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Integrating centrality measures and multi-criteria decision-making for enhanced food safety risk assessment: a RASFF-based approach

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The increasing complexity of global food supply chains makes early detection and response to food safety risks a persistent challenge. This study proposes a hybrid framework that integrates multilayer, directed network analysis with entropy-weighted multi-criteria decision making (MCDM) to prioritize hazards, products, and countries from RASFF notifications (2020–2024). RASFF data are modelled as a network with origin→notifier edges, partitioned by notification type (Alerts, Border Rejections, Information for Attention, Information for Follow-up). Node roles are quantified using degree, betweenness, closeness (for directed/disconnected graphs), and eigenvector centrality, then synthesized with burden indicators (frequency, severity, product–hazard mix) via an MCDM ensemble (TOPSIS, VIKOR, PROMETHEE II) under entropy weighting. Results reveal a stable EU core (Germany, Netherlands, France, Belgium) and type-specific elevation of Turkey, India, China, Spain, and Poland in border-facing layers; category priorities concentrate in Fruits & Vegetables, Nuts/Seeds, and Poultry. Cross-method convergence and weight-sensitivity checks indicate stable top ranks. The framework supports risk-based allocation (e.g., reinforcing core hubs, tightening pre-border controls for recurrent origins) and provides a transparent, reproducible basis for surveillance.

KEYWORDS
Centrality measures, complex networks, Food Safety, MCDM, RASFF, risk assessment

1 Introduction

Globalized agri-food supply chains and an evolving hazard landscape ranging from chemical contaminants to resurging microbiological threats continue to challenge Europe's food-safety surveillance system. The *EU One Health 2023 Zoonoses Report* noted higher human case counts for major zoonoses compared with 2022, while EFSA's *2024 Emerging Risks & Horizon Scanning* program highlighted a widening set of early-warning issues (The European Union One Health 2023 Zoonoses report, 2024). Together, these trends underscore the need for analytical methods that move beyond simple statistics toward structure-aware, decision-oriented insights.

Within this context, the Rapid Alert System for Food and Feed (RASFF) serves as the EU's cross-border notification backbone under the Official Controls Regulation (EU) 2017/625. Through the public RASFF Window, reproducible and typology-consistent data can be extracted for Alerts, Border Rejections, and Information (for Attention/Follow-up). This institutional and data framework supports longitudinal, multi-layer analyses across countries, products, and hazards (European Commission, n.d.a).

Despite this potential, most secondary analyses of RASFF data remain descriptive, focused on counts or rankings while overlooking the relational pathways through which risks propagate. From a network-science perspective, structural influence and risk intensity do not always align: key spreaders may occupy central positions within the network (e.g., in k-core regions) rather than simply exhibiting high degree or betweenness. Moreover, in directed or fragmented alert networks, harmonic closeness offers a more appropriate measure of reach and efficiency. Few studies, however, integrate these structural diagnostics with multicriteria decision-making (MCDM) to produce transparent, regulator-ready risk priorities.

Purpose and Aim. This study develops a framework that combines network structure and risk intensity from (European Commission, n.d.d) RASFF notifications (2020–2024) to generate transparent, evidence-based priority lists for inspections and import controls. We integrate multi-layer network analytics with MCDM so that both structurally important and high-intensity actors, countries, products, hazards, or dyads are reflected in a single, reproducible pipeline. The approach applies Brandes betweenness for brokerage, harmonic closeness for reach, and entropy-weighted ranking methods (EWM with TOPSIS, VIKOR, and PROMETHEE II) for prioritization.

Empirical Preview. Results from 2020–2024 reveal a stable structural core in Germany, the Netherlands, France, and Belgium dominating both centrality and MCDM rankings. Origin–notifier heatmaps show corridor concentration, while category-level priorities highlight fruits & vegetables, nuts & seeds, poultry, and cereals/bakery, consistent with known contamination patterns and supporting corridor-focused risk control.

Objectives. This study develops a transparent, data-driven framework that couples network analytics with multi-criteria decision analysis to support risk-based food-safety surveillance. We assemble a time-resolved, multi-layer RASFF graph that links hazards, products, and reporting countries while preserving notification typologies (alerts, border rejections, and information for attention/follow-up). Structural position is quantified through complementary indicators of exposure (in/out-degree), brokerage (betweenness), reach in directed or partially disconnected layers (closeness), and embedded influence (eigenvector and k-core). In parallel, we derive harmonized risk-intensity measures, including notification frequency, severity attributes, and serious-risk flags. These structural and intensity signals are then integrated via an entropy-weighted MCDM pipeline (TOPSIS, VIKOR, PROMETHEE II) to yield composite, regulator-ready priority rankings. Robustness is assessed through temporal back-testing, targeted weight perturbations, and agreement across methods measured by rank-correlation analyses.

Contributions. This research introduces a multi-layer, typology-aware representation of RASFF notifications that enables directed network analysis of the European food-safety system. It applies an axiomatically grounded set of centrality measures, including Brandes betweenness and harmonic closeness, specifically adapted to the structural characteristics of alert networks. The study further develops a hybrid network–MCDM framework that integrates structural importance and risk intensity to identify both central and peripheral but critical actors within the surveillance network. In addition, it establishes a robustness and validation protocol that enhances the reproducibility and policy relevance of the resulting country- and category-level risk priorities.

Novelty and Contribution. Multi-layer typology-aware network construction: Unlike (Lorenzen et al., 2021), which constructed a single aggregate network, our framework partitions notifications into five distinct network layers (Total, Alerts, Border Rejections, Information-Attention, Information-Follow-up), enabling layer-specific risk characterization. Hybrid network-MCDM integration: While (Sari et al., 2025) applied entropy-weighted MCDM to food safety indicators; their approach did not incorporate network structural features. Our framework uniquely combines topological metrics with risk severity indicators in a unified decision matrix. Harmonic closeness centrality: We employ harmonic closeness rather than standard closeness centrality, which properly handles disconnected or weakly connected directed graphs prevalent in sparse notification networks. Cross-method validation: Our framework applies three complementary MCDM methods (TOPSIS, VIKOR, PROMETHEE II) representing distinct ranking philosophies, with empirical demonstration of convergent validity.

2 Background and related work

2.1 RASFF as a surveillance infrastructure

The EU Rapid Alert System for Food and Feed (RASFF) is the core cross-border risk-communication backbone of the EU food-safety regime. It operates within the Alert and Cooperation Network (ACN) alongside the Administrative Assistance and Cooperation mechanism (AAC) and other specialized modules under Regulation (EU) 2017/625 (Official Controls Regulation) (European Commission, n.d.b; Regulation (EU) 2017/625 of the European Parliament and of the Council of 15 March 2017 on official controls and other official activities performed to ensure the application of food and feed law, rules on animal health and welfare, plant health and plant protection products, amending Regulations (EC) No 999/2001, (EC) No 396/2005, (EC) No 1069/2009, (EC) No 1107/2009, (EU) No 1151/2012, (EU) No 652/2014, (EU) 2016/429 and (EU) 2016/2031 of the European Parliament and of the Council, Council Reg, n.d.). RASFF disseminates notifications on food, feed, and food-contact materials (FCMs) to support rapid, coordinated control actions across member states and partners. This institutional remit and modular ACN architecture motivate longitudinal, multi-layer analytics (e.g., by notification type) and cross-entity network modelling (European Commission, n.d.e).

