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Cross-lingual social sensing for disaster monitoring: A pan-European framework for cross-border information flow analysis and antifragility indicators

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ABSTRACT

Disasters routinely propagate across administrative boundaries and linguistic communities, yet social sensing instruments for monitoring them remain largely monolingual and single-city. This paper presents a cross-lingual social sensing framework for disaster and disruption monitoring at pan-European scale. A supervised multilingual classifier was applied to 13,388 social media posts from 23 countries in 10 languages, categorising disruption discourse into 11 event types with held-out accuracy of approximately 0.83 (Cohen's $\kappa \approx 0.79$). Posts were geographically normalised across five pilot Areas of Interest, and a geolinguistic information-flow network was constructed to characterise cross-border disaster communication pathways. Five pilot antifragility indicators were defined with baseline measurement architectures. Transport disruptions constituted the dominant signal (23.8% of classified discourse). Sentiment was predominantly neutral (94.5%), suggesting urgency-based classification affords greater discrimination than polarity for monitoring applications. Cross-border information flows clustered along geographic and linguistic boundaries whilst sustaining bridging channels carrying disaster signals across jurisdictions. The framework contributes a replicable cross-lingual sensing pipeline for disaster monitoring, a cross-border communication analysis, and a pilot indicator layer for antifragility-oriented disaster system assessment, aligned with Sendai Framework Priorities 1 and 4.

List of Abbreviations

AOI	Area of Interest
DRR	Disaster Risk Reduction
NLP	Natural Language Processing
RQ	Research Question
VGI	Volunteered Geographic Information

1. Introduction

Disasters and associated disruptions, including floods, transport network failures, energy outages, and security incidents, routinely propagate across administrative boundaries, infrastructure layers, and linguistic communities. In the European context, where mobility systems, jurisdictions, and linguistic communities routinely overlap, a rail disruption originating in one member state may affect commuters and freight operators in several others, whilst a flood warning issued in one language may fail to reach residents who communicate in another. The Sendai Framework for Disaster Risk Reduction 2015–2030 accordingly emphasises the need for improved understanding of disaster risk (Priority 1) and for enhanced preparedness for effective response (Priority 4) across scales and borders [1]. Meeting those priorities requires monitoring arrangements that can operate across cities, countries, and languages within a unified framework.

Existing social sensing arrangements for disaster risk reduction face three interrelated limitations. First, most social media analytics for disaster management remain confined to single-city, monolingual datasets, which constrains cross-border situational awareness and comparative analysis [2,3]. Second, cross-lingual classification of disaster-related discourse remains underdeveloped as a monitoring capability; the few multilingual approaches available have not been deployed at pan-European scale as instruments for structured disaster and disruption monitoring [4,5]. Third, cross-border information flows during disasters are poorly mapped in the communication dimension, despite

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evidence that infrastructure and mobility effects propagate across jurisdictions and that early warning depends critically on the speed at which disaster information reaches exposed populations [6,7].

The citizen-as-sensor paradigm [8,9] offers a distributed, participatory data source of considerable value for disaster monitoring. Citizens register disruption signals through social media activity with a speed and local granularity that formal reporting systems seldom achieve [3,10]. Within disaster informatics, social media data have been shown to support event detection, risk communication, and situational awareness during emergencies [11,12]. However, no pan-European framework currently combines multilingual classification, geographic normalisation for cross-border comparison, and cross-border information-flow analysis for disaster monitoring.

This paper addresses that gap through four contributions to disaster informatics and disaster risk reduction:

1. A cross-lingual social sensing framework for disaster and disruption monitoring, applied across 23 countries and 10 languages, demonstrating that multilingual classification is feasible at pan-European scale;
2. An 11-category multilingual classifier validated on a held-out corpus (accuracy $\approx$0.83; Cohen's κ $\approx$0.79), presented as a disaster monitoring instrument for structured, cross-border observation;
3. A cross-border disaster communication analysis, implemented as a geolinguistic information-flow network, that maps discourse structure and identifies clustering and bridging pathways across European cities and countries;
4. A pilot indicator framework for antifragility-oriented disaster system assessment, with baseline measurement architectures connecting cross-lingual sensing outputs to longitudinal evaluation.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on social sensing for disaster management, cross-lingual NLP for multilingual event detection, disaster monitoring and spatial decision-support, and information flow, disaster communication cascades, and antifragility. Section 3 presents the methodology, including corpus construction, classifier design, geographic normalisation, network analysis, and the pilot indicator framework. Section 4 reports the findings structured around three research questions. Section 5 discusses the contributions to disaster monitoring, cross-border disaster communication, multilingual disaster risk communication, and antifragility-oriented assessment, together with limitations. Section 6 concludes with a summary and directions for future work.

2. Background and related work

This section reviews four bodies of literature that define the space within which the present study is situated: social sensing and citizen-generated data for disaster management; cross-lingual NLP and multilingual disaster event detection; disaster monitoring systems and spatial decision-support for disaster risk reduction; and information flow, disaster communication cascades, and antifragility.

2.1. Social sensing and citizen-generated data for disaster management

The proposition that citizens function as distributed sensors during disasters and disruptions has deep theoretical roots in the volunteered geographic information (VGI) literature. [8] articulated the foundational insight that individuals equipped with location-aware devices generate geographic information with immediacy and local granularity that formal surveying cannot match. [9] extended this through a typology of participation, distinguishing passive digital traces from deliberate contributions. Within disaster informatics, social media data have since been used for event detection, situational awareness, and early damage assessment [2,10,13].

[2] demonstrated that supervised NLP classification could categorise urban events from geo-fenced Twitter data in a single European city into a seven-category risk taxonomy with 88.5% accuracy, establishing the technical feasibility of social media event detection at the city level. That study did not, however, address the cross-lingual, multi-city, and multi-platform challenges that arise at pan-European scale. [14] showed that VGI from navigation platforms can contribute usable incident reporting for flash floods, whilst [15] documented growing use of citizen-generated data in flood risk assessment and resilience planning. Moreover, recent practice-oriented reviews have drawn attention to the participatory value of these data sources for disaster managers and emergency responders under conditions in which official channels may be delayed or disrupted [3,12].

A persistent gap is that the evidential value of social sensing for disaster risk reduction is often treated as self-evident. As [16] argued in a broader smart-city context, the value of participatory data lies not in the data themselves but in whether they can be translated into structured, comparable analytical outputs for decision-support. For social sensing to serve disaster monitoring, it must be embedded within a framework that specifies how classified signals are geographically normalised, cross-border comparisons constructed, and information-flow structures analysed.

2.2. Cross-lingual NLP and multilingual disaster event detection

The application of NLP to disaster-related social media has matured substantially. [10] provided an early survey identifying classification, information extraction, and summarisation as key tasks for processing social media during mass emergencies. Subsequent work extended these techniques to multilingual and multimodal settings [5], whilst advances in cross-lingual representation learning [17] have made it feasible to train classifiers that perform across languages without requiring separate annotated corpora for each.

