**D2.1**

Urban Event Mapping

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Revision v0.1

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Abstract

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| Deliverable D2.1 presents a pan‑European mapping of urban disruptions, incorporating pilot sites (Odessa, Bratislava, Larissa, Thessaloniki) within a wider continental dataset. A two‑axis taxonomy of event domain (transport, environment/weather, utilities/connectivity and public space/social) and scale (daily, mid‑scale, large‑scale) underpins the classification. The methodology integrates primary data from a multilingual survey (140 respondents across 15 European countries), systematic literature review, EM‑DAT disaster records, Copernicus satellite data and social‑media analytics. Quantitative analyses assess frequency, severity and spatial–temporal patterns, while qualitative grounded‑theory coding elucidates adaptive responses. Findings reveal that transport‑related disruptions dominate the European risk landscape, with road works and public‑transport delays affecting over 60% of respondents, and that social‑media discourse mirrors these patterns. Cross‑site synthesis highlights data gaps (e.g., under‑reported large utility disruptions in Odessa) and low perceived resilience in many areas of interest. The resulting event catalogue and taxonomy align heterogeneous data streams and provide a baseline for antifragile strategy design and the development of WP2 tools. |

Keywords

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| Urban Disruption, Antifragility, Mobility Resilience, Event Mapping, Risk Taxonomy, Social‑Media Analysis, EM‑DAT. |

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| Nature of the deliverable | **to specify: R, DEM, DEC, OTHER\*** |

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| Dissemination level | | |
| PU | Public, fully open. e.g., website |  |
| CL | Classified information as referred to in Commission Decision 2001/844/EC |  |
| CO | Confidential to GENOMED4ALL project and Commission Services | ✔ |

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| **\* Deliverable types:**  **R:** document, report (excluding periodic and final reports).  **DEM:** demonstrator, pilot, prototype, plan designs.  **DEC:** websites, patent filings, press and media actions, videos, etc.  **OTHER:** software, technical diagrams, etc. |

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Abbreviations

|  |  |
| --- | --- |
| AI | Artificial Intelligence |
| WP | Work Package (e.g. WP2 refers to Work Package 2) |
| AOI | Areas Of Interest |
| T | Task (e.g. T2.1 refers to Task 2.1) |
| CU | Cardiff University (deliverable lead organisation) |
| EC | European Commission |
| DEM / DEC | Demonstrator / Dissemination and communication (deliverable types) |
| PU / CL / CO | Public / Classified / Confidential (dissemination levels) |
| EM‑DAT | Emergency Events Database |
| PRISMA | Preferred Reporting Items for Systematic Reviews and Meta‑Analyses |
| OFDA/BHA | Office of U.S. Foreign Disaster Assistance / Bureau for Humanitarian Assistance |
| USAID | United States Agency for International Development |
| AHEPA | AHEPA University Hospital in Thessaloniki (pilot site) |
| PT | Public Transport |
| ICT | Information and Communication Technology |
| GDPR | General Data Protection Regulation |
| SJR | Scimago Journal Rank (journal quality metric) |
| SPSS | Statistical Package for the Social Sciences |
| TF‑IDF | Term Frequency–Inverse Document Frequency (text‑analysis metric) |
| NVivo | Qualitative data‑analysis software |
| CEMS | Copernicus Emergency Management Service |
| EMS | Emergency Management Services |
| API | Application Programming Interface |
| AOI | Area of Interest |
| IQR | Interquartile Range |
| ID | Identifier |

# Executive summary

This deliverable presents the outcomes of Work Package 2 (WP2) of the AntifragiCity project, a foundational effort to understand urban events, assess their impacts, and develop frameworks for mobility management and urban resilience. Through an iterative co-creation process involving four demonstration sites; Odessa, Bratislava, Larissa, and AHEPA (University Hospital in Thessaloniki), we have mapped urban events. Key findings include a comprehensive mapping of urban events ranging from daily stressors to large-scale disruptions. This work lays the groundwork for enhancing urban resilience and mobility management across the AntifragiCity project.

# Introduction

Deliverable D2.1, "Urban Event Mapping," is the key output of Task T2.1 within Work Package 2 (WP2) of the AntifragiCity project. This task aims to map the diverse range of events occurring in urban environments, identify their associated risks, and assess their impacts, with a specific focus on mobility. The purpose is to provide a foundational understanding that supports the development of antifragile urban systems capable of adapting to and thriving in the face of disruptions.

This deliverable results from a collaborative effort with representatives from four demonstration sites, Odessa, Bratislava, Larissa, and AHEPA, using a co-creation approach to ensure the mapping reflects real-world urban challenges.