Public interfaces (RASFF Window) and ACN documentation enable reproducible data extraction and typology-consistent segmentation Alert, Border Rejection, Information for Attention, and Information for Follow-up, which is essential for methodological clarity when constructing directed, type-specific graphs and decision matrices (European Commission, n.d.c).

2.2 Network analytics for food-risk intelligence

Classical centrality indices quantify complementary structural roles: degree (exposure/participation), betweenness (brokerage along geodesics), closeness (access/reach), and eigenvector (importance by association). Freeman formalized (Freeman, 1977) betweenness and clarified centrality concepts, while Brandes introduced (Brandes, 2001) the near-linear-time algorithm, which is now standard at scale. For directed or not strongly connected layers typical in alert networks, harmonic closeness has strong axiomatic support and a clear interpretation via network efficiency (Boldi and Vigna, 2014), addressing path-incompleteness where standard closeness becomes ill-posed. Beyond definitions, axiomatic and efficiency-based treatments justify preferring harmonic variants on these graphs, improving the interpretability of "peripheral yet risk-critical" actors that are widely reachable but have limited outreach (Latora and Marchiori, 2001). Food systems and public health applications show that network structure concentrates risk along recurrent corridors. Recent RASFF-focused studies (Katikou, 2023) construct origin–distribution graphs to examine long-horizon patterns and bottlenecks; the RASNEX tool illustrates how supply-chain relations can be mined from notifications for incident analysis (Lorenzen et al., 2021). Empirically, structural centrality and risk intensity need not coincide, motivating dual-lens analysis. Network science further shows that influential spreaders often sit in k-core regions rather than at the highest degree or betweenness, explaining observed divergences and supporting multilayer/sensitivity analyses (Kitsak et al., 2010).

2.3 MCDM for food safety and regulatory prioritization

Multi-criteria decision making (MCDM) synthesizes heterogeneous indicator counts, severities, centralities, and trade volumes into auditable priority lists (Hwang and Yoon, 1981). The Entropy Weighting Method (EWM) derives objective criterion weights from dispersion (Shannon entropy), thereby avoiding subjective elicitation and enabling cross-scenario sensitivity tests. EWM is frequently coupled with distance or outranking-based rankers in food-risk contexts to balance frequency/severity against structural factors (Zhu et al., 2020; Kumar et al., 2021). Among rankers, TOPSIS (closeness to positive/negative ideals) and VIKOR (compromise programming via S, R, and Q indices) are classical choices with well-studied behavior under normalization and weighting; PROMETHEE II offers an outranking perspective (net flows) that can be simplified to step-function preferences when robust ordering is prioritized over fine-grained trade-offs (Brans et al., 1986; Opricovic and Tzeng, 2004). These methods form reliable baselines for inspection design and regulatory prioritization. Emerging strands fuzzy MCDM (to encode linguistic uncertainty) and DEMATEL (to model causal influence among criteria) complement EWM+TOPSIS/VIKOR/PROMETHEE when expert judgment, causal structure, or uncertainty must be explicit (Hajiaghaei-Keshteli et al., 2023; Hezam et al., 2024; Ulutaş et al., 2024; Esmaeili et al., 2025).

2.4 Hybrid network–MCDM approaches

An increasingly used, yet still methodologically limited, line of work integrates network analytics with multi-criteria decision-making (MCDM) to prioritize interventions in food systems and public health. Typical pipelines compute centrality measures from single- or multi-layer networks to capture structural importance, and then fuse these indicators with notification volume and severity variables using entropy-weighted TOPSIS/VIKOR or PROMETHEE. Weight-perturbation sensitivity analyses are often applied to evaluate the stability of the resulting rankings (Sari et al., 2025). RASFF-based network studies consistently reveal uneven risk corridors and recurring origin-notifier dyads. Moreover, product-hazard niches can elevate otherwise peripheral nodes to risk-critical status; this divergence between structural centrality and risk intensity is precisely what hybrid network MCDM frameworks aim to surface and operationalize for targeted inspections and import-control prioritization. Table 1 contrasts representative prior approaches with the present study, which integrates network analysis and MCDM to address limitations related to risk prioritization, structural characterization, and reliance on a single decision model.

3 Methodology

3.1 Data collection and preprocessing

The dataset consists of RASFF notifications from 2020 to 2024, covering food, feed, and food-contact materials. It includes the following fields: notification, date, classification (Alert, Border Rejection, Information-Attention, Information-Follow-up), origin, distribution, concern, and auxiliary text (subject/measures) used upstream for de-duplication and taxonomy harmonization. All records are cleaned by replacing missing values with empty strings and normalized to a consistent country and taxonomy vocabulary. The processed data are then used to produce two downstream outputs: (a) decision matrices for multicriteria decision-making (MCDM), represented by summary files such as mcdm1.csv for countries and product_summary.csv for product categories, where each row corresponds to a country or category and columns capture criteria such as centrality indicators in the total graph and volume or severity-weighted alert metrics; and (b) Edge lists were conceptually defined and used within the NetworkX framework to compute centrality measures for each notification type and for the overall (Total) network, although explicit graph visualization was not part of the workflow.

TABLE 1 Comparative review of food safety risk assessment studies.

Study	Method	Dataset	Key focus	Gap addressed
(Lorenzen et al., 2021)	Network analysis	RASFF 2000-2017	Supply chain mining	No risk prioritization
(Sari et al., 2025)	Entropy-MCDM	Food safety indicators	Risk ranking	No network structure
Present study	Network + MCDM	RASFF 2020-2024	Multi-layer integration	Addresses all above

3.2 Network construction

The surveillance pathways are modelled as directed graphs comprising four strata: Total (all notifications), Alert, Border Rejection, Information for Attention, and Information for Follow-up. The nodes represent countries mentioned in the origin, distribution, or concern fields. For each notification, directed edges are established from each origin country to each distribution country (excluding self-links and non-country tokens) and from each distribution country to each concerned country. When the distribution field is empty or excluded during processing, fallback edges are created directly from the origin to the concern.

Edge-weight treatment. Networks are constructed as unweighted, binary directed graphs: an edge indicates the presence of at least one observed origin–distribution or distribution–concern linkage. Multiple notifications producing the same ordered pair are collapsed into a single edge (i.e., no parallel edges), thereby avoiding duplication of signal intensity in the network structure. Notification frequency and severity are captured separately as criteria in the MCDM decision matrices, thereby preventing double-counting.

Self-link handling. Self-loops are excluded by enforcing $u \neq v$ for every candidate edge $u \rightarrow v$.

Formally, for each notification: (i) for every origin country $i$and distribution country j, add an edge $i \rightarrow j$ if $i \neq j$; (ii) for every distribution country j and concerned country k, add an edge $j \rightarrow k$ if $j \neq k$ and (iii) if the distribution field is empty after filtering, add a fallback edge $i \rightarrow k$ (subject to $i \neq k$). The resulting edges are organized into separate directed graphs corresponding to each notification category: total, alerts, border rejections, information for attention, and information for follow-up. Each edge is assigned to its respective graph based on the notification classification, which is standardized to consistent lowercase labels such as "alert notification" and "border rejection notification" for each notification type.

3.3 Centrality measures

All centralities are computed on each layer L (and on Total), then min–max scaled to $[0, 1]$ for comparability:

$$z(x_i) = \frac{x_i - \min_k x_k}{\max_k x_k - \min_k x_k} \in [0, 1] \tag{1}$$

- Out-degree/In-degree (frequency): (Wasserman and Faust, 1994)

$$D_i^{\text{out}} = \sum_j A_{ij}, \; D_i^{\text{in}} = \sum_j A_{ji} \tag{2}$$

- Betweenness: (Freeman, 1978)

$$B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{3}$$

where σ_{st} is the number of shortest (directed) paths $s \rightarrow t$ and $\sigma_{st}(i)$ those passing through i.

- Closeness: (Sabidussi, 1966)

  For a node i in a graph with n nodes,

$$C(i) = \frac{n-1}{\sum_{j \neq i} d(i,j)} \tag{4}$$

where $d(i,j)$ is the shortest-path distance from i to j.

- Eigenvector centrality (influence): (Bonacich, 1972)

$$x = \lambda^{-1} A x, \; ||x||_2 = 1 \tag{5}$$

computed on the largest strongly connected subgraph if necessary.

These centralities (plus simple volumes like alert counts or severity-weighted counts) become the criteria for MCDM.

3.4 Decision matrices for MCDM

We prepare two matrices:

- Countries: $X^{cty} \in \mathbb{R}^{n \times m}$, rows = countries, columns = criteria (normalized centralities, counts, severity-weighted counts, etc.) from summary mcdm1.csv.
- Product categories: $X^{cat} \in \mathbb{R}^{n_c \times m_c}$, rows = categories, columns = analogous criteria from product summary.csv.

All criteria are treated as beneficial (larger⇒higher risk/priority). Any cost-type indicators are inverted upstream.

Column normalization (Min–Max), applied to each column j:

$$z_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \in [0, 1] \tag{6}$$

3.5 Entropy weighting (objective)

Form column proportions $p_{ij} = z_{ij} / \sum_i z_{ij}$ (with a tiny constant for zeros). Entropy and divergence (Kumar et al., 2021):

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad d_j = 1 - e_j \tag{7}$$

Normalize to get weights:

$$w_j = \frac{d_j}{\sum_{\ell=1}^{m} d_\ell} \tag{8}$$

3.6 Ranking methods

(a) TOPSIS (distance to ideal) (Hwang and Yoon, 1981)

Weighted matrix $v_{ij} = w_j z_{ij}$. Positive/negative ideals:

$$a_j^+ = \max_i v_{ij}, \quad a_j^- = \min_i v_{ij} \tag{9}$$

Euclidean distances and closeness:

$$D_i^+ = \sqrt{\sum_j (v_{ij} - a_j^+)^2}, \quad D_i^- = \sqrt{\sum_j (v_{ij} - a_j^-)^2}, \quad CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{10}$$

Rank by CC_i descending.

(b) VIKOR (compromise) (Opricovic and Tzeng, 2004)

Let $f_j^* = \max_i z_{ij}, f_j^- = \min_i z_{ij}$.

Define:

$$S_i = \frac{\sum_j w_j (f_j^* - z_{ij})}{\sum_j w_j (f_j^* - f_j^-)}, \quad R_i = \frac{\max_j w_j (f_j^* - z_{ij})}{\max_j w_j (f_j^* - f_j^-)} \tag{11}$$

With $S^* = \min_i S_i$, $S^- = \max_i S_i$ and R^*, R^- Analogously, the index

$$Q_i = v \frac{S_i - S^*}{S^- - S^* + \varepsilon} + (1 - v) \frac{R_i - R^*}{R^- - R^* + \varepsilon} \tag{12}$$

using $v = 0.5$ *and* $\varepsilon \approx 10^{-9}$. Rank by Q_i ascending.

(c) PROMETHEE II (simplified, as coded) (Brans and Vincke, 1985)

Binary preference per criterion:

$$P_j(a, b) = 1\{z_{aj} > z_{bj}\}, \quad \pi(a, b) = \sum_j w_j P_j(a, b) \tag{13}$$

Leaving-flow surrogate:

$$\phi(a) = \sum_{b \neq a} \pi(a, b) \tag{14}$$

Rank by $\phi(a)$ descending.

3.7 Sensitivity analysis (weight robustness)

Generate perturbed weights $\tilde{w}$ by multiplicative noise and renormalization (Triantaphyllou and Sánchez, 1997):

$$\tilde{w}_j \propto w_j \left(1 + \sigma \epsilon_j\right), \quad \epsilon_j \sim \mathcal{N}(0, 1), \sigma = 0.1 \tag{15}$$

For each $\tilde{w}$, recompute TOPSIS ranks; report the average rank over 100 runs as a stability summary.

3.8 Interpretation of outputs and connection to results

Centrality measures summarize how the surveillance network is organized and which countries or product categories play key structural roles. For example, some actors function as hubs with many connections, others act as brokers that link otherwise separate parts of the network, and some occupy positions that allow information to reach them quickly. The multi-criteria decision-making (MCDM) framework then combines these network-based signals with notification volume and severity information to produce risk-priority rankings for both countries and product categories. Comparing rankings from different sources, for instance, an MCDM-based ranking versus a structure-only ranking, helps distinguish actors that are high-risk despite limited network prominence from those that are structurally central but not necessarily risk-intensive. This distinction supports more targeted and defensible choices in inspection planning and other control measures.

3.9 Validation and robustness checks

To assess robustness beyond descriptive reporting, we evaluate cross-method rank agreement, weight-perturbation sensitivity ($\sigma = 0.1$, 100 iterations; renormalized), and temporal consistency via year-wise backtesting over 2020–2024. Agreement is measured using Spearman's ρ and Kendall's τ over rank vectors with two-sided tests (Table 2), indicating strong concordance across methods.

4 Results and discussion

4.1 Network-level structural analysis

Table 3 summarizes network-level metrics across the five notification layers. The Total and Alert layers are comparatively dense (0.1081 and 0.1100, respectively), whereas the Border Rejection layer is substantially sparser (0.0372), reflecting a narrower set of pathways specific to import-control actions. Average clustering is high in the Total and Alert layers (approximately 0.76), indicating pronounced triadic closure and tightly connected subnetworks, consistent with regional coordination among closely interacting member states.

Across all layers, degree assortativity is negative (from −0.2827 to −0.5575), implying disassortative mixing in which high-degree hubs preferentially connect to lower-degree peripheral nodes. This hub–periphery organization is consistent with surveillance systems where a small set of highly connected countries concentrates reporting and redistribution links. Finally, the network diameter remains small (3–4) across layers, suggesting short paths and efficient reachability, such that notification linkages can traverse the network within a few steps.

4.2 Network overview and corridor concentration (2020–2024)

The directed origin-to-notifier adjacency heatmap (Figure 1) exhibits a strongly right-tailed distribution of alert flows: a relatively small set of high-intensity dyads (at or above the 90th percentile, annotated) accounts for a disproportionate share of notifications. Restricting the visualization to the top-20 origins and top-20 notifiers highlights persistent corridors linking major import gateways with recurrent exporting partners. Self-flows are removed to emphasize cross-border pathways and to support corridor-level targeting rather than diffuse, uniform surveillance.