[11] demonstrated that social media platforms mediate disaster risk communication differently depending on event type and platform architecture, with implications for how disaster signals are classified and interpreted across linguistic communities. [12] further showed that information-sharing behaviour during disasters varies systematically across platforms and user populations. For pan-European disaster monitoring, the multilingual dimension is not a peripheral technical challenge but a fundamental requirement of equitable risk communication. [4] argued that language choice shapes who receives warnings, who participates in discourse, and whose risk becomes institutionally visible; this observation is of direct relevance to the Sendai Framework's emphasis on accessible and inclusive early warning. [3] provided a recent critical review concluding that, whilst social media analytics for disaster management has matured, persistent problems of bias, filtering, and uneven geographic coverage remain.

The present study applies a supervised multilingual classifier across 10 European languages. The contribution lies not in the NLP technique per se, but in the demonstration that cross-lingual classification can be deployed as a disaster monitoring instrument for pan-European observation and cross-border comparison.

2.3. Disaster monitoring systems and spatial decision-support for DRR

Disaster monitoring systems have evolved from early smart city dashboards towards integrated, data-driven frameworks for cross-border situational awareness. [18] showed how crowdsourced information could be combined with Earth Observation systems in a GDPR-compliant European setting, providing a spatial integration benchmark for disaster risk management. [19] developed a decision-support system for smart urban management coupling atmospheric and geospatial data. [20] combined agent-based, network-based, and system-oriented simulation with layered spatial indicators for risk assessment.

Within spatial disaster analysis, [7] simulated street-network disruptions globally, demonstrating that connectivity and redundancy metrics dampen cascading effects at high-centrality nodes. [21] fused OpenStreetMap, WorldPop, GPS traces, and flood modelling for infrastructure criticality assessment across cities. [22] mapped the knowledge structure of urban resilient infrastructure research, documenting growing AI uptake in spatial data-fusion workflows. [23] identified systematic biases in large-scale mobility datasets that affect multi-source spatial harmonisation and hence the reliability of disaster-impact inferences drawn from them.

For mobility-specific applications, [24] demonstrated how large-scale mobility data can capture delayed and compound disruption effects. [25,26] argued for data-driven complex systems approaches to disaster resilience, whilst [27] documented regional differences in social and physical system resilience using Bayesian spatial modelling. [28] called for multi-source emergency response architectures functioning under uncertainty, whilst [29] advanced digital-twin representations of socio-technical systems for crisis management.

A common thread is that disaster monitoring arrangements are most useful when they support comparison across sites, integration across data types, and structured spatial analysis. The present paper extends this literature by adding a cross-lingual, multi-country social sensing layer with demonstrated geographic normalisation and network-analytical capabilities.

2.4. Information flow, disaster communication cascades, and antifragility

Information cascades and disaster-related propagation are increasingly studied through network-analytical methods. [30] applied percolation theory to compound flood scenarios, revealing that efficiency-oriented network design can heighten vulnerability. [31] used motif analysis on temporal mobility networks to show that sub-structural impacts persist beyond apparent global recovery. [32] demonstrated that feedbacks between social and physical layers can amplify or attenuate cascades, requiring multi-domain perspectives on disaster communication.

Antifragility, as introduced by [33], describes systems that benefit from stressors rather than merely resisting them. The concept extends conventional resilience by distinguishing fragile (degrades under stress), resilient (returns to prior state), and antifragile (improves through exposure) system dispositions. [34] brought the concept into urban planning, linking it to experimentation and optionality. [35] proposed a research agenda for antifragile urban form. [36] explored antifragility as a property of urban systems alongside resilience. [37] extended the discussion to critical infrastructure, stressing learning from disorder as a system property of direct relevance to disaster risk reduction. [38] observed that antifragility has gained limited traction in policymaking partly because it has resisted measurable formalisation. [39] validated antifragile behaviour across 27 cities, identifying strategic diversity and positive network redundancy as measurable pillars.

For disaster system assessment, the relevance of antifragility lies in whether it can be connected to measurable, computable indicators derived from disaster monitoring data. It is hypothesised in the wider literature, and tested in the present study, that disaster communication systems should improve through repeated exposure to events; information-flow velocity is accordingly proposed as the most direct social sensing expression of this idea, such that faster and broader diffusion of disaster signals across jurisdictions may indicate improving cross-border communication.

2.5. Summary and research gaps

Three research gaps emerge from this review. First, no multilingual NLP framework currently exists for pan-European disaster discourse classification capable of supporting structured cross-border comparison. Second, cross-border disaster communication cascades remain poorly characterised through network-analytical methods, despite evidence that infrastructure effects, population movements, and information flows propagate across jurisdictions. Third, social sensing outputs are seldom linked to computable monitoring indicators capable of supporting longitudinal disaster system assessment, such as information-flow velocity or coping repertoire diversity. It is this combined gap, theoretical as well as methodological, that the present study addresses: the absence of an explicit linkage between multilingual disaster information-flow structure and the adaptiveness of the disaster communication systems in which it is embedded.

Table 1 positions the present study relative to closely related prior work, making the scope of extension explicit.

The present study addresses these gaps by combining multilingual NLP classification, geographic normalisation for cross-border comparison, and network-based information-flow analysis, then piloting a compact set of antifragility-oriented monitoring indicators on the resulting outputs for disaster system assessment.

3. Methodology

3.1. Theoretical framing, hypothesis, and research questions

The methodology is framed by two theoretical propositions grounded in the preceding literature. First, that social sensing data, when systematically collected and classified across multiple languages and countries, can serve as a reliable data source for disaster and disruption monitoring and enable structured cross-border comparison, consistent with the citizen-as-sensor paradigm [8,9]. Second, that the resulting classified and geolocated corpus can support network-based analysis of cross-border disaster communication pathways and provide the measurement architecture for pilot antifragility indicators suited to longitudinal disaster system assessment [33,38]. The theoretical lens for the indicator layer is drawn from antifragility theory [33]: the five candidate indicators defined in Section 3.6 specify what an improving, rather than merely surviving, disaster communication system would look like in informational terms.

The overarching hypothesis, extracted from the theoretical lineage sketched in Sections 2.1–2.4, is stated as follows:

It is hypothesised that cross-lingual social sensing data, systematically collected and classified across European areas of interest, can produce structured and comparable disaster and disruption monitoring outputs, reveal the network structure of cross-border disaster communication pathways, and provide the measurement architecture for computing pilot antifragility indicators suited to longitudinal disaster system assessment.

Three research questions translate this hypothesis into testable form:

- **RQ1:** What types and distributions of disaster and disruption events are detectable through cross-lingual social sensing across European areas of interest?
- **RQ2:** What cross-border communication patterns and information-flow dynamics characterise disaster signals in the corpus?
- **RQ3:** To what extent can antifragility-oriented monitoring indicators be computed and meaningfully piloted on the collected corpus for disaster system assessment?