## Event Taxonomy & Definitions

To ensure consistency across datasets, we adopt a two-axis taxonomy: **(A) thematic domain** (from the questionnaire) and **(B) disruption scale** (daily → midscale → largescale).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Event Category | Definition | Examples | Affects Passenger Mobility | Affects Freight Mobility | Affects Infrastructure |
| Transport-related | Any interruption or degradation of passenger/freight movement due to infrastructure, operations or regulation. | Congestion, PT delays, roadworks, strikes | ✓ | ✓ | ✓ |
| Environment & Weather | Natural phenomena altering mobility conditions or infrastructure integrity. | Heatwaves, floods, snow/ice, storms | ✓ | ✓ | ✓ |
| Utilities & Connectivity | Failures in essential services that indirectly/ directly constrain mobility. | Power/water outage, ICT breakdown | ✓ | ✓ |  |
| Public Space / Social Events | Planned/unplanned socio-spatial activities affecting flows. | Protests, festivals, sports events, security incidents | ✓ | ✓ |  |

**Table 1.** Event Taxonomy (Domain × Scale)

**Scale definitions**

* Daily Stressor: High-frequency, low-severity events manageable within routine operations (e.g., minor PT delay).
* Mid‑scale Disruption: Medium-frequency/impact events requiring adaptive responses and coordination (e.g., localized flooding).
* Large‑scale Crisis: Low-frequency, high-impact events exceeding standard capacity (e.g., pandemic wave, major earthquake).

**Severity classification link:** The 5-level severity scheme used in the survey specifications will be used as an internal modifier within each scale.

All subsequent analyses, social-media (§3.3.6), EM-DAT (§3.3.4), and survey outputs, must cite the **numeric code plus the common label** on first mention (e.g., Level 4 – High).

|  |  |  |
| --- | --- | --- |
| Numeric level | Common label (use in all sections) | Social-media label (keep as alias) |
| 5 | Critical / Immediate | Critical |
| 4 | High / Priority | High |
| 3 | Moderate / Standard | Moderate |
| 2 | Low / Background | Low |
| 1 | Very Low / Informational | Very Low |

**Table 2.** Severity / Urgency Equivalence



























## Taxonomy Alignment & Cross-walk

To ensure that all evidence streams feed a single, harmonised classification, we reconcile the internal survey taxonomy (four disruption domains) with the two external schemes used later in the deliverable:

* **11-category social-media risk taxonomy** applied in §3.3.6, derived from European risk-communication patterns.
* **Five high-level EM-DAT disaster groups** used in §3.3.4.
* **Survey questionnaire domains** introduced in §2.1.

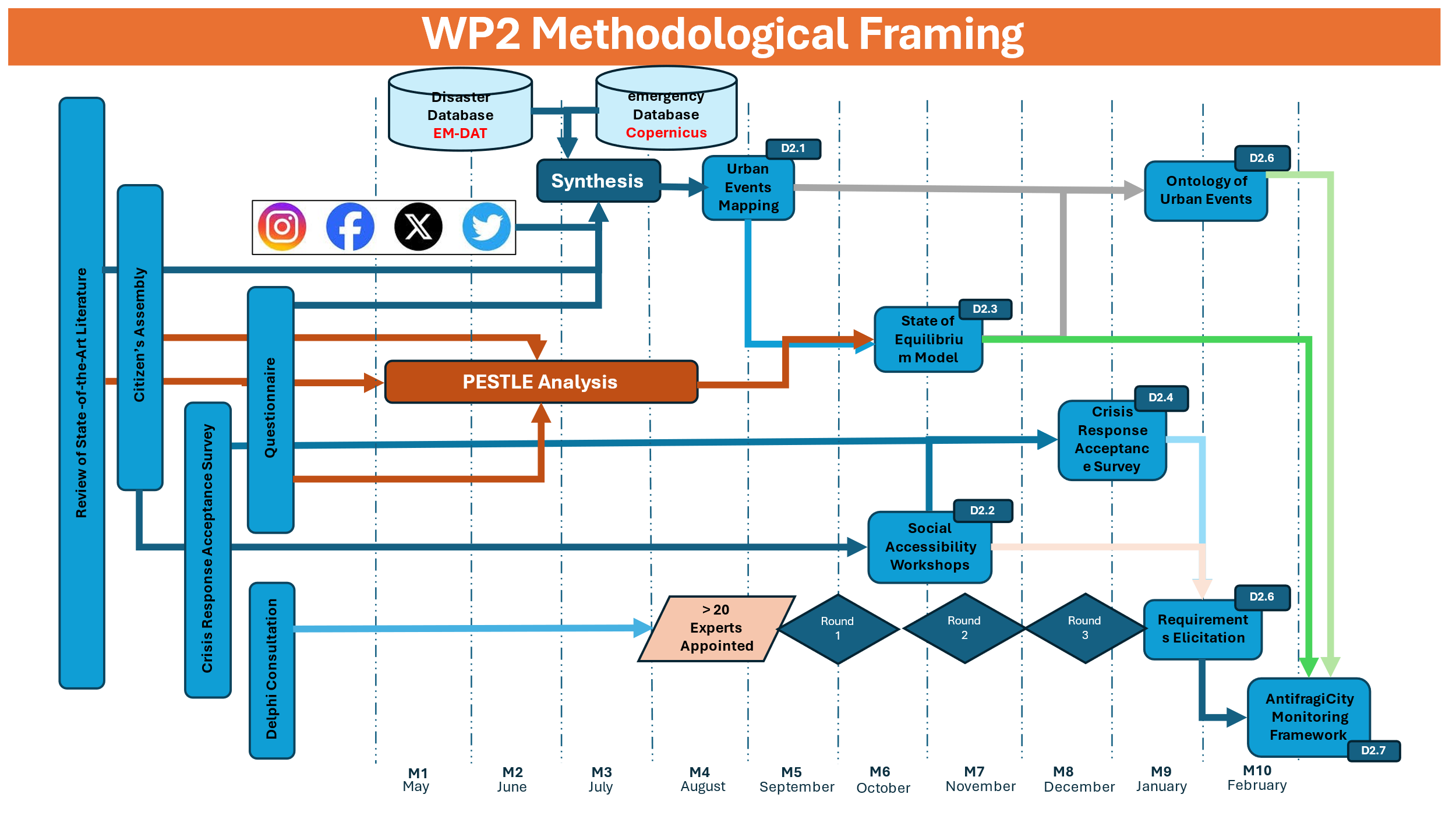
The cross-walk below provides the lookup table that WP 3.4’s synthesis script will use to auto-tag events from heterogeneous sources. Cross‑walk linking survey domains to social‑media categories and EM‑DAT and Copernicus.