TABLE 2 Verified rank correlations.

Method pair	Spearman ρ	Kendall τ	p-value
TOPSIS vs. VIKOR	0.981	0.897	< 0.001
TOPSIS vs. PROMETHEE II	0.993	0.946	< 0.001
VIKOR vs. PROMETHEE II	0.988	0.915	< 0.001

4.3 Country-level structural roles across notification types

Country roles vary markedly across notification types. A compact EU core of Germany, the Netherlands, France, and Belgium remains structurally prominent in most layers, whereas border rejections elevate additional actors (notably Turkey, India, and China) into type-specific, risk-critical positions. Tables 4–8 summarize the centrality profiles underlying these patterns.

Brokerage (betweenness). Betweenness centrality concentrates in a small set of brokers, but the leading broker shifts by layer (Table 4). In the Total and Alerts layers, France and Belgium dominate brokerage (e.g., Total: France 0.0691; Belgium 0.0674; Alerts: France 0.0834). In Border Rejections, brokerage pivots to entry-point interfaces, led by Germany and Spain (Germany 0.1043; Spain 0.1039), with Cyprus, Turkey, and India also salient. Information-for-Attention exhibits especially strong brokerage in Belgium (0.1860), while Information-for-Follow-up returns to a compact broker set headed by France and Belgium.

Reach and accessibility (in-degree, closeness). In the Total and Alerts layers, Belgium and Germany show near-maximal reach and accessibility, reflected in high in-degree and closeness (Total closeness ≈ 0.9314; Alerts ≈ 0.9482; Tables 5, 8). In Border Rejections, closeness peaks at Germany (0.5442) and remains high for Poland, Turkey, the Netherlands, and India, consistent with concentrated inspection touchpoints and port-of-entry interfaces.

Out-degree indicates outward signaling and dissemination (Table 6). In the Total and Alerts layers, outbound ties are strongest for Belgium and France (e.g., Total: Belgium 0.8193; France 0.8149; Alerts: France 0.8605; Belgium 0.8461). In Border Rejections, outbound prominence shifts toward major exporting origins (Turkey 0.2870; India 0.2685; China 0.2500) alongside Germany (0.2500), highlighting recurrent origin-linked rejection pathways.

Embedded influence (eigenvector; k-core). Eigenvector centrality indicates embedded influence within well-connected neighborhoods (Table 7). In the aggregate network, scores are tightly clustered across the core (e.g., Germany 0.1269; Belgium 0.1268; Netherlands 0.1266), reflecting a mutually reinforcing backbone. In Border Rejections, influence steepens and concentrates in the Netherlands (0.2712) and Germany (0.2611), consistent with gateway amplification through second-order connectivity.

TABLE 3 Network-level metrics across notification layers.

Network	Nodes	Edges	Density	Avg cluster	Diam.	Assort.	SCC
Total	225	5,448	0.1081	0.7608	3	−0.5557	81
Alerts	205	4,601	0.1100	0.7580	3	−0.5575	81
Border rejection	108	430	0.0372	0.0631	4	−0.2827	81
Info-Attention	177	1,512	0.0485	0.5447	3	−0.4927	81
Info-Follow-up	177	2,617	0.0840	0.6408	4	−0.5453	81

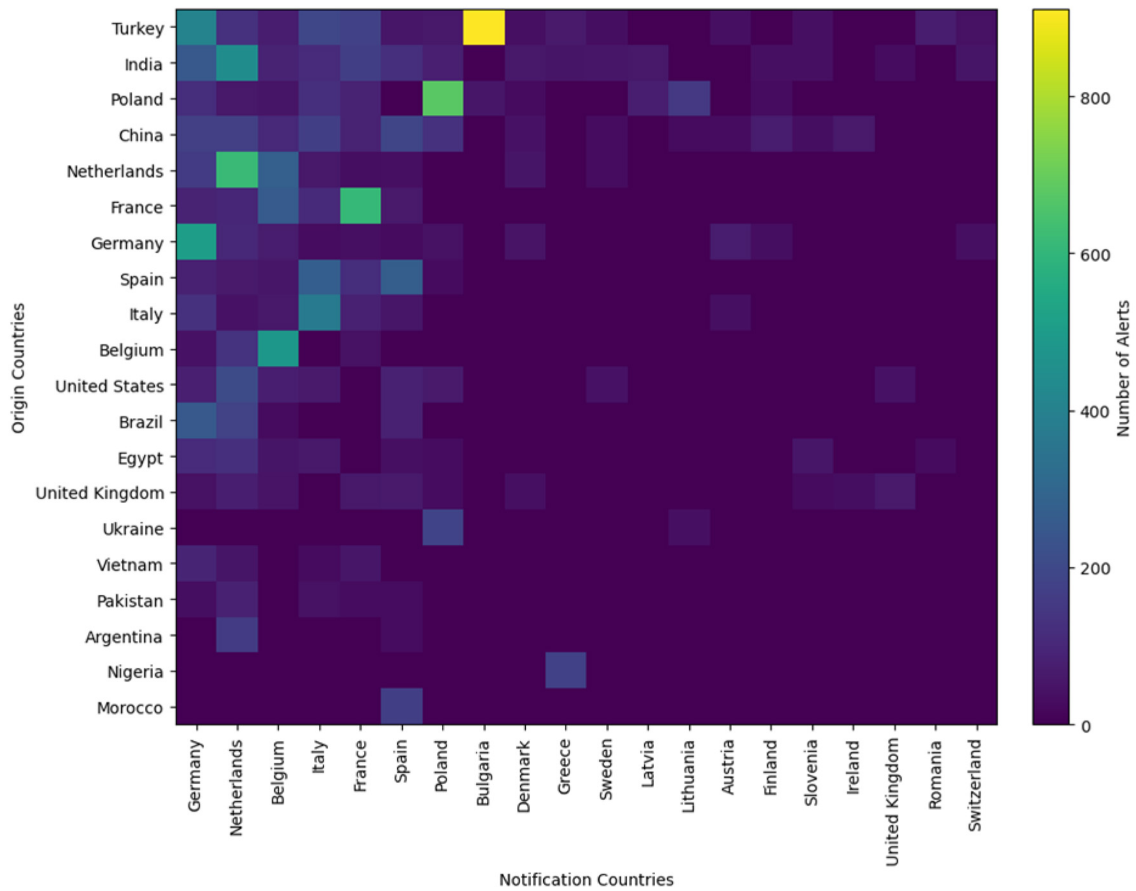

FIGURE 1
Adjacency heatmap of the heaviest origin–notifier alert flows (RASFF, 2020-2024).

TABLE 4 Top 15 countries by betweenness centrality (RASFF 2020–2024).

Total	Alerts	Border rejection	Information for Attention	Information for follow-up
France: 0.0691	France: 0.0834	Germany: 0.1043	Belgium: 0.1860	France: 0.0699
Belgium: 0.0674	Belgium: 0.0665	Spain: 0.1039	France: 0.1410	Belgium: 0.0652
Netherlands: 0.0592	Poland: 0.0495	Cyprus: 0.0708	Netherlands: 0.0668	Germany: 0.0608
Poland: 0.0492	Netherlands: 0.0448	Finland: 0.0680	Germany: 0.0497	Poland: 0.0599
Germany: 0.0438	Germany: 0.0417	Turkey: 0.0679	Poland: 0.0428	Spain: 0.0521
Italy: 0.0384	Italy: 0.0358	India: 0.0673	United Kingdom: 0.0422	Italy: 0.0482
Spain: 0.0261	Spain: 0.0339	Croatia: 0.0617	Spain: 0.0371	Netherlands: 0.0455
United Kingdom: 0.0217	Portugal: 0.0193	Greece: 0.0609	Italy: 0.0329	China: 0.0405
China: 0.0200	China: 0.0179	Poland: 0.0589	Ireland: 0.0194	Ireland: 0.0299
Hungary: 0.0178	United Kingdom: 0.0173	Egypt: 0.0522	Austria: 0.0170	Denmark: 0.0231
Portugal: 0.0173	Austria: 0.0165	Latvia: 0.0514	Denmark: 0.0133	Sweden: 0.0208
Ireland: 0.0150	Hungary: 0.0158	United Kingdom: 0.0492	Czech Republic: 0.0107	Switzerland: 0.0186
Denmark: 0.0147	Denmark: 0.0146	Belgium: 0.0464	Latvia: 0.0101	Lithuania: 0.0185
Austria: 0.0147	Ireland: 0.0143	China: 0.0428	Norway: 0.0093	United Kingdom: 0.0181
Greece: 0.0130	Czech Republic: 0.0142	Ukraine: 0.0394	Switzerland: 0.0091	Austria: 0.0161

TABLE 5 Top 15 countries by in-degree centrality (RASFF 2020–2024).

Total	Alerts	Border rejection	Information for attention	Information for follow-up
Belgium: 0.9339	Belgium: 0.9519	Germany: 0.3457	Belgium: 0.8055	Germany: 0.9269
Germany: 0.9339	Germany: 0.9519	Poland: 0.2990	France: 0.7777	France: 0.9101
Netherlands: 0.9118	France: 0.9423	Finland: 0.2897	Germany: 0.7777	Spain: 0.8876
France: 0.9030	Netherlands: 0.9230	Croatia: 0.2803	Netherlands: 0.7722	Netherlands: 0.8820
Italy: 0.8986	Spain: 0.9230	Cyprus: 0.2710	Italy: 0.7111	Italy: 0.8820
Spain: 0.8898	Italy: 0.9230	United Kingdom: 0.2616	Spain: 0.7111	Belgium: 0.8764
Denmark: 0.8854	Portugal: 0.9134	Spain: 0.2616	Poland: 0.7111	Poland: 0.8707
Poland: 0.8810	Poland: 0.9086	Netherlands: 0.2616	Denmark: 0.7000	Austria: 0.8314
Portugal: 0.8810	Switzerland: 0.9038	Turkey: 0.2149	Switzerland: 0.6833	Romania: 0.8202
Greece: 0.8766	Denmark: 0.9038	Italy: 0.2056	Austria: 0.6833	Portugal: 0.8146
Austria: 0.8678	Austria: 0.8990	Belgium: 0.2056	Czech Republic: 0.6777	Luxembourg: 0.8146
Luxembourg: 0.8678	Czech Republic: 0.8990	Latvia: 0.1775	Norway: 0.6722	Ireland: 0.8146
Ireland: 0.8634	Greece: 0.8990	India: 0.1775	Ireland: 0.6666	Czech Republic: 0.7977
Switzerland: 0.8634	Ireland: 0.8846	Greece: 0.1775	Romania: 0.6666	Denmark: 0.7921
Hungary: 0.8634	Hungary: 0.8846	France: 0.1588	Sweden: 0.6611	Sweden: 0.7865

TABLE 6 Top 15 countries by out-degree centrality (RASFF 2020–2024).

Total	Alerts	Border rejection	Information for attention	Information for follow-up
Belgium: 0.8193	France: 0.8605	Turkey: 0.2870	Belgium: 0.7055	Germany: 0.6910
France: 0.8149	Belgium: 0.8461	India: 0.2685	France: 0.6000	Belgium: 0.6853
Netherlands: 0.7488	Italy: 0.7836	China: 0.2500	Netherlands: 0.4555	China: 0.6853
Italy: 0.7488	Spain: 0.7740	Germany: 0.2500	Germany: 0.4444	France: 0.6797
Poland: 0.7444	Poland: 0.7740	United Kingdom: 0.2222	Spain: 0.4055	Spain: 0.6685
Germany: 0.7400	Germany: 0.7692	United States: 0.2129	Italy: 0.4000	Poland: 0.6516
Spain: 0.7224	Netherlands: 0.7692	Egypt: 0.2129	Ireland: 0.3722	Italy: 0.6067
India: 0.7004	India: 0.7211	Finland: 0.2037	Poland: 0.3722	Netherlands: 0.5561
China: 0.6916	United Kingdom: 0.6682	Ireland: 0.1944	United Kingdom: 0.3666	Ireland: 0.5280
United Kingdom: 0.6563	Turkey: 0.6394	Ukraine: 0.1851	India: 0.3166	Denmark: 0.5112
Denmark: 0.6079	Portugal: 0.6201	Belgium: 0.1759	Denmark: 0.3111	Austria: 0.5112
Turkey: 0.6079	China: 0.6201	Pakistan: 0.1666	Austria: 0.3055	Czech Republic: 0.4887
Portugal: 0.6079	Austria: 0.6105	Cyprus: 0.1666	Sweden: 0.2833	Cyprus: 0.4887
Ireland: 0.6035	Denmark: 0.6105	Greece: 0.1574	Czech Republic: 0.2833	United Kingdom: 0.4831
Austria: 0.5947	Switzerland: 0.5961	Croatia: 0.1574	Norway: 0.2722	Switzerland: 0.4831

To complement shortest-path and eigenvector-based measures, additional centrality diagnostics, including PageRank, HITS hub and authority scores, and *k*-Core membership was examined. These measures provide convergent evidence regarding the core-periphery organization of the network and clarify whether a country primarily functions as a disseminator of notifications (hub) or as a recipient or endpoint (authority). The results for the top ten countries in the Total network are summarized in Table 9, where consistently high PageRank values, maximal *k*-Core membership, and balanced hub–authority scores identify a tightly connected core of influential member states.

4.4 Zero-value analysis

Zero prevalence varies substantially across criteria, and several measures exhibit notable sparsity (e.g., betweenness shows a high proportion of zeros). Under entropy weighting, such sparsity can increase discriminative power by amplifying differences among

TABLE 7 Top 15 countries by eigenvector centrality (RASFF 2020–2024).

Total	Alerts	Border rejection	Information for attention	Information for follow-up
Germany: 0.1269	Germany: 0.1286	Netherlands: 0.2712	Belgium: 0.1749	Germany: 0.1527
Belgium: 0.1268	Belgium: 0.1286	Germany: 0.2611	Germany: 0.1735	Spain: 0.1521
Netherlands: 0.1266	Netherlands: 0.1284	United Kingdom: 0.2330	Netherlands: 0.1733	France: 0.1515
Italy: 0.1264	France: 0.1283	Poland: 0.2249	France: 0.1728	Belgium: 0.1514
Denmark: 0.1261	Italy: 0.1282	Turkey: 0.2132	Italy: 0.1718	Italy: 0.1513
Spain: 0.1261	Spain: 0.1281	China: 0.2115	Denmark: 0.1704	Poland: 0.1508
Ireland: 0.1260	Poland: 0.1280	India: 0.2053	Poland: 0.1702	Portugal: 0.1502
France: 0.1260	Portugal: 0.1280	Egypt: 0.2020	Spain: 0.1701	Austria: 0.1498
Portugal: 0.1260	Greece: 0.1280	Italy: 0.1983	Switzerland: 0.1692	Ireland: 0.1495
Poland: 0.1258	Austria: 0.1278	Croatia: 0.1887	Norway: 0.1683	Romania: 0.1494
Norway: 0.1256	Denmark: 0.1278	Ukraine: 0.1879	Austria: 0.1676	Netherlands: 0.1492
Austria: 0.1256	Switzerland: 0.1277	Belgium: 0.1803	Ireland: 0.1673	Czech Republic: 0.1489
Switzerland: 0.1255	Romania: 0.1275	Finland: 0.1773	Sweden: 0.1667	Switzerland: 0.1487
Cyprus: 0.1254	Sweden: 0.1272	Cyprus: 0.1752	Romania: 0.1657	Luxembourg: 0.1478
Malta: 0.1254	Ireland: 0.1272	France: 0.1720	Czech Republic: 0.1654	Denmark: 0.1476

TABLE 8 Top 15 countries by closeness centrality (RASFF 2020–2024).

Total	Alerts	Border rejection	Information for attention	Information for follow-up
Belgium: 0.9314	Belgium: 0.9482	Germany: 0.5442	Belgium: 0.8080	Germany: 0.9256
Germany: 0.9314	Germany: 0.9482	Poland: 0.5189	France: 0.7857	France: 0.9111
Netherlands: 0.9116	France: 0.9393	Turkey: 0.5162	Germany: 0.7857	Spain: 0.8924
France: 0.9040	Netherlands: 0.9220	Netherlands: 0.5162	Netherlands: 0.7814	Netherlands: 0.8878
Italy: 0.9002	Spain: 0.9220	India: 0.5109	Italy: 0.7369	Italy: 0.8878
Spain: 0.8927	Italy: 0.9220	United Kingdom: 0.5083	Spain: 0.7369	Belgium: 0.8833
Denmark: 0.8890	Portugal: 0.9135	Egypt: 0.5083	Poland: 0.7369	Poland: 0.8789
Poland: 0.8854	Poland: 0.9094	Cyprus: 0.4933	Denmark: 0.7293	Austria: 0.8488
Portugal: 0.8854	Switzerland: 0.9053	China: 0.4909	Switzerland: 0.7182	Romania: 0.8406
Greece: 0.8817	Denmark: 0.9053	Italy: 0.4723	Austria: 0.7182	Portugal: 0.8366
Austria: 0.8746	Austria: 0.9012	Ukraine: 0.4701	Czech Republic: 0.7146	Luxembourg: 0.8366
Luxembourg: 0.8746	Czech Republic: 0.9012	Spain: 0.4679	Romania: 0.7075	Ireland: 0.8366
Ireland: 0.8710	Greece: 0.9012	Finland: 0.4658	Norway: 0.7075	Czech Republic: 0.8247
Switzerland: 0.8710	Ireland: 0.8892	Belgium: 0.4658	Ireland: 0.7040	Denmark: 0.8208
Hungary: 0.8710	Hungary: 0.8892	United States: 0.4636	Slovakia: 0.7006	Sweden: 0.8170

non-zero observations. To ensure numerical stability during entropy computation, zero entries are replaced with a small constant $\varepsilon = 10^{-12}$ before logarithmic operations. As shown in Table 10, highly sparse metrics such as betweenness receive larger entropy weights, whereas metrics with negligible sparsity, including eigenvector centrality and PageRank, provide stable baseline contributions. As an external check, alternative weighting schemes produce highly consistent rankings (Entropy vs. CRITIC: $\rho = 0.9568$; Entropy vs. equal weights: $\rho = 0.9714$; both $p < 0.001$), supporting the robustness of the weighting choice.

4.5 Integrated prioritization (MCDM) and rank stability

We integrate structural indicators and risk-intensity criteria using an entropy-weighted MCDM ensemble to obtain regulator-ready priorities. TOPSIS and VIKOR produce a stable top tier Germany (1), the Netherlands (2), France (3), and Belgium (4), followed by Italy, Spain, and Poland (Table 11). PROMETHEE II corroborates this ordering, and sensitivity ranks indicate minimal volatility for the top tier but increasing method/weight dependence

TABLE 9 Additional centrality metrics (top 10 countries, total network).

Country	PageRank	k-Core	HITS hub	HITS auth
France	0.0274	40	0.0185	0.0151
Belgium	0.0265	40	0.0185	0.0150
Netherlands	0.0246	40	0.0175	0.0151
Germany	0.0221	40	0.0178	0.0150
Croatia	0.0186	40	0.0067	0.0123
Spain	0.0183	40	0.0179	0.0142
Denmark	0.0174	40	0.0133	0.0137
Sweden	0.0164	40	0.0131	0.0143
United Kingdom	0.0160	40	0.0152	0.0137
Poland	0.0158	40	0.0173	0.0141

TABLE 10 Zero value prevalence by criterion (country-level, $n = 225$).

Criterion	Zero %	Entropy weight
notifications originated	28.44%	0.1389
severity score	30.22%	0.1392
distribution reach	32.44%	0.1585
coordination score	36.44%	0.1378
in degree	3.11%	0.0496
out degree	32.44%	0.0735
Betweenness	53.33%	0.1991
harmonic closeness	3.11%	0.0041
Eigenvector	0.00%	0.0363
Pagerank	0.00%	0.0630

in mid- and lower-rank positions (Table 12). Overall, convergence across distance-to-ideal (TOPSIS), compromise programming (VIKOR), and outranking (PROMETHEE II) supports robustness of the leading recommendations, while lower tiers warrant periodic re-estimation to detect rank drift.

4.6 Category-level priorities and risk niches

At the category level, the ensemble consistently prioritizes Fruits and Vegetables, followed by Nuts/Seeds and Poultry (Table 13). Cereals & Bakery forms the upper-middle tier, while Dietetic foods/supplements and Herbs & Spices remain consistently important, aligning with persistent residue and contamination niches. Food-contact materials and fish occupy the mid-tier, supporting targeted sampling rather than blanket intensification. Taken together, the country- and category-level shortlists suggest pairing corridor-focused controls at core hubs (Germany, the Netherlands, France, Belgium) with intensified sampling in horticulture and poultry, and strengthening documentation and pre-shipment checks for recurrent exporting origins (e.g., Turkey, India, China) in persistently high-ranked categories.