Table 1
Comparative positioning relative to prior disaster monitoring and social sensing studies.

Study	Scope	Languages	Analytical approach	Computational contribution	Output type
Hodorog et al. (2022)	Single city	English only	Risk taxonomy (Coburn et al.)	MRA correlation analysis	Event detection + citizen satisfaction
Liu et al. (2023)	Multi-city (China)	Monolingual	Mobility recovery modelling	Statistical modelling of compound effects	Delayed impact assessment
Boeing & Ha (2024)	Global	N/A (network)	Street-network simulation	Disruption propagation metrics	Network resilience assessment
Zafeiropoulos et al. (2023)	European	N/A (EO-based)	Resilience support	Earth Observation integration	Decision support system
Present study	**23 countries, 5 pilot cities**	**10 languages**	**Cross-lingual NLP + geolinguistic network analysis**	**Multilingual classifier + information-flow network + pilot indicators**	**Pan-European disaster monitoring framework**

3.2. Data collection and corpus description

The empirical foundation is a multilingual social media corpus collected between May and August 2025 across a pan-European geographic scope. After preprocessing and deduplication, the pilot corpus contained 13,388 posts from 23 countries in 10 languages. Data were retrieved from a single platform (Twitter/X) subject to API constraints: approximately 300 requests per 15-minute window, with a processing delay between ingestion and classification of typically 5–10 min.

Posts were mapped to five pilot Areas of Interest (AOIs), Athens, Thessaloniki, Amsterdam, Barcelona, and Berlin, whilst the wider corpus supported pan-European country-level and language-level analysis. The five AOIs were selected to represent geographic, linguistic, and infrastructure diversity across southern, western, and central Europe. Temporal coverage was restricted to a four-month window, sufficient for pilot validation but insufficient for longitudinal assessment. This four-month window (May to August 2025) was a deliberate pilot scope; the underlying observation was maintained as a continuous metadata time-series across the full period, from which the classified content corpus is a sample, and the collection infrastructure supports continuous extension to the longitudinal horizon the indicator layer requires [40–42]. The weekly coverage of this observation across the window is shown in Fig. 3. English was over-represented in the retrieved corpus (21.1%), a limitation revisited in Section 5.

For data anonymisation, only a generic unique identifier, timestamp, and post text were retained; no personally identifiable information was stored. The study was conducted in accordance with GDPR provisions for the processing of publicly available social media data. The lawful basis for processing is the legitimate-interests provision of the General Data Protection Regulation (Article 6(1)(f)), the legitimate interest being disaster risk reduction research in the public interest, with processing limited to data already made public by users. No special-category data were sought, and the principle of data minimisation was applied throughout: only an anonymised identifier, a timestamp, and post text were retained, raw content is not redistributed, and re-identification risk is mitigated by discarding direct identifiers at ingestion and reporting only aggregated, jurisdiction-level results. The work was conducted under the research-ethics governance of the host institution and the funded project.

3.3. Taxonomy and classifier design

A supervised multilingual classifier was developed using an expert-annotated corpus of disruption-related posts. Eleven fine-grained categories were used at the training stage, drawn from a standardised disruption taxonomy established in a companion study [43]; these were subsequently collapsed into a smaller set of reporting domains for cross-border comparison. The detailed codebook and annotation guidance are provided in Supplementary Table S1.

The classifier is framed as a disaster monitoring instrument rather than as a contribution to NLP methodology in its own right. The practical question for disaster informatics is whether it is sufficiently accurate to support structured classification of disaster discourse across multiple languages and geographic contexts at pan-European scale. Model evaluation relied on a stratified held-out validation set. The classification pipeline is built on multilingual transformer models: an XLM-RoBERTa model fine-tuned for three-way polarity (`cardiffnlp/twitter-xlm-roberta-base-sentiment`) and an mDeBERTa-v3 multilingual natural-language-inference model (`MoritzLaurer/mDeBERTa-v3-base-xnli-multilingual`) applied to the eleven-category disruption taxonomy. Posts were deduplicated prior to analysis, and performance was assessed on a stratified held-out portion of the expert-annotated corpus. Performance was assessed using overall accuracy and Cohen's kappa, the latter employed to test agreement beyond chance in a multilingual classification setting. Cross-lingual performance was evaluated by examining accuracy variation across languages, though the uneven distribution of the corpus across languages limits the strength of per-language conclusions.

3.4. Geographic normalisation and cross-lingual processing

Each post was assigned a language label and a geographic reference where sufficient metadata or text-level indicators were available. Geolocation was handled conservatively: the aim was to support city-level and country-level aggregation for cross-border disaster comparison rather than to claim precise user location for each post. Posts were then mapped to pilot AOIs using the defined geographic boundaries, enabling comparison across the five cities, whilst the wider corpus supported pan-European country-level and language-level analysis.

Geographic normalisation followed a population-weighted approach where applicable, enabling domain-level comparisons that account for differences in population size across AOIs. The geolinguistic layer served two purposes: it made structured cross-border disaster comparison possible using a shared reporting framework, and it enabled the construction of country-to-country and language-to-language flow representations for subsequent network analysis.

Sentiment analysis was applied as a secondary interpretive layer using a three-way distinction (negative, neutral, positive). In parallel, an urgency score was assigned to distinguish routine commentary from posts signalling active disruption or immediate response needs. The urgency layer is more useful than sentiment alone for disaster monitoring applications, because disaster-related discourse is predominantly informational rather than overtly emotional.

3.5. Cross-border information-flow and network analysis

To characterise how disaster information travels across jurisdictional and linguistic boundaries, network analysis was used to convert classified posts into a geolinguistic information-flow representation of cross-border disaster communication pathways. Nodes represent cities, countries, or languages depending on the level of aggregation, and directed edges represent observed information-flow ties inferred from the geolinguistic structure of the dataset. Two complementary visualisations were produced: a node-link network to show clustering structure and a Sankey diagram to show the principal country-to-country and language-to-language channels. These ties are interpreted as communication linkages in disaster-related discourse rather than as verified person-to-person transmission paths.

The network outputs are analysed for clustering structure (geographic and linguistic clustering coefficients), bridging patterns (nodes and edges connecting otherwise separate clusters), and geographic-linguistic co-occurrence (the degree to which spatial proximity and shared language jointly predict information-flow tie strength). These metrics are reported in Section 4.2.

3.6. Pilot antifragility indicator framework for disaster system assessment

Five candidate monitoring indicators are defined to connect the social sensing outputs to a longitudinal disaster system assessment framework. They are presented as a pilot interpretive layer rather than as a fully validated outcome framework. Indicator 3 (information-flow velocity) is the direct social sensing centrepiece; the remaining indicators draw on baseline values from the companion taxonomy study where necessary [43]. To avoid over-claiming, this layer is presented as a conceptual measurement proposal rather than as a validated outcome framework. Information-flow velocity (V_{info}, Indicator 3) is defined but not yet computed on the present corpus, since it requires temporally matched event data, and four of the five indicators draw on companion-study baselines rather than being estimated end-to-end here. The contribution at this stage is therefore the measurement architecture itself, to be calibrated under sustained longitudinal deployment. The full survey instrument underpinning those baselines is provided in Supplementary Material S2.

Indicator 1: Delay variance reduction. For comparable disruptions, an improving system should exhibit less variance in recovery time over successive events:

$$\Delta\sigma_D^2 = \frac{\sigma_{D,t_2}^2 - \sigma_{D,t_1}^2}{\sigma_{D,t_1}^2} \times 100\% \tag{1}$$

where σ_{D,t_1}^2 and σ_{D,t_2}^2 denote delay variance at baseline and follow-up. Improvement criterion: $\Delta\sigma_D^2 < 0$. Provisional threshold: a reduction of at least 15% [26].

Indicator 2: Mode-shift capacity index. Antifragile mobility systems should redistribute demand across modes during disruption:

$$M_{\text{cap}} = \frac{\sum_{m=1}^{M} w_m \cdot U_{m,\text{post}}}{\sum_{m=1}^{M} w_m \cdot U_{m,\text{pre}}} \tag{2}$$

where U_m is utilisation of mode m and w_m is a criticality weight. Improvement criterion: $M_{\text{cap}} > 1.0$. Provisional threshold: $M_{\text{cap}} \geq 1.10$.

Indicator 3: Information-flow velocity. Cross-border information propagation speed serves as the principal social sensing expression of collective learning:

$$V_{\text{info}} = \frac{1}{|E|} \sum_{(i,j)\in E} \frac{d_{ij}}{\Delta t_{ij}} \tag{3}$$

where E is the set of information-flow edges, d_{ij} is geographic distance, and Δt_{ij} is propagation time. Improvement criterion: rising V_{info} across comparable events. Provisional threshold: a 20% increase between comparable event pairs.

Indicator 4: Preparedness trajectory.

$$P_{\text{traj}} = \frac{P_{t_2} - P_{t_1}}{t_2 - t_1} \times 12 \text{ months} \tag{4}$$

where P_t is the share of respondents reporting high preparedness at time t. Improvement criterion: $P_{\text{traj}} > 0$. Provisional threshold: an annual increase of at least five percentage points.

Indicator 5: Coping repertoire diversity.

$$H_{\text{cope}} = -\sum_{s=1}^{S} p_s \log_2(p_s) \tag{5}$$

where p_s is the share of coping strategy s. Improvement criterion: $\Delta H_{\text{cope}} > 0$. Provisional threshold: an increase of at least 0.3 bits. The baseline entropy value is drawn from the companion taxonomy study [43].

4. Findings

4.1. Disaster and disruption type distributions across European pilot areas (RQ1)

RQ1 asks what types and distributions of disaster and disruption events are detectable through cross-lingual social sensing across European areas of interest. On the stratified held-out validation set, the multilingual classifier achieved an overall accuracy of approximately 0.83 and Cohen's kappa of approximately 0.79. Cohen's κ here quantifies agreement between the automated classification and the expert annotations beyond chance, a value of approximately 0.79 corresponding to substantial agreement. Per-language accuracy was examined to assess cross-lingual stability, with the caveat that the uneven distribution of the corpus across languages limits the precision of the per-language estimates. This level of agreement supports domain-level use across multiple languages, whilst leaving room for improvement in finer-grained category distinctions. The result is noteworthy because the classification task is both multilingual and geographically distributed, conditions under which classifier performance typically degrades more rapidly than in monolingual benchmarks.

Transport-related disruptions constituted the most prominent reporting domain, accounting for 23.8% of classified posts. This pattern is consistent with the thematic structure reported in the companion taxonomy study, where transport also dominated citizen survey responses, although the two datasets are not temporally aligned [43]. The convergence supports thematic corroboration rather than event-level validation. To address the absence of external validation, this revision cross-checks the social-sensing signal against an independent authoritative source, namely Copernicus Emergency Management Service (EMS) activation records, across the Areas of Interest covered by the observation. The volume of risk-relevant social signal aligns positively with officially recorded emergency activity: at the level of individual city-by-risk-domain cells the association is weak but statistically significant (Spearman $\rho \approx 0.25$; 95% CI 0.10–0.39; $p < 0.01$; $n = 167$ cells across 24 cities), whilst at the level of the overall risk-domain profile the agreement is strong (Spearman $\rho \approx 0.73$; $p < 0.05$), with the closest city-level correspondence in the health and utilities domains (Fig. 1). The social signal therefore recovers the broad structure of officially recorded emergency activity whilst remaining noisier at fine spatial granularity, consistent with its intended role as a complementary rather than a substitute monitoring layer.

Language coverage was uneven. English represented 21.1% of the total corpus, making it the most over-represented language in the pilot dataset. This is of direct relevance to disaster risk communication, because multilingual reach in principle does not guarantee balanced multilingual observation in practice, and residents who communicate in under-represented languages may therefore be less visible to any monitoring system built on such a corpus.

Sentiment analysis yielded a finding with implications for disaster monitoring system design. Fully 94.5% of posts were classified as neutral, indicating that disruption discourse in the mobility domain is predominantly informational and logistical. For disaster monitoring, urgency-based classification (distinguishing active disruptions from routine commentary) provides greater discrimination than sentiment polarity alone. This revision adds three figures generated from the study's own data: the language balance of the corpus (Fig. 2), the

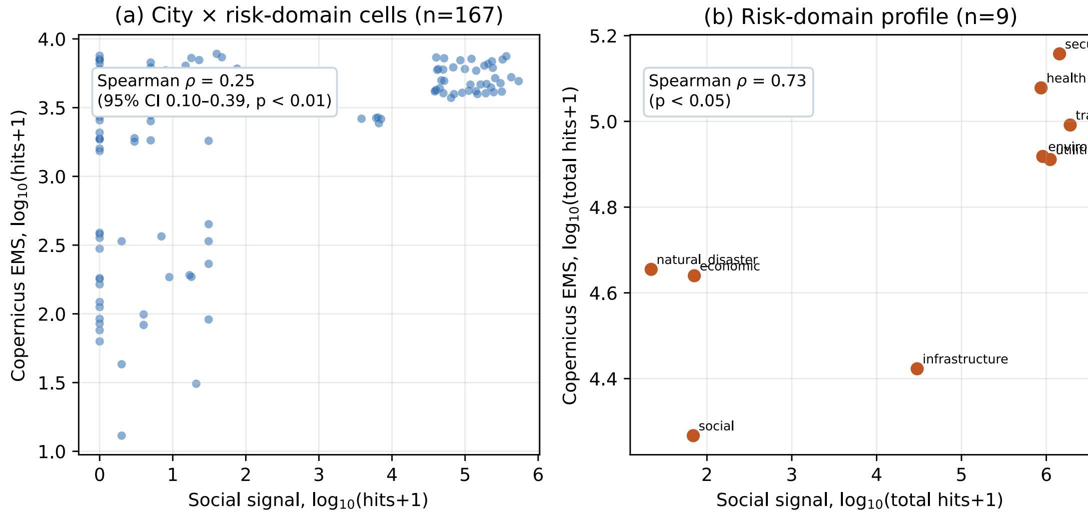

Fig. 1. External validation of the social-sensing signal against Copernicus Emergency Management Service (EMS) activation records, May–August 2025. (a) Per city-by-risk-domain cell ($n = 167$ across 24 shared cities); (b) by overall risk-domain profile ($n = 9$). Both axes are $\log_{10}(\text{hits} + 1)$.