|  |  |  |  |
| --- | --- | --- | --- |
| Survey domain (4) | Key social-media category/ies | Mapped EM-DAT group | Illustrative sub-events |
| Transport-related | Transport; Infrastructure | Operational | Congestion, PT delays, roadworks, strikes |
| Environment & Weather | Natural disaster; Environment | Natural | Floods, storms, heatwaves, air-quality alerts |
| Utilities & Connectivity | Utilities; Infrastructure | Technological / Infrastructure | Power outage, water-supply failure, network outage |
| Public Space / Social Events | Social; Security; Crime; Political unrest; (Health) | Human-induced / Social; Systemic / Structural | Protests, festivals, sports events, unrest, epidemic restrictions |

**Table 3.** Cross‑walk linking survey domains to social‑media categories and EM‑DAT/Copernicus disaster groups used in WP 3.4.

# Methodology

The methodology employs a mixed-methods approach, integrating qualitative and quantitative analyses to develop a comprehensive understanding of urban mobility disruptions and their systemic impacts.



**Figure 1.** Methodology Overview for urban event mapping

## Research Design and Stakeholder Engagement

Given the temporal constraints of the project timeline, stakeholder engagement was conducted through structured questionnaires distributed to partners in Odessa, Bratislava, Larissa, and AHEPA. This asynchronous approach ensured comprehensive input while accommodating project deadlines.

* **Digital Questionnaires:** Structured instruments capturing local perspectives on mobility disruptions, system vulnerabilities, and adaptive responses.
* **Partner Validation:** Iterative feedback loops with pilot sites to verify event categorizations and impact assessments.
* **Cross-site Synthesis:** Comparative analysis of responses to identify common patterns and context-specific variations.

## Data Sources

### Primary Data Sources:

* **Stakeholder Questionnaires (n=140):** Structured responses from urban mobility managers, planners, and operators across four pilot cities

### Secondary Data Sources:

* **Academic Literature Corpus:** 123 peer-reviewed papers (2015-2025) on urban mobility disruptions, systematically selected from Web of Science, Scopus, and transportation databases
* **Social Media Dataset:** Real-time event reports and citizen observations from Twitter/X, local platform 2020-July 2025)
* **EM-DAT Database:** Historical disaster events affecting urban areas (2000-July 2025), filtered for mobility impact indicators
* **Copernicus Database:** Historical disaster events affecting urban areas (2012-July 2025).

We will report on Cronbach’s α only for the multi-item scales to demonstrate document survey reliability. For all other datasets, we will rely on domain-appropriate validation metrics listed above, avoiding a statistic that would be mathematically invalid and potentially misleading in those contexts. In EM-DAT, each column captures different real-world attributes; rows are independent cases, not items of a scale. Inter-item covariance (needed for α) is meaningless there. For social media monitoring, labels are outputs of an algorithm, not self-reported items; “internal consistency” is evaluated via classifier accuracy, not α. For Literature/NVivo codebook, codes are descriptive, multi-dimensional; they purposely diverge. Covariance across codes is expectedly low or negative, violating α assumptions. For Copernicus dataset, continuous geophysical measurements are not survey items; α offers no insight into spatial or measurement error.

## Analytical Methods

This section outlines the analytical techniques applied to the three data sources; literature review, social media, and EM-DAT, and presents the key findings from each. The methods and findings are organized into dedicated subsections for clarity. A systematic thematic analysis was employed to synