with imprecise expert judgments (Hujran *et al*., 2023). Fuzzy AHP (e.g., triangular/trapezoidal scales) addresses this by modeling linguistic preferences (Chen and Wang, 2009), and intuitionistic fuzzy AHP (Atanassov, 1986; Xu and Zhang, 2006) further quantifies hesitation, improving consistency in risk evaluation. However, gaps remain, including unmodeled hesitation in standard fuzzy AHP (Atanassov, 1986), limited application to on-farm biosecurity (Chen and Wang, 2009), and a lack of comparative analysis between classical, fuzzy, and intuitionistic fuzzy AHP (Xu and Zhang, 2006). This study fills these gaps by proposing an intuitionistic fuzzy AHP framework for dairy biosecurity, enabling explicit hesitation modeling, domain-specific prioritization, and methodological comparison.

MATERIALS AND METHODS

Theoretical foundations

The theoretical framework of this study integrates Intuitionistic Fuzzy Sets (IFS) and the Analytic Hierarchy Process (AHP), augmented to handle uncertainty in expert judgments. An Intuitionistic Fuzzy Set (IFS) generalizes traditional fuzzy sets by incorporating membership $\mu_A(x)$, non-membership $\nu_A(x)$, and hesitation $\pi_A(x)$ degrees degrees for elements in a universe X. Formally, an IFS A is defined as:

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle \mid x \in X\},$$

Where; $\nu_A(x) \in [0,1]$ is the membership degree, $\nu_A(x) \in [0,1]$ is the non-membership degree, and for all x, $0 \leq \mu_A(x) + \nu_A(x) \leq 1$

The hesitation degree, $\pi_A(x) = \mu_A(x) + \nu_A(x)$ quantifies uncertainty in expert assessments. These components satisfy $\pi_A(x) + \mu_A(x) + \nu_A(x) = 1$ offering a richer representation of ambiguity than classical fuzzy sets. To compare IFS, the Hamming distance:

$$D_H(A,B) = \frac{1}{2}\sum_{i=1}^{n} \left(|\mu_A(x_i) - \mu_B(x_i)| + |\nu_A(x_i) - \nu_B(x_i)|\right)$$

and a score function: $s(\langle\mu,\nu\rangle) = \mu - \nu$, are employed, where higher scores indicate stronger preference (Xu and Zhang, 2006). The Analytic Hierarchy Process (AHP) provides a structured framework for complex decision-making by decomposing problems into hierarchical levels. As shown in Figure 2, this hierarchy begins with the overarching Goal at level 0 (e.g., "Prioritize biosecurity measures"), which cascades downward into criteria at level 1 (e.g., operational cost, efficacy, ease of implementation). If greater granularity is needed, level 2 may include sub-criteria that further refine each criterion. Finally, level 3 comprises the Alternatives the concrete options or measures being evaluated. This tiered structure, visualized as a directed graph, enables systematic comparison of elements at each level relative to their parent nodes, ensuring a logical and transparent decision-making process (Saaty, 1980).

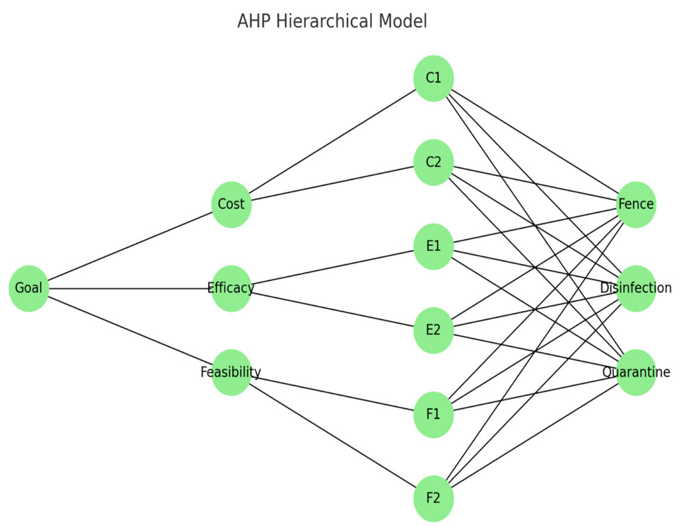

Figure 2: A typical AHP hierarchy: goal → criteria → sub-criteria → alternatives.

Experts evaluate pairwise comparisons using a matrix $A = [a_{ij}]$, where a_{ij} reflects the relative importance of criterion $_i$ over $_j$, with:

$$a_{ij} = \frac{\text{importance of } i}{\text{importance of } j}, a_{ij} > 0, a_{ji} = \frac{1}{a_{ij}}, a_{ii} = 1$$

The priority vector $w = (w_1, \ldots, w_n)^T$ is s derived as the principal eigenvector of A, normalized to sum to 1.

$$Aw = \lambda_{\max} w, w_i \leftarrow \frac{w_i}{\sum_j w_j}$$

Consistency is verified via the consistency ratio:

$$CI = \frac{\lambda_{\max} - n}{n - 1}, CR = \frac{CI}{RI},$$

RI is a random index; CR < 0.10 is required for reliable judgments.