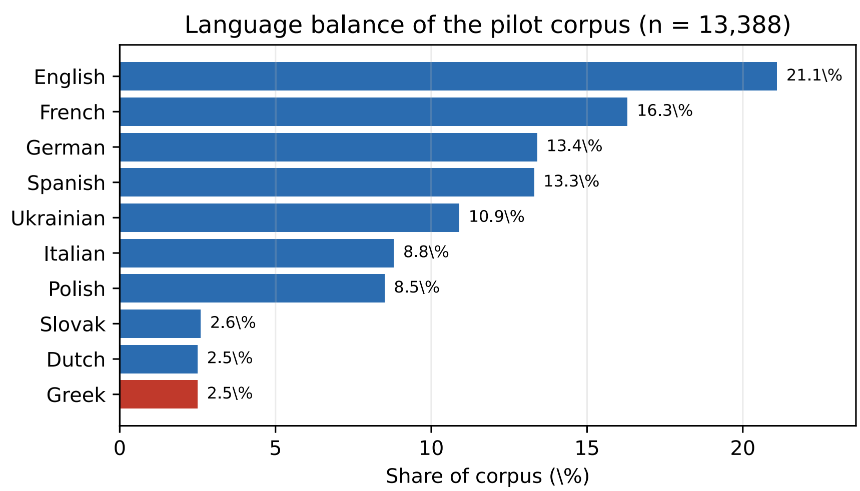

Fig. 2. Language balance of the pilot corpus ($n = 13{,}388$): English is over-represented (21.1%) relative to the other nine languages.

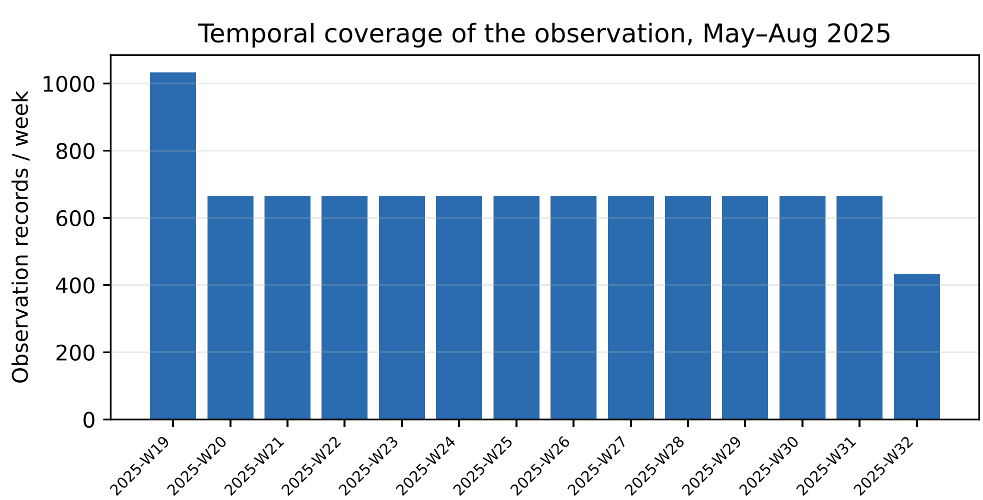

Fig. 3. Temporal coverage of the social-sensing observation over the May–August 2025 window (weekly observation records).

temporal coverage of the observation over May–August 2025 (Fig. 3), and the social-signal-versus-Copernicus comparison (Fig. 1).

Table 2 reports the normalised domain distribution across five pilot AOIs. Transport is particularly prominent in Athens and Thessaloniki,

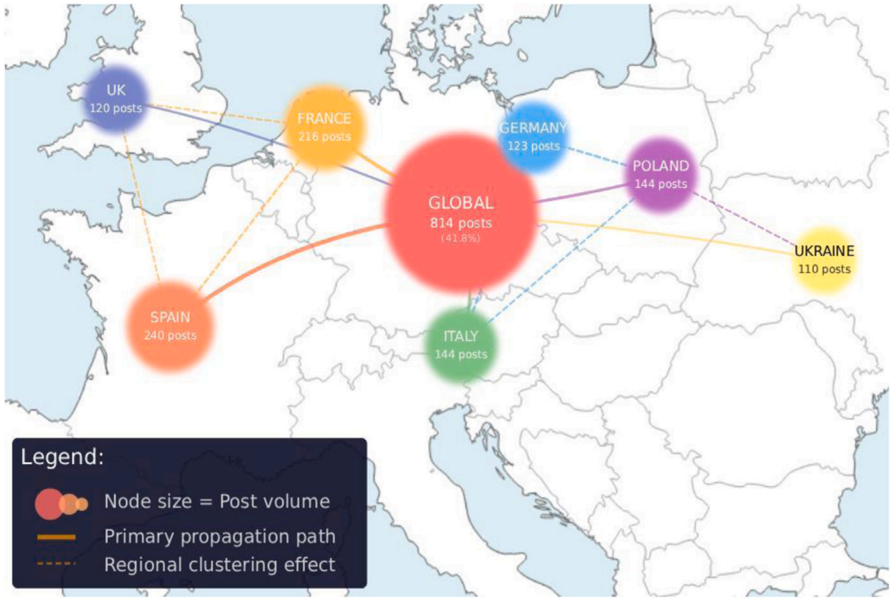

Fig. 4. Network visualisation of disaster-related discourse across European regions (social media data). Node-link structure shows geographic and linguistic clustering, with bridging ties connecting otherwise separate clusters.

Table 2
Normalised disruption percentages by domain across pilot AOIs (social media data, May–August 2025). "Other" aggregates lower-frequency categories not reported separately in the city comparison.

AOI	Transport%	Weather/Env.%	Security%	Utilities%	Other%	*n*
ATH_GR	47.1	14.7	11.8	0.0	26.4	34
THS_GR	58.3	16.7	8.3	0.0	16.7	12
AMS_NL	7.1	7.1	21.4	0.0	64.4	14
BCN_ES	30.0	20.0	10.0	0.0	40.0	10
BER_DE	0.0	6.1	3.0	0.0	90.9	33

AOI = Area of Interest. ATH = Athens; THS = Thessaloniki; AMS = Amsterdam; BCN = Barcelona; BER = Berlin.
n = number of classified posts mapped to each AOI (inferred from the reported percentages).

clearly visible in Barcelona, and less dominant in Amsterdam and Berlin, where the "Other" grouping absorbs a larger share of discourse. The per-AOI denominators are small (n = 10–34 classified posts per city; rightmost column of Table 2), so the cross-AOI comparison should be read as illustrative of the framework's capability rather than as a precise estimate of national disruption profiles.