4.7 Robustness and correlation analysis

Robustness was assessed via cross-method agreement of the resulting rank orders at both the country and category levels. We quantified concordance using Spearman's ρ and Kendall's τ computed on rank vectors, with two-sided significance testing. At the country level, correlations are near unity, indicating that TOPSIS, VIKOR, and PROMETHEE II yield essentially the same ordering of alternatives (Table 14). Category-level rankings show similarly strong concordance across all method pairs (Table 15). Together, these results indicate that the core conclusions are stable across distinct MCDM paradigms and are unlikely to be artifacts of any single solver.

4.8 Structure vs. risk intensity: divergence and operational meaning

A consistent finding in the 2020–2024 results is that being structurally central does not always mean being risk-intensive. Centrality measures (e.g., betweenness, closeness, eigenvector, and core membership) indicate which countries sit on major pathways and frequently connect different parts of the network. In contrast, risk intensity captured by notification volume, serious-risk flags, and the category–hazard profile reflects where the burden is concentrated and where incidents tend to be more severe. At the country level, the main EU notifiers (Germany, the Netherlands, France, and Belgium) remain central across layers (Tables 4–8). However, border rejections highlight additional actors, including third-country origins (Turkey, India, and China) and some EU members (e.g., Spain and Poland), that become risk-critical within specific notification types even if they are not among the most central overall. At the category level, the MCDM ensemble consistently ranks Fruits & Vegetables, Nuts/Seeds, and Poultry highest (Table 8), pointing to recurring hazard niches (residues, mycotoxins, and microbiological hazards) that can intensify risk along particular origin→notifier corridors even when those corridors are not structurally dominant.

From a practical perspective, centrality is useful for understanding where signals can spread quickly, but it is not sufficient on its own to decide where inspections should be concentrated. Our hybrid approach addresses this by combining structural indicators (to identify key intermediaries and highly connected hubs) with intensity indicators (to target the highest-burden corridors). This produces a layer-aware allocation that both maintains capacity at core hubs and strengthens controls along risk-intensive routes that may lie outside the aggregate core.

High betweenness countries, France (0.0734), Belgium (0.0685), and the Netherlands (0.0524) act as brokerage nodes (information chokepoints), consistent with evidence that intermediaries can disproportionately influence diffusion processes (Kitsak et al., 2010). The negative degree assortativity coefficient (−0.506) further indicates disassortative mixing, whereby high-degree hubs preferentially connect to lower-degree peripheral countries, yielding hub periphery corridors (Latora and Marchiori, 2001). Figure 2 visualizes the 2020-2024 country-level RASFF network (225 countries, 5,448 connections), with node size proportional to degree centrality and node color encoding

TABLE 11 Country prioritization across TOPSIS and VIKOR (entropy-weighted MCDM).

Country	TOPSIS score	TOPSIS rank	VIKOR score	VIKOR rank
Germany	0.9481003636978695	1	0.0	1
Netherlands	0.8560559863283621	2	0.13793643414600912	2
France	0.6603942658469665	3	0.3075029960276402	3
Belgium	0.6043711264495362	4	0.382000851571176	4
Italy	0.5847353974115238	5	0.4506841920572793	6
Spain	0.574324113397648	6	0.4542875321279051	7
Poland	0.5741870211184033	7	0.4502507629757976	5
Turkey	0.4098864541093932	8	0.7735587852552623	10
India	0.27749013790776855	9		-
China	0.25311475295833674	10	-	-
Bulgaria	0.24714358861861843	11	0.8154864288834595	14
Austria	0.24058239372785242	12	0.7846685029537425	12
United Kingdom	0.23150566997368222	13	0.759690212145118	8
Denmark	0.22615918769024956	14	0.7652999276557249	9
Sweden	0.20316092343147152	15	0.7843283836947342	11

betweenness centrality. France attains the maximum betweenness (0.0874), while Belgium exhibits the maximum degree (297). For readability, the plot displays only the top 40 countries by degree.

4.9 Policy implications

Our findings support a layer-aware, corridor-focused surveillance strategy. Capacity should remain concentrated at the core hubs. Germany, the Netherlands, France, and Belgium, while pre-border and entry-point controls are intensified for recurrently implicated origins (notably Turkey, India, and China) in fruits & vegetables, nuts/seeds, and poultry. Alerts should trigger rapid risk communication and targeted sampling along high-betweenness dyads; border rejections motivate documentation checks and supplier verification at ports; information for follow-up guides the diffusion of post-incident actions from hubs with high outreach. Composite priorities from the entropy-weighted TOPSIS/VIKOR/PROMETHEE ensemble should be recomputed quarterly, with operational triggers defined on rank changes and brokerage spikes to anticipate shifts in risk corridors.

TABLE 12 PROMETHEE II and rank stability.

Country	Promethea Score	Promethea Rank	Average sensitivity rank
Germany	671.514653598046	1	1.0
Netherlands	671.2315738847254	2	2.0
France	668.7804654775659	3	3.0
Belgium	667.8112980269691	4	4.15
Italy	667.4924549655433	5	4.88
Poland	667.4880994357686	6	4.88
Spain	667.4804156032517	7	6.34
United Kingdom	661.0271294312048	8	12.75
Denmark	660.5760210240453	9	13.78
Sweden	658.322248506817	10	15.48
Austria	657.9590616879342	11	11.55
Bulgaria	656.3885703666188	12	11.39
Turkey	656.2896937090454	13	8.0
Czech Republic	655.6346354162298	14	16.94
Greece	655.4153450590543	15	18.06

4.10 Limitations and avenues for extension

Results inherit the properties of RASFF notifications, including potential differences in reporting intensity and follow-up practices. Although we adopt closeness and conduct weight perturbation and cross-method checks, centrality and MCDM outputs remain sensitive to edge definitions, normalization choices, and latent under-reporting. Future work should examine multiplex, time-resolved constructions (e.g., hazard-specific layers), integrate trade-flow and supplier-network data, and test fuzzy/causal MCDM (e.g., DEMATEL/ANP) to represent criterion interdependence. Prospective back-testing and pilot deployments with inspectorates can quantify detection yield and refine cost-effective inspection portfolios.

TABLE 13 Category prioritization across methods.

Category	TOPSIS score	TOPSIS rank	VIKOR score	VIKOR rank	PROMETHEE score	PROMETHEE rank	Average sensitivity rank
Fruits and vegetables	1.0	1	0.0	1	35.99999999999999	1	1.0
Nuts, nut products, and seeds	0.7244372792573563	2	0.28769653297588016	2	34.99999999999999	2	2.0
Poultry meat and poultry meat products	0.5012901089391801	3	0.5373546205510902	3	33.75406532429765	3	3.0
Cereals and bakery products	0.4414700136651926	4	0.6177742790462033	5	32.21647056243019	4	4.0
Dietetic foods, food supplements, and fortified foods	0.4244547030363842	5	0.6589971876646639	6	32.18254175474844	5	5.25
Herbs and spices	0.42149556192498433	6	0.6066737909617645	4	31.564614905682472	6	5.75
Food contact materials	0.30741879091486485	7	0.7464144660852025	8	29.207117929106307	7	7.08
Fish and fish products	0.29310165605283156	8	0.7123329120514417	7	29.17049052741813	8	7.93
Other food product/mixed	0.27172022125061795	9	0.7768247937415599	9	27.423588491536496	10	8.99
Meat and meat products (other than poultry)	0.2357884824017472	10	0.7900475728324736	10	28.009352633323882	9	10.0
Feed materials	0.20382944226182473	11	0.8092988193220476	11	25.60587562173566	11	11.0
Milk and milk products	0.1783224733971246	12	0.8651680864023308	12	24.62239154347556	13	12.0
Prepared dishes and snacks	0.16856323098067097	13	0.8672152938718793	13	24.74471269097377	12	13.0
Confectionery	0.15115082029755	14	0.875619415259482	14	23.498778015271423	14	14.0
Cocoa and cocoa preparations, coffee, and tea	0.13354340742228912	15	0.8928565604250409	15	21.462405238132533	15	15.0