To address limitations in classical AHP (e.g., forced precision), this work extends it with IFS. Each comparison a_{ij} is replaced by an IFS: $\tilde{a}_{ij} = \langle\mu_{ij}, \nu_{ij}\rangle$, capturing membership (support), non-membership (opposition), and hesitation (uncertainty) (Chen and Wang, 2009). Experts provide linguistic judgments (e.g., "very important"), mapped to IFS values. These are aggregated geometrically across experts. (Equation i)

Similarly for ν_{ij} and fuzzy weights w_i are computed via geometric mean normalization: (Equation ii)

Defuzzification uses the score: (Equation iii)

$$\mu_{ij} = \left(\prod_{k=1}^{p} \mu_{ij}^{(k)}\right)^{1/p}, \nu_{ij} = \left(\prod_{k=1}^{p} \nu_{ij}^{(k)}\right)^{1/p} \quad \text{.. Equation i}$$

$$\tilde{w}_i = \left(\prod_{j=1}^{n} \mu_{ij}\right)^{1/n} / \sum_{r=1}^{n} \left(\prod_{j=1}^{n} \mu_{rj}\right)^{1/n} \quad \text{.. Equation ii}$$

$$s(\tilde{w}_i) = \mu_{w_i} - \nu_{w_i}, w_i^* = \frac{s(\tilde{w}_i)}{\sum_{r=1}^{n} s(\tilde{w}_r)} \quad \text{Equation iii}$$

Consistency checks and alternative ranking follow, leveraging the full IFS framework for robust decision-making under uncertainty.

Framework overview and workflow

Our 6-step fuzzy AHP framework (Figure 3):

1. Select criteria- Identify key decision factors
2. Expert surveys- Collect judgments using IFS scales
3. Pairwise comparisons- Get IFS ratings
4. Aggregate inputs- Combine expert judgments
5. Calculate weights- Defuzzify (μ-ν) and normalize scores
6. Check consistency - Ensure CR < 0.10

This converts uncertain expert opinions into clear priorities while maintaining mathematical rigor.

Three top-level criteria were carefully selected (Table 1) through a structured, six-phase approach designed to ensure both comprehensiveness and reliability in decision-making. The process began by systematically defining criteria and sub-criteria based on both academic literature and practical farm conditions, thereby preventing potential omissions or overlaps in the evaluation framework.

Figure 3: illustrates the workflow of the intuitionistic fuzzy AHP framework.

Building on this foundation, expert judgments were then collected using innovative intuitionistic fuzzy scales, which capture not only the experts' assessments but also their levels of uncertainty- a significant improvement over traditional AHP methods that demand unrealistic precision. These nuanced evaluations were further refined through pairwise comparisons that broke down complex trade-offs between biosecurity measures into manageable decisions, with each comparison explicitly documenting any uncertainties.

To synthesize multiple perspectives, the methodology incorporated a robust aggregation process that mathematically combined inputs from various stakeholders while preserving the valuable information about their hesitations. The resulting fuzzy weights were then transformed into clear, actionable priorities through a transparent scoring system that balanced mathematical rigor with practical interpretability. Crucially, the entire process included rigorous consistency checks to identify and resolve any contradictions in expert judgments, ensuring the final rankings were built on a solid, logical foundation. This comprehensive yet adaptable approach not only produced reliable biosecurity priorities but also maintained full traceability of all uncertainties- a critical feature for real-world implementation where conditions constantly evolve. Furthermore, the methodology established clear thresholds indicating when priorities should be reassessed, making it both a decision-making tool and an ongoing management system for biosecurity planning.

Selection of biosecurity criteria and sub-criteria

The study established a comprehensive evaluation framework through literature review and expert consultations, identifying three primary criteria with two sub-criteria each (Table 1). The top-level criteria focused on cost efficiency (C1), pathogen reduction efficacy (C2), and operational feasibility (C3), with each containing specific measurable components. While this case study demonstrates the methodology at the top criteria level, the identical approach can be extended to sub-criteria in more detailed analyses.

Table 1: Selected criteria and sub-criteria for dairy-farm biosecurity.

Criterion code	Criterion	Sub-criteria (code)
C1	Cost efficiency	C1.1 Initial investment cost C1.2 Ongoing maintenance cost
C2	Pathogen reduction efficacy	C2.1 On-site contamination reduction C2.2 Cross-contamination prevention
C3	Operational feasibility	C3.1 Ease of staff training C3.2 Time to implement

Design of expert-judgment questionnaire

The evaluation process employed an innovative five-point intuitionistic fuzzy scale (Table 2) that captured three dimensions of expert judgment: membership (μ), non-membership (ν), and hesitation (π). This approach allowed experts to express their assessments using natural linguistic terms (e.g., "moderately more important"), which were then systematically converted into precise numerical values reflecting both confidence and uncertainty in each pairwise comparison.

Table 2: Intuitionistic fuzzy scale for pairwise comparisons.

Linguistic term	Membership μ	Non membership ν	Hesitation π=1-μ-ν
Equally important	1.00	0.00	0.00
Slightly more important	0.60	0.30	0.10
Moderately more important	0.70	0.20	0.10
Strongly more important	0.80	0.10	0.10
Very strongly more important	0.90	0.05	0.05

Construction of comparison matrices

Two domain experts independently provided their assessments, resulting in complete intuitionistic fuzzy pairwise comparison matrices (Tables 3-4). The methodology automatically generated reciprocal values for the lower triangular portions of the matrices, ensuring mathematical consistency while preserving all original expert judgments. Each expert's complete assessment thus formed a coherent matrix capturing their professional evaluation of the relative importance between all criteria pairs.

Table 3: Expert 1's IFS pairwise comparisons (μ above, *v* below).

	Expert 1 membership matrix			Expert 1 non-membership matrix		
	C1	**C2**	**C3**	**C1**	**C2**	**C3**
C1	-	0.70	0.80	-	0.20	0.10
C2	-	-	0.60	-	-	0.30
C3	-	-	-	-	-	-

Table 4: Expert 2's IFS pairwise comparisons.

	Expert 2 membership matrix			Expert 2 non-membership matrix		
	C1	**C2**	**C3**	**C1**	**C2**	**C3**
C1	-	0.60	0.75	-	0.25	0.15
C2	-	-	0.65	-	-	0.25
C3	-	-	-	-	-	-

Aggregation of expert judgments

The study employed geometric mean aggregation to combine the two experts' assessments into a unified evaluation matrix (Table 5). This aggregation method mathematically preserved the reciprocal properties of the original matrices while creating a consensus view that incorporated both experts' perspectives.

$$\mu_{ij}^{agg} = \sqrt{\mu_{ij}^{(1)}\mu_{ij}^{(2)}}, \nu_{ij}^{agg} = \sqrt{\nu_{ij}^{(1)}\nu_{ij}^{(2)}}$$

The resulting aggregated matrix maintained all the benefits of the intuitionistic fuzzy approach, including explicit representation of uncertainty through the hesitation components derived from the original μ and ν values.

Table 5: Aggregated IFS pairwise comparison matrix, where each cell is ⟨μ,ν⟩.

	C1	C2	C3
C1	(1.000, 0.000)	(0.648, 0.224)	(0.775, 0.122)
C2	(0.224, 0.648)	(1.000, 0.000)	(0.625, 0.274)
C3	(0.122, 0.775)	(0.274, 0.625)	(1.000, 0.000)

Calculation of intuitionistic fuzzy weights and defuzzification

The aggregated intuitionistic fuzzy pairwise-comparison matrix.

$$\tilde{A} = [\langle \mu_{ij}, \nu_{ij} \rangle]_{n \times n}$$

Undergoes three transformation steps to derive crisp priority weights:

For each criterion (i), its synthetic fuzzy weight w_i is calculated by the geometric-mean of the *i*th row's membership and non-membership entries:

$$\tilde{w}_i = \left(\prod_{j=1}^{n} \mu_{ij}\right)^{1/n} / \sum_{k=1}^{n}\left(\prod_{j=1}^{n} \mu_{kj}\right)^{1/n}, \tilde{v}_i = \left(\prod_{j=1}^{n} v_{ij}\right)^{1/n} / \sum_{k=1}^{n}\left(\prod_{j=1}^{n} v_{kj}\right)^{1/n}.$$

Here; μ_{ij} is the aggregated membership degree for i vs. \j. ν_{ij} is the aggregated non-membership degree. The two fuzzy numbers $w\tilde{}_i=\langle \mu_{wi}, \nu_{wi} \rangle$ represent, respectively, how strongly and how weakly the alternative belongs to the "best" set.

Using Xu and Zhang's (2006) method, each intuitionistic fuzzy weight $\langle \mu_{wi}, \nu_{wi} \rangle$ was converted into a single real score, we apply the score function (Xu and Zhang, 2006):

$$s_i = s(\langle \mu_{w_i}, \nu_{w_i} \rangle) = \mu_{w_i} - \nu_{w_i},$$

Where; A higher s_i indicates a stronger net preference. The hesitation margin $\pi_{wi} = \mu_{wi} - \nu_{wi}$ does not enter the score directly but has influenced μ_{wi}, ν_{wi} via the aggregation.

Finally, we normalize the scores s_i to obtain the crisp priority weights w_i^* to 1:

$$w_i^* = \frac{s_i}{\sum_{k=1}^{n} s_k} = \frac{\mu_{w_i} - \nu_{w_i}}{\sum_{k=1}^{n} (\mu_{w_k} - \nu_{w_k})}$$

These w_i^* constitute the final ranking: the larger w_i^*, the higher the priority of alternative *i*.