The analytical value of this table is not that cities are equivalent but that the same framework can expose cross-border differences in disaster and disruption profiles in a consistent and comparable manner. The capacity to produce structured, normalised, cross-border comparisons of disaster discourse using a shared classification pipeline is itself a contribution to disaster monitoring, because it enables benchmarking of disaster information environments across comparable European areas and provides evidence of the framework's utility for disaster monitoring across diverse national and linguistic contexts.

4.2. Cross-border disaster communication dynamics (RQ2)

RQ2 asks what cross-border communication patterns and information-flow dynamics characterise disaster signals in the corpus. The network analysis reveals that disaster-related discourse does not spread evenly across Europe but follows structured pathways shaped by geographic proximity and linguistic accessibility (Fig. 4).

The Sankey diagram in Fig. 5 complements this by showing the principal country-to-country and language-to-language channels. Posts tagged in one country feed into wider language communities, and those language communities act as conduits for broader cross-border circulation of disaster information.

Two broad patterns are discernible. First, discourse clusters are partly geographic: neighbouring countries or cities tend to exhibit denser exchange than distant ones. Second, the clusters are also linguistic: widely shared languages provide bridging capacity that can carry disaster signals beyond the immediate site of the event. Geographic proximity and linguistic reach interact rather than compete. A local disruption may first intensify within a city- or country-level cluster and then expand through broader language channels, a propagation pattern that the network layer makes analytically visible and, in principle, usable for cross-border early warning routing.

The pilot evidence is consistent with identifiable cross-border disaster communication cascades, particularly where mobility-related disruptions have consequences beyond the originating city. Transport discourse is the clearest example, because it concerns routes, delays, closures, and rerouting information that often matters to users outside the originating jurisdiction. The present dataset is not temporally matched to official disaster event registers, so these cascades should be interpreted as communication cascades rather than as validated mobility-impact chains. The network layer demonstrates that cross-border propagation of disaster information is observable and structured rather than anecdotal.

RQ2 is answered in two parts: the dominant flow patterns are clustered, not diffuse, and those clusters align with both geographic and linguistic boundaries, whilst bridging channels are sufficiently strong to generate cross-border disaster communication cascades. These findings characterise the structure of European cross-border disaster communication in a form directly relevant to disaster managers and cross-border early warning planning.

4.3. Pilot antifragility indicators for disaster system assessment (RQ3)

RQ3 asks to what extent antifragility-oriented monitoring indicators can be computed and meaningfully piloted on the collected corpus for disaster system assessment. The principal output at this stage is an information-flow topology across 23 countries and 10 languages, from which V_{info} (Eq. (3)) may be computed once temporally matched event data become available. Full calibration of information-flow velocity

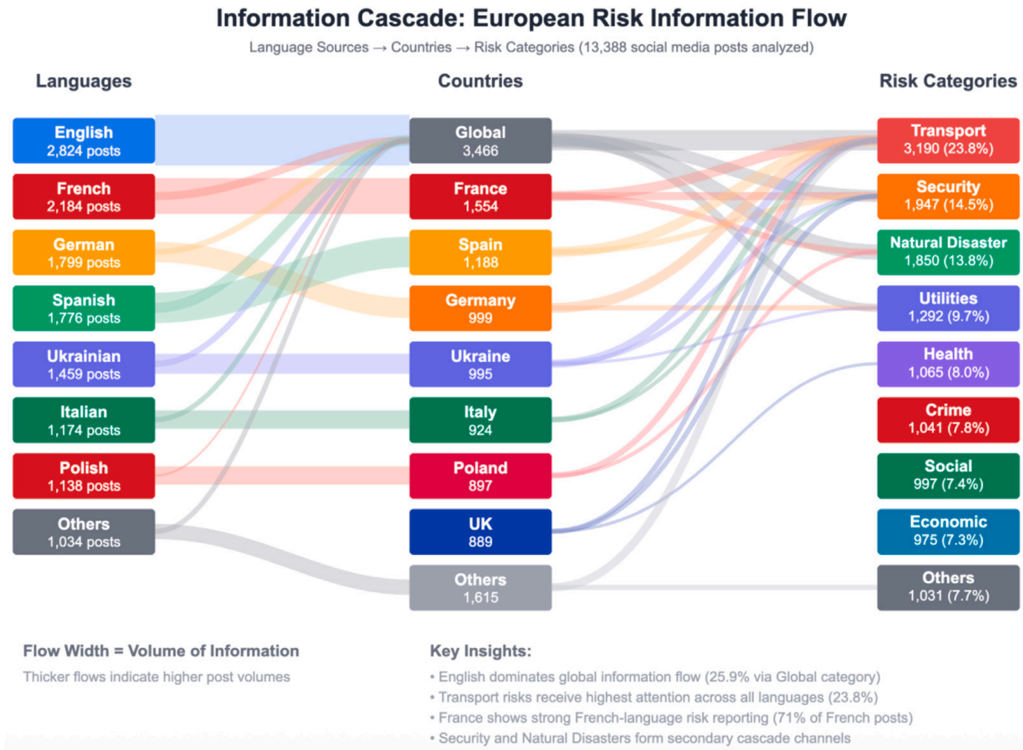

Fig. 5. Sankey diagram of information flows between countries and languages (social media data). The figure highlights the principal cross-border disaster communication channels.

requires such data, because the denominator depends on propagation time between observed communication nodes. The contribution here is therefore a demonstrated measurement architecture rather than a completed longitudinal estimate.

A second baseline derives from coping diversity. Using the coping distribution reported in the companion taxonomy study, the estimated Shannon entropy of the coping repertoire is approximately $H_{cope} \approx 2.9$ bits [43]. This value provides a reference point against which future measurements can be compared.

To support interpretation, the wider research programme identified five empirical mechanisms through grounded-theory analysis of a 123-paper corpus: redundancy activation, innovation acceleration, behavioural learning, institutional evolution, and cross-system integration. These mechanisms support theoretical propositions for future testing (detailed in the companion study). In the present paper, they provide conceptual context for the indicator framework rather than constituting independent empirical contributions.

The answer to RQ3 is cautious but positive: the monitoring infrastructure is in place and the baselines established. Social sensing outputs can serve as baseline inputs for candidate antifragility indicators, particularly through information-flow structure and future velocity estimation, thereby contributing a starting methodology for antifragility-oriented disaster system assessment. What remains is the sustained longitudinal deployment (12–24 months with temporally matched multi-source data) required to convert these candidate indicators into calibrated monitoring metrics.