5 Conclusion

In this study, we analyze RASFF data (2020–2024) in two steps: first, network centrality measures to map how countries connect; second, an entropy-weighted MCDM ranking (TOPSIS, VIKOR, PROMETHEE II) that combines structure with risk (frequency, severity, product–hazard mix). The network shows a tight EU core, Germany, the Netherlands, France, and Belgium, while border-facing activity highlights Turkey, India, and China, and within the EU, Spain and Poland, as important in specific layers. The MCDM results provide stable, decision-ready priorities: the same top group of countries appears across methods, and categories led by Fruits & Vegetables, Nuts/Seeds, and Poultry remain highest, with Food-Contact Materials and Fish in the middle. Robustness rests on cross-method agreement and weight-perturbation checks (Average Sensitivity Rank) showing minimal movement at the top. For practice, maintain strong capacity at core hubs, tighten pre-border/entry checks for recurrent origins, and prioritize horticulture and poultry in sampling, with quarterly updates and clear review triggers. Results depend on RASFF reporting practices and the origin→notifier link, but together the two methods provide a clear, defensible basis for risk-based surveillance.

TABLE 14 Cross-method rank correlation (country-level, $n = 225$).

Method pair	Spearman ρ	p-value	Kendall τ	p-value
TOPSIS vs. VIKOR	0.9955	7.89e-230	0.9484	2.01e-99
TOPSIS vs. PROMETHEE II	0.9959	9.69e-235	0.9529	2.35e-100
VIKOR vs. PROMETHEE II	0.9994	<1e-300	0.9894	4.81e-108

TABLE 15 Cross-method rank correlation (category-level, $n = 37$).

Method pair	Spearman ρ	p-value	Kendall τ	p-value
TOPSIS vs. VIKOR	0.9704	3.55e-23	0.8889	9.73e-15
TOPSIS vs. PROMETHEE II	0.9832	1.97e-27	0.9369	3.32e-16
VIKOR vs. PROMETHEE II	0.9938	4.97e-35	0.9520	1.11e-16

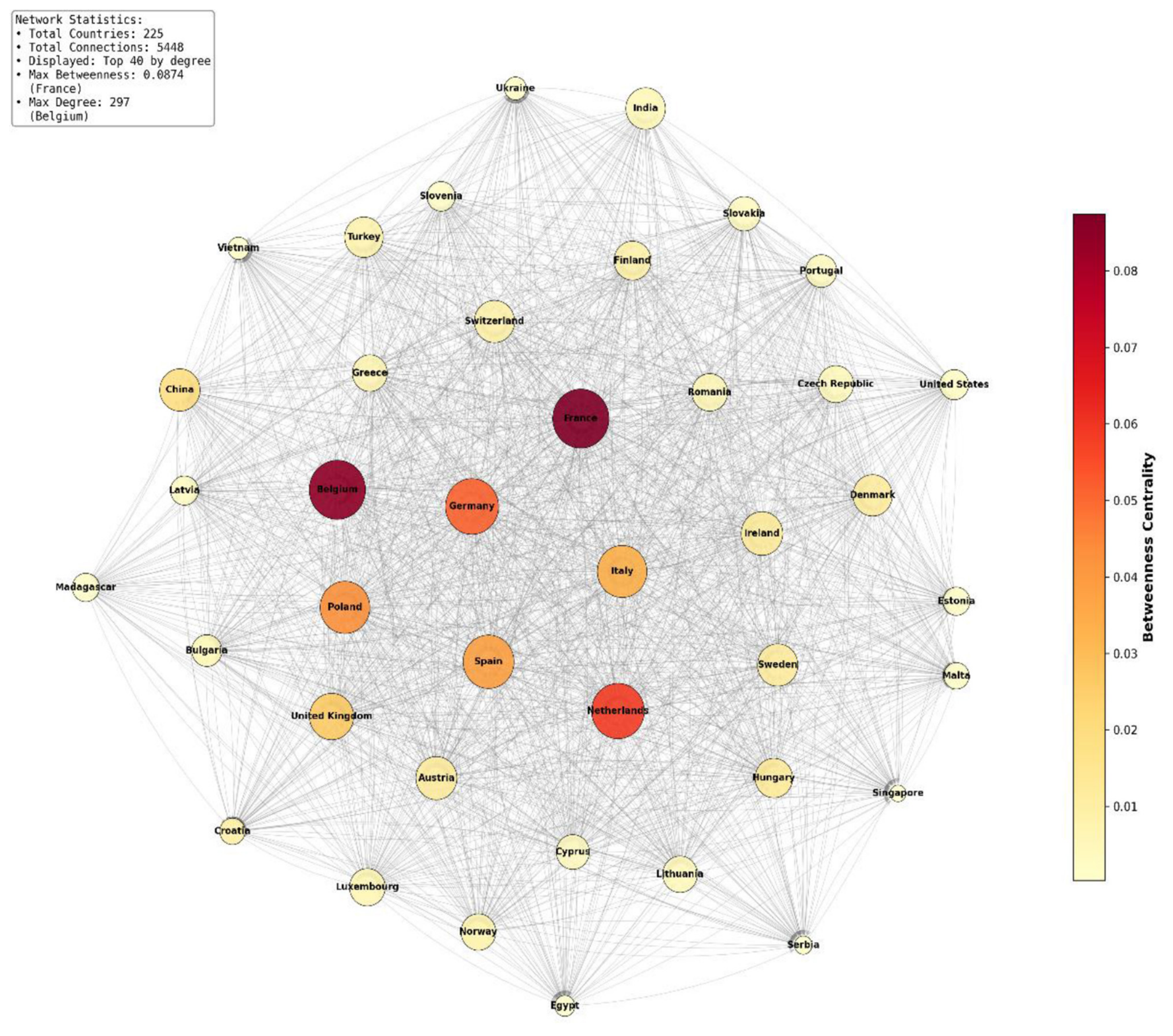

FIGURE 2
RASFF food safety notification network (2020–2024) illustrating country-level interactions in food safety alerts.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The dataset used in this study was obtained from the Rapid Alert System for Food and Feed (RASFF) portal (https://webgate.ec.europa.eu/rasff-window/screen/search). The raw data are publicly accessible through the RASFF system. Processed data and analysis files generated during this study are available from the corresponding author upon reasonable request.

Author contributions

CS: Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft. AP: Investigation, Supervision, Validation, Writing – review & editing.

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Conflict of interest

The author(s) declared that that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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