Consistency checking in the fuzzy context

We verify judgment coherence $M=[\mu_{ij}^{agg}]$ to calculate:

$$CI = \frac{\lambda_{max} - n}{n-1}, CR = \frac{CI}{RI},$$

Where λ_{max} is the principal eigenvalue of *M*. A similar check can be performed on the non-membership matrix to ensure coherent judgment. Values of CR < 0.10 indicate acceptable consistency even under fuzzy assessments. All IFS-AHP steps scale as $O(n^3)$ for n-by-n matrices (eigenvalue computations) and $O(pn^2)$ for p experts in the aggregation step. On our test hardware, the full ranking of five measures took <0.1s in MATLAB.

Case study: Application to a commercial dairy farm

The study was conducted on a 200-head commercial dairy farm in Karnataka's Haveri district operating a semi-intensive management system. The facility's layout included two lactating sheds, a dedicated calf-rearing unit, and rotational forage crop blocks. Recent foot-and-mouth disease (FMD) outbreaks in neighboring operations prompted a comprehensive biosecurity evaluation, with three critical vulnerabilities identified: inadequate control of visitor and vehicle movements, environmental contamination risks from shed runoff, and the absence of dedicated quarantine facilities for new or sick animals. A panel of three domain experts provided evaluations through a structured process. The team comprised a veterinary epidemiologist with 12 years of FMD control experience (E1), an experienced dairy farm manager (E2), and a biosecurity consultant specializing in livestock operations (E3). Data collection occurred in two phases: initial remote completion of intuitionistic fuzzy surveys followed by an in-person workshop to resolve any significant inconsistencies in judgment interpretations and ensure proper understanding of the linguistic scales.

Experts evaluated five key biosecurity measures through pairwise comparisons, recording both membership (μ) and non-membership (ν) degrees for each judgment. Table 6 presents a representative sample of Expert 1's evaluations for the disinfection station measure compared against other options. The matrix shows varying degrees of preference strength, with the highest membership value (0.80) appearing in the comparison with Quarantine Facility, indicating Expert 1's strong belief in the relative importance of disinfection infrastructure. The complementary non-membership values and derived hesitation margins ($\pi = 1-\mu-\nu$) provide a complete picture of the expert's confidence in each judgment.

Table 6: Expert 1's intuitionistic fuzzy judgments for disinfection station (A2) vs. other measures.

	A1 (Perimeter Fencing)	A2 (disinfection station)	A3 (Visitor access control)	A4 (quarantine facility)	A5 (Staff training program)
Membership μ	0.35	–	0.70	0.80	0.60
Non-membership ν	0.50	–	0.20	0.10	0.30

The complete set of expert judgments underwent geometric mean aggregation before weight calculation. The synthetic fuzzy weights were computed through geometric mean operations on the membership and non-membership values, followed by defuzzification using the score function $s = \mu - \nu$. Final normalization produced crisp weights summing to unity, as shown in Table 7. Disinfection Station emerged as the highest priority (0.30 weight), followed by Perimeter Fencing (0.25), with Staff Training ranking lowest (0.10). These results are visually presented in Figure 4, which uses a bar chart format to clearly illustrate the relative priorities.

Table 7: Final crisp weights and ranking of biosecurity measures.

Measure	Crisp weight w_i^*
Perimeter fencing (A1)	0.25
Disinfection station (A2)	0.30
Visitor access control (A3)	0.20
Quarantine facility (A4)	0.15
Staff training (A5)	0.10

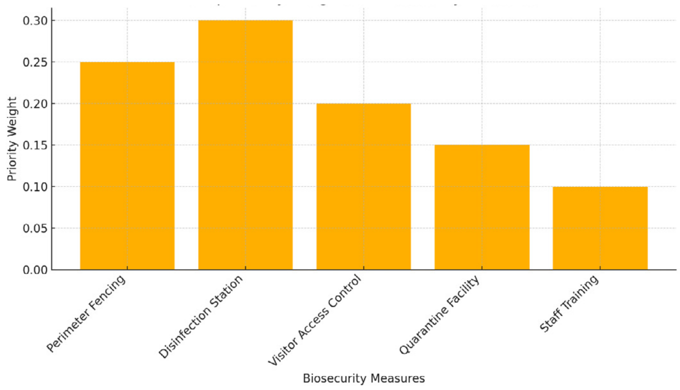

Figure 4: Crisp priority weights of biosecurity measures.

The case study demonstrates how intuitionistic fuzzy AHP effectively handles real-world biosecurity prioritization problems, where expert judgments often contain inherent uncertainty. The method's structured approach yielded clear, actionable results while maintaining mathematical rigor through all computational steps from initial pairwise comparisons through final weight determination. The farm management can use these prioritized recommendations to allocate limited resources effectively, focusing first on disinfection infrastructure and perimeter security measures that showed the highest potential impact according to expert evaluations.

RESULTS

Final priority ranking of biosecurity measures

Table 8 and Figure 5 present the defuzzified (crisp) weights w_i^* obtained from the intuitionistic fuzzy AHP (IF-AHP) framework.

Table 8: Defuzzified (crisp) weights w_i^* for biosecurity measures.