5. Discussion

5.1. Contribution to disaster monitoring and disaster risk reduction

The principal contribution of this paper lies in demonstrating that a social sensing pipeline combining multilingual text classification, geographic normalisation, and network-based information-flow analysis can operate across 23 countries and 10 languages to produce structured, comparable disaster and disruption monitoring outputs. The classifier achieves accuracy sufficient for domain-level monitoring use (≈0.83; Cohen's κ ≈0.79) in a multilingual and geographically distributed setting, conditions that typically degrade classifier performance. For disaster managers and emergency responders, the practical significance is that pan-European situational awareness need not be built separately for every language community; a shared framework can support cross-border observation of disaster and disruption signals.

The approach extends prior social sensing work for disaster management in three respects. First, it moves from single-city to pan-European analysis, demonstrating that a shared classification framework can expose meaningful cross-border differences in disruption profiles (Table 2). Second, it moves from monolingual to cross-lingual operation, addressing a persistent limitation in disaster social sensing and directly supporting Sendai Framework Priority 1 on understanding disaster risk. Third, it adds a network-analytical layer that makes cross-border information-flow structure visible, rather than treating each city or country as an isolated observation. Moreover, the evidence here is consistent with the hypothesis advanced in Section 3.1: cross-lingual social sensing data, when systematically classified, can indeed yield comparable disaster monitoring outputs at pan-European scale. The evidence for this component of the hypothesis is strong. This pan-European, cross-lingual scope is what distinguishes the present framework from the prevailing state of the art. In a systematic review of transformer-based disaster analytics, [44] found the field to remain overwhelmingly monolingual and concentrated on a single platform, so the demonstration here that one shared classifier supports structured comparison across ten languages and 23 countries addresses a documented gap rather than offering an incremental refinement. The held-out accuracy of approximately 0.83 is, as would be expected, lower than the 88.5% reported by [2] for a single-city, single-language, seven-category classifier; the difference reflects the substantially harder cross-lingual, multi-country, eleven-category setting rather than a regression in method. The finding that urgency affords greater discrimination than sentiment polarity is consistent with [45], whose review of sentiment analysis in disaster risk management likewise concludes that polarity is weakly informative for the predominantly factual register of disaster discourse.

5.2. Contribution to cross-border disaster communication analysis

The network layer represents a substantive analytical result rather than an accessory visualisation. The clustering patterns (geographic and linguistic), the bridging ties (connecting otherwise separate clusters), and the propagation pathways (from local clusters through shared-language channels) characterise the structure of European disaster-related discourse in ways that have direct implications for cross-border early warning. [7] demonstrated that network connectivity metrics can characterise resilience at the street-network level; the present study extends network-analytical thinking to the information-flow dimension of disaster communication, operating at the city-to-city and country-to-country scale. Of particular interest for disaster managers is the observation that bridging ties through widely shared languages carry disaster signals beyond the immediate site of the event, which suggests that cross-border alerting arrangements could be routed along empirically observed communication pathways rather than along administrative boundaries alone. Methodologically, the geolinguistic information-flow network is closely related to the approach of [46], who reconstructed spatial information-diffusion networks from heterogeneous agents and text content; the present contribution differs in operating across national and linguistic boundaries rather than within a single information space, which is precisely the dimension that transboundary European crises demand [47]. The finding also has an institutional counterpart: in a cross-national interview study of European disaster managers, [48] found social-media practice to remain largely nationally bounded, so the cross-border bridging ties observed here describe a communication structure that current institutional arrangements do not yet exploit.

The evidence relating to the second component of the hypothesis is likewise supportive: cross-border disaster communication is structured rather than diffuse, and the network layer makes that structure analytically tractable. This finding aligns with the Sendai Framework's Priority 4 emphasis on effective preparedness and response, particularly the call for multi-hazard early warning and risk communication that reaches all segments of society.

5.3. Contribution to multilingual disaster risk communication

The cross-lingual dimension of the framework is substantive rather than merely technical. The uneven language distribution in the corpus (with English over-represented at 21.1%) is itself a finding of disaster-risk-communication significance: it demonstrates that multilingual reach does not guarantee balanced multilingual observation. For disaster monitoring, this means that the visibility of a disaster in the social media stream is shaped by the linguistic profile of the affected population and the platform's geographic reach. [4] argued that language choice shapes who receives warnings and whose risk becomes institutionally visible; the present framework makes this asymmetry measurable and comparable across European countries, which is a prerequisite for designing equitable cross-border disaster warning systems. The over-representation of English (21.1%) can be read as a quantified instance of what [49] termed "disaster linguicism", the systematic disadvantaging of linguistic minorities in disaster settings, a pattern that [50] also document in emergency planning. Framing balanced multilingual observation as a precondition for inclusive early warning aligns directly with the achievements and persistent gaps that [51] identify for multi-hazard early-warning systems under the Sendai Framework.

It is noteworthy that urgency classification provides greater analytical discrimination than sentiment polarity for disaster monitoring, given the predominantly neutral tone of disaster-related discourse (94.5%). This has practical implications for the design of real-time disaster dashboards, which have often defaulted to sentiment-based filters that are ill-suited to an inherently informational discourse register.

5.4. Antifragility as a disaster system assessment lens

The antifragility indicators, particularly information-flow velocity (V_{info}), have potential as longitudinal disaster system assessment metrics. If critical disaster information is observed to reach relevant jurisdictions more quickly after repeated events, that may be interpreted as evidence of improving cross-border disaster communication. The coping entropy baseline complements this by offering a community-level reference point; together, these indicators provide a starting measurement architecture for antifragility-oriented disaster system assessment as advocated in the theoretical literature [33,34,38]. To our knowledge this is among the first attempts to express antifragility as a set of computable indicators for disaster monitoring using empirical social-sensing data, and it directly answers the agenda of [52], who call for rethinking disaster risk through a transformative-resilience lens but stop short of computable instruments. Conceptually, the proposed indicators differ from conventional disaster-resilience indices, which [53] synthesise as predominantly return-to-baseline constructs: information-flow velocity is designed to capture improvement through exposure rather than recovery to a prior state alone.

Revisiting the hypothesis with respect to this third component, the evidence is cautious but positive. The measurement architecture is in place and baselines have been established; full calibration will require sustained longitudinal deployment with temporally matched multi-source data. These indicators are therefore candidate constructs at this stage rather than validated metrics, and should be interpreted accordingly by disaster managers and policymakers.

5.5. Practical implications for disaster managers and government agencies

The framework translates into several concrete recommendations for civil-protection authorities and government agencies. First, a single cross-lingual monitoring pipeline can replace the language-specific or city-specific tools that agencies currently operate in parallel, lowering the running cost of pan-European situational awareness and serving Sendai Framework Priority 1 on understanding disaster risk. Second, the empirically observed bridging ties through widely shared languages provide an evidence base for routing cross-border early-warning messages along the channels through which disaster information already travels, rather than along administrative boundaries alone, in support of Sendai Priority 4 on preparedness and response; this directly addresses the nationally bounded social-media practice documented among European disaster managers [48]. Third, real-time monitoring dashboards should prioritise urgency-based filtering over sentiment polarity, which the predominantly neutral tone of disaster discourse (94.5%) renders weakly informative. Fourth, because platform-based monitoring systematically under-represents some linguistic and demographic groups [54], agencies adopting such systems should institute periodic representational audits and treat social sensing as a complement to, not a replacement for, official reporting and field-based situational awareness.