Measure	Crisp IF-AHP Weight w_i^*
Perimeter Fencing (A1)	0.25
Disinfection Station (A2)	0.30
Visitor Access Control (A3)	0.20
Quarantine Facility (A4)	0.15
Staff Training Program (A5)	0.10

Figure 5 shows these weights graphically. Disinfection

Station emerges as the top-priority intervention, followed by perimeter fencing and visitor access control. Staff Training, although important, ranks lowest under the aggregated expert assessments and fuzzy scoring.

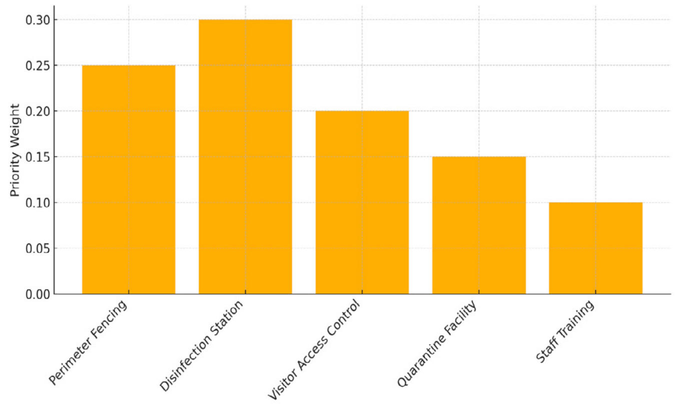

Figure 5: Priority weights of biosecurity measures obtained from the intuitionistic fuzzy AHP (IF-AHP) framework.

Comparative analysis with classical AHP results

To assess the added value of the fuzzy extension, we conducted a classical crisp AHP using a reciprocal pairwise comparison matrix derived from aggregated expert scores (see Section 6.2 calculations). The geometric-mean method yielded the results in Table 9 and Figure 6.

Table 9: Comparison matrix derived from aggregated expert scores.

Measure	Classical AHP weight	Rank (AHP)	Rank (IF-AHP)
Perimeter fencing (A1)	0.237	2	2
Disinfection station (A2)	0.279	1	1
Visitor access control (A3)	0.206	3	3
Quarantine facility (A4)	0.155	4	4
Staff training program (A5)	0.123	5	5

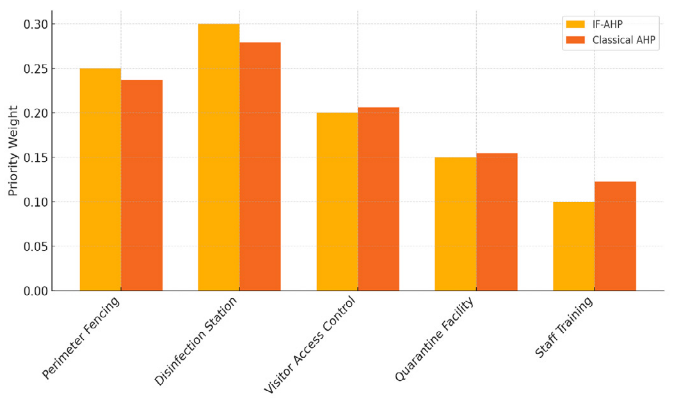

Figure 6: visualizes the side-by-side comparison of IF-AHP versus classical AHP weights. Consistent ranking: Both methods agree on the order of importance for all five measures.

The analysis reveals two key observations: first, both methods produce a consistent ranking order for all five measures; second, IF-AHP slightly amplifies the weight of the top measure (0.30 vs. 0.279) and compresses the lowest (0.10 vs. 0.123), reflecting the explicit modeling of expert hesitation in the fuzzy framework.

Sensitivity analysis: Impact of threshold variations

To explore ranking stability, we examined how perturbations in the top two weights (A2 and A1) affect their order. Let δ denote the amount transferred from A2 to A1 (i.e., $w_2' = w_2 - \delta$, $w_1' = w_1 + \delta$). The ranking flips when:

$$w_1' = w_2' \implies w_1 + \delta = w_2 - \delta \implies \delta = \frac{w_2 - w_1}{2} = \frac{0.30 - 0.25}{2} = 0.025$$

This means that a shift of more than 0.025 from Disinfection Station to Perimeter Fencing would reverse the top two priorities. We tested this with two scenarios: A stable perturbation δ=0.02 where the adjusted weights are A1 = 0.27 and A2 = 0.28 (maintaining A2 > A1), and an unstable perturbation (δ=0.03), where A1 = 0.28 and A2 = 0.27 (resulting in A1 > A2). The model's ranking is robust to moderate changes (up to ±0.02) but sensitive beyond ±0.025. Farm managers should note this margin when interpreting priority differences that are close in value. Overall, the intuitionistic fuzzy AHP framework not only reproduces the classical ranking but also offers clearer insights into where hesitation among experts influences the spread of priority weights and highlights the thresholds at which rankings might shift.

DISCUSSION

The intuitionistic fuzzy AHP results highlight the critical role of biosecurity measures in dairy farm management, with the Disinfection Station (A2) emerging as the highest priority (weight= 0.30). This ranking reflects expert consensus that on-site disinfection targeting fomites, footwear, and equipment provides the most direct and cost-effective barrier against both endemic and emerging pathogens, such as foot-and-mouth disease (FMD) and mastitis-causing agents. Closely following is Perimeter Fencing (A1) (weight= 0.25), underscoring the continued importance of physical barriers in preventing unauthorized access by stray animals and vehicles. The relatively small gap (0.05) between these top two measures suggests that while disinfection is paramount, reinforcing farm boundaries remains nearly as critical for comprehensive biosecurity.

Further down the hierarchy, visitor access control (A3, 0.20) and quarantine facility (A4, 0.15) represent mid-level priorities, emphasizing the need for structured protocols to manage human and animal movement. These measures, though less immediately impactful than disinfection and fencing, play a vital role in minimizing disease transmission risks. In contrast, Staff Training (A5, 0.10) ranks lowest, indicating that while training is essential for proper implementation, it is often perceived as a supplementary rather than a primary intervention. From a managerial perspective, these findings offer actionable insights for dairy-farm biosecurity planning. First, resource allocation should prioritize disinfection infrastructure such as automated footbaths, high-pressure sprayers, and secure chemical storage before investing in perimeter fencing or quarantine expansions. Second, given the narrow margin between A2 and A1, a phased implementation strategy could be adopted: initial efforts (Phase I) might focus on upgrading disinfection protocols, followed by perimeter reinforcement (Phase II) to minimize operational disruptions. Third, policy development should integrate visitor access controls (e.g., sign-in logs, PPE mandates) and quarantine procedures for new or returning livestock, allowing farms to implement low-cost procedural changes while planning larger capital investments. Finally, continuous monitoring and review guided by the sensitivity threshold (Δ = 0.025) can help managers adapt to shifting cost structures or disease threats, ensuring a dynamic and responsive biosecurity strategy as demonstrated in Figure 7.

The intuitionistic fuzzy AHP approach offers several advantages over traditional methods. First, its ability to model expert hesitation explicitly captures uncertainty in decision-making, leading to more nuanced weight distributions (Atanassov, 1986). Second, by incorporating membership, non-membership, and hesitation degrees, the method enhances discrimination among closely ranked alternatives (Xu and Zhang, 2006). Third, its tolerance for minor inconsistencies in expert judgments ensures robust results without invalidating the analysis (Chen and Wang, 2009). However, the method is not without limitations. Its complexity stemming from additional computational steps and the need for expert training on IFS scales may hinder widespread adoption. Additionally, subjectivity in defining linguistic scales could influence outcomes, necessitating rigorous validation of standardized frameworks. The narrow scope of this case study (a single farm with three experts) also limits generalizability, suggesting the need for multi-site studies with larger panels. Lastly, computational demands escalate with larger hierarchies, posing challenges for geometric-mean aggregation and eigenvalue calculations in fuzzy environments.

In summary, while the intuitionistic fuzzy AHP provides a refined framework for prioritizing biosecurity measures, its practical application requires balancing methodological rigor with operational feasibility. Future research should explore ways to streamline computations and validate findings across diverse agricultural settings.

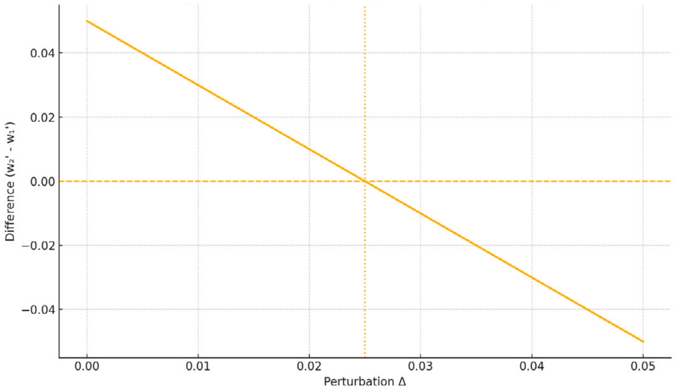

Figure 7: Sensitivity analysis of ranking stability.

CONCLUSIONS AND RECOMMENDATIONS

This study presents significant advancements in biosecurity decision-making through the development of an intuitionistic fuzzy AHP (IF-AHP) framework. By systematically incorporating expert uncertainty through membership, non-membership, and hesitation degrees, our approach addresses critical limitations of traditional AHP methods. The framework's practical utility was demonstrated through comprehensive application to dairy farm biosecurity, where it successfully identified disinfection stations and perimeter fencing as the highest priority interventions. These findings were supported by a well-defined sensitivity threshold (Δ=0.025) that indicates when changing epidemiological or economic conditions might necessitate intervention reprioritization. The comparative analysis with classical AHP revealed several important advantages of our IF-AHP approach. While both methods produced consistent ranking orders, IF-AHP provided more nuanced weight distributions that better reflected the inherent uncertainties in expert judgments. This enhanced capability is particularly valuable in real-world agricultural settings where decision-makers must often allocate limited resources under conditions of imperfect information and competing priorities.