5.6. Limitations

Several limitations define the current boundary of interpretation.

The dataset derives from a single platform, so demographic and behavioural platform bias remains unavoidable. English is over-represented in the corpus, which affects both the visibility of non-Anglophone disasters and the structure of bridging ties in the network. The temporal window is narrow (May–August 2025), sufficient for pilot validation but insufficient for the longitudinal disaster system assessment that the indicator framework is designed to support. Sentiment analysis adds limited discrimination in this domain (94.5% neutral), reinforcing the case for urgency-based classification. The candidate antifragility indicators are defined and baseline values established, but they are not yet calibrated against longitudinal outcome data.

The grounded-theory mechanisms are literature-derived and have not been empirically tested on event-matched social media sequences. The network ties are inferred from geolinguistic co-occurrence rather than from verified person-to-person transmission, and should be interpreted as communication structure rather than as causal propagation.

Each limitation points to a specific remediation pathway. The single-platform constraint reflects a structural property of publicly accessible social data rather than an oversight: [55,56] establish that platform samples carry population and behavioural biases by construction, and [54] show that disaster social-media data systematically over- and under-represent particular places and populations. The corresponding remedy is multi-platform ingestion, the feasibility of which beyond Twitter/X following recent application-programming-interface restrictions is demonstrated by [57]. The over-representation of English is a language-resource artefact common to crisis natural-language processing [58]; the remedy is per-language fairness auditing together with cross-lingual transfer to lower-resource languages. The narrow temporal window is best addressed not by a single longer extraction but by continuous, study-time collection, because social-media composition drifts over time [40,56] and near-real-time monitoring depends on an ongoing stream rather than a one-off batch [41]. The uncalibrated indicators require the 12–24 month deployment already noted, and the literature-derived cascade mechanisms require event-matched testing against external registers. Two further limitations of a statistical nature should be acknowledged: the per-AOI domain percentages in Table 2 rest on small per-city denominators and should be read as indicative of the framework's capability rather than as precise national estimates, and the headline accuracy and κ are reported as point estimates rather than with confidence intervals.

These limitations do not invalidate the pilot. They clarify what can be concluded now (multilingual classification is feasible for disaster monitoring, cross-border communication structure is observable and non-random, and social sensing can be embedded within a DRR-oriented framework) and what must follow: temporally aligned deployment, multi-platform expansion, richer event matching against official disaster registers, and sustained measurement over 12–24 months.

5.7. Ethical considerations and data governance

Any framework that repurposes citizen-generated social media content for disaster monitoring raises ethical questions. The present study processed only publicly available posts, retained no personally identifiable information, and stored only anonymised identifiers, timestamps, and post text, in accordance with GDPR provisions for the processing of publicly available data.

Beyond individual privacy, the aggregation of social media data for disaster monitoring creates risks of surveillance creep, representational bias (populations less active on the platform are less visible to the monitoring system), and false monitoring confidence (the availability of real-time data may discourage investment in complementary data collection). Disaster management authorities deploying social sensing frameworks should develop explicit protocols addressing these risks, including periodic representational audits and clear boundaries on permissible data uses.

6. Conclusion

This paper has developed and piloted a cross-lingual social sensing framework for disaster and disruption monitoring at pan-European scale. The framework makes three interrelated contributions to disaster informatics and disaster risk reduction.

First, it provides a replicable multilingual classification pipeline capable of supporting structured, cross-border disaster and disruption monitoring across 23 countries and 10 languages, showing that cross-lingual social sensing is feasible as a disaster monitoring capability aligned with Sendai Framework Priority 1. Second, it presents a cross-border disaster communication analysis indicating that disaster-related discourse follows structured pathways, clustering along geographic and linguistic boundaries whilst exhibiting bridging channels that enable transnational cascade propagation, with direct relevance to Sendai Framework Priority 4 on preparedness and early warning. Third, it proposes a pilot indicator framework for antifragility-oriented disaster system assessment, with baseline measurement architectures that connect social sensing outputs to longitudinal monitoring.

RQ1. The multilingual classifier achieved accuracy sufficient for domain-level disaster monitoring use (≈0.83; Cohen's κ ≈0.79). Transport-related disruptions constitute the dominant signal (23.8%), and the framework exposes meaningful cross-border differences in disruption profiles, supporting comparative disaster monitoring across European pilot areas.

RQ2. Cross-border information flows in disaster discourse are structured, not random. They cluster along geographic and linguistic lines whilst exhibiting bridging channels that carry disaster signals across jurisdictions. The network layer makes this communication structure analytically measurable and, in principle, usable for routing cross-border early warnings.

RQ3. Social sensing outputs can serve as baseline inputs for candidate antifragility indicators. The information-flow topology, the coping-entropy baseline (≈2.9 bits), and the theoretically derived mechanisms together provide a starting point for longitudinal disaster system assessment, though full calibration requires sustained deployment with temporally aligned multi-source data.

Future work should extend the framework through multi-platform deployment, expanded geographic and temporal coverage, and event-level cross-validation against official disaster databases such as EM-DAT and Copernicus Emergency Management Service. The companion taxonomy and citizen survey baselines [43] provide the complementary evidence infrastructure for full indicator calibration. A longer-term objective is to integrate the social sensing layer with cross-border early warning systems, enabling disaster information monitoring that operates across languages, countries, and jurisdictions within a unified framework aligned with the Sendai Framework for Disaster Risk Reduction 2015–2030.

CRediT authorship contribution statement

Ali Ghoroghi: Writing – review & editing, Writing – original draft, Validation, Methodology, Conceptualization. **Andrei Hodorog:** Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Yacine Rezgui:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Afrouz Ghaemi:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **Cristina De Nardi:** Writing – review & editing, Conceptualization.

Declaration of generative AI use

During the preparation of this work, the authors used AI-assisted tools for language editing and structural organisation. The authors reviewed and edited all content and take full responsibility for the content of the publication.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.pdisas.2026.100715.

Data availability

The social media posts analysed in this study were collected from publicly available sources. Raw post text cannot be shared openly because redistribution may conflict with the platform's terms of service and GDPR-related privacy safeguards. The annotation codebook and the survey instrument underpinning the pilot indicators are provided as Supplementary Material (Supplementary Table S1 and Supplementary Material S2). The aggregate datasets that support the findings (per-Area-of-Interest disruption-domain distributions, per-language post counts, weekly observation counts, and the Copernicus EMS comparison tabulations), together with other derived metadata, are available from the corresponding author upon reasonable request.

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