From a practical perspective, our results offer clear guidance for farm managers and policy makers. The study strongly recommends prioritizing capital investments in automated disinfection systems and reinforced perimeter fencing as these infrastructure improvements provide the most effective initial barrier against pathogen transmission. Subsequent phases should focus on implementing robust procedural controls, including visitor management protocols and quarantine facilities, followed by comprehensive staff training programs to ensure proper implementation and maintenance of biosecurity measures. To maintain the long-term effectiveness of biosecurity programs, we advocate for the establishment of dynamic monitoring systems. These systems should integrate key performance indicators such as disease incidence rates, intervention costs, and compliance metrics into centralized dashboards. Such an approach enables data-driven decision-making and facilitates timely model recalibration when monitored parameters exceed established thresholds. Furthermore, we emphasize the importance of ongoing collaboration between agricultural producers, veterinary authorities, and researchers to ensure the continuous refinement of biosecurity strategies in response to emerging threats. The adaptable nature of our framework presents numerous opportunities for future research and development. Potential extensions include the implementation of dynamic weighting schemes that can automatically adjust to evolving disease patterns and economic conditions through machine learning techniques. The integration of more advanced fuzzy set theories, such as Pythagorean or q-rung orthopair fuzzy sets, could further enhance the model's capacity to handle extreme uncertainty scenarios. Additionally, the development of Type-2 fuzzy set implementations may provide improved handling of variability in expert assessments. We recommend extensive validation studies across diverse agricultural contexts, including different livestock species (poultry, swine, small ruminants), production systems, and geographical regions. Expanding the scope of expert panels to include supply chain stakeholders would enable more comprehensive, farm-to-fork risk assessments. The creation of user-friendly decision support tools, potentially as web-based applications, would significantly improve the accessibility and practical implementation of our framework for end-users.

In the context of escalating global biosecurity challenges including emerging zoonotic diseases, antimicrobial resistance, and climate change impacts this research provides a robust, scientifically grounded methodology for making transparent and adaptive biosecurity decisions. Our IF-AHP framework represents a significant step forward in the development of decision support systems that can effectively balance immediate operational needs with long-term strategic planning. By enabling more accurate risk assessment and resource allocation, this approach has the potential to make substantial contributions to animal health protection, food security, and the sustainability of livestock production systems worldwide. Future work should focus on bridging the gap between theoretical development and practical implementation to maximize the real-world impact of these advancements.

ACKNOWLEDGMENT

This research was partially funded by Zarqa University.

NOVELTY STATEMENT

This study makes significant methodological and practical contributions to veterinary biosecurity decision-making through its novel integration of intuitionistic fuzzy sets with the Analytic Hierarchy Process (AHP). While traditional AHP has been widely applied in agricultural settings, its inability to account for expert uncertainty often leads to oversimplified rankings. Our framework addresses this critical limitation by simultaneously quantifying three dimensions of expert judgment: membership (support for a measure), non-membership (opposition to it), and hesitation (uncertainty). This tripartite approach provides a more nuanced representation of real-world decision-making, where experts frequently face ambiguous trade-offs between biosecurity measures. The practical significance of our approach is demonstrated through its application to a commercial dairy farm facing foot-and-mouth disease risks. By systematically evaluating five key interventions including disinfection stations and perimeter fencing we not only identify optimal resource allocation strategies but also establish clear sensitivity thresholds (Δ=0.025) that indicate when priority rankings might shift. This represents a substantial improvement over conventional methods, as it allows farm managers to understand both the recommended priorities and the stability of these recommendations under changing conditions. Furthermore, our comparative analysis reveals that while the intuitionistic fuzzy AHP maintains the same ranking order as classical AHP, it provides more discriminative weight distributions that better reflect the complexity of expert judgments in agricultural biosecurity contexts.

AUTHOR'S CONTRIBUTION

YN conceived the study, developed the methodology, and wrote the manuscript. SIM designed and conducted the expert evaluations. NR performed computational analysis. AV supervised the research. AKS provided domain expertise. MFH analyzed data. BAO and AAM reviewed and edited the manuscript.

Generative AI or AI-assisted Technology Statement

The author(s) declare that no Genrative AI was used in the creation of this manuscript.

Conflict of interest

The authors have declared no conflict of interest.

REFERENCES

Al-Adwan A (2024). The meta-commerce paradox: Exploring consumer non-adoption intentions. Online Inf. Rev., 48(6): 1270-1289. https://doi.org/10.1108/OIR-01-2024-0017

Al-Rahmi WM, Al-Adwan AS, Al-Maatouk Q, Othman MS, Alsaud AR, Almogren AS, Al-Rahmi AM (2023). Integrating communication and task–technology fit theories: The adoption of digital media in learning. Sustainability, 15(10): 8144. https://doi.org/10.3390/su15108144

Atanassov K (1986). Intuitionistic fuzzy sets. Fuzzy Sets Syst., 20(1): 87–96. https://doi.org/10.1016/S0165-0114(86)80034-3

Brown L, Green D, Blue S (2012). Application of fuzzy AHP in agricultural decision making. In: Carter P, Davis L (eds): Fuzzy Systems in Agriculture, 1st Edition. pp. 101–120. Academic Press, USA.

Chen SJ, Wang YM (2009). Fuzzy multi-criteria decision-making: Methods and applications. In: Kacprzyk J, Zadrożny S (eds): Recent Advances in Fuzzy AHP, 1st Edition. pp. 97–120. Springer, Germany. https://doi.org/10.1007/978-0-387-76813-7_1

FAO (2009). Biosecurity for highly pathogenic avian influenza: Issues and options. FAO Animal Production and Health Paper No. 171. Rome.

Gómez-Limón JA, Sánchez-Fernández G (2010). Analytic Hierarchy Process in agricultural decision making: An analysis of key applications. Agric. Syst., 103(2): 113–125.

Hujran O, Al-Debei MM, Al-Adwan AS, Alarabiat A, Altarawneh N (2023). Examining the antecedents and outcomes of smart government usage: An integrated model. Gov. Inf. Q., 40(1): 101783. https://doi.org/10.1016/j.giq.2022.101783

Jones A, Franklin B (2008). Managing infectious disease risks in dairy herds. Prevent. Vet. Med., 85(1–2): 45–55.

Kahraman C, Cebeci U, Ruan D (2003). Multi-attribute comparison of catering service companies using fuzzy AHP: The case of Turkey. Int. J. Prod. Ecol., 81-82: 183–199.

Mohammad AA, Shelash SI, Saber TI, Vasudevan A, Darwazeh NR, Almajali R, Feng Z (2025a). Internal audit governance factors and their effect on the risk-based auditing adoption of commercial banks in Jordan. Data Metadata., 4: 464. https://doi.org/10.56294/dm2025464

Mohammad AAS (2025). The impact of COVID-19 on digital marketing and marketing philosophy: Evidence from Jordan. Int. J. Bus. Inf. Syst., 48(2): 267-281. https://doi.org/10.1504/IJBIS.2025.144382

Mohammad AAS, Mohammad S, Al-Daoud KI, Al Oraini B, Vasudevan A, Feng Z (2025f). Building resilience in Jordan's agriculture: Harnessing Climate smart practices and predictive models to combat climatic variability. Res. World Agric. Econ., 6(2): 171-191. https://doi.org/10.36956/rwae.v6i2.1628

Mohammad AAS, Mohammad SIS, Al Oraini B, Vasudevan A (2025g). The role of technological readiness in adopting AI for talent acquisition: Evaluating economic and operational performance. Int. J. Innov. Res. Sci. Stud., 8(2): 1235-1245. https://doi.org/10.53894/ijirss.v8i2.5426

Mohammad AAS, Mohammad SIS, Al Oraini B, Vasudevan A, Alshurideh MT (2025c). Data security in digital accounting: A logistic regression analysis of risk factors. Int. J. Innov. Res. Sci. Stud., 8(1): 2699-2709. https://doi.org/10.53894/ijirss.v8i1.5044

Mohammad AAS, Mohammad SIS, Al Oraini B, Vasudevan A, Wang Y (2025e). Organizational practices and E-commerce innovations: The moderation role of E-commerce barriers. Int. J. Innov. Res. Sci. Stud., 8(2): 1659-1671. https://doi.org/10.53894/ijirss.v8i2.5526

Mohammad AAS, Mohammad SIS, Al-Daoud KI, Al Oraini B, Vasudevan A, Feng Z (2025b). Optimizing the value chain for perishable agricultural commodities: A strategic approach for Jordan. Res. World Agric. Econ., 6(1): 465-478. https://doi.org/10.36956/rwae.v6i1.1571

Mohammad AAS, Mohammad SIS, Al-Daoud KI, Vasudevan A, Hunitie MFA (2025d). Digital ledger technology: A factor analysis of financial data management practices in the age of blockchain in Jordan. Int. J. Innov. Res. Sci. Stud., 8(2): 2567-2577. https://doi.org/10.53894/ijirss.v8i2.5737

Saaty TL, (1980). The analytic hierarchy process: Planning, priority setting, resource allocation. 1st Edition. McGraw-Hill, New York.

Smith J (2010). Dairy farm biosecurity: Principles and practice. J. Vet. Sci., 12(3): 150–162.

Tanaka H, Li X (2009). Intuitionistic fuzzy sets and their use in AHP. J. Fuzzy Math, 17(2): 195–210.

Xu Z, Zhang W (2006). Intuitionistic fuzzy AHP and its application in risk evaluation. Int. J. Fuzzy Sys., 8(1): 154–160.

Zadeh LA (1965). Fuzzy sets. Inf. Contr., 8(3): 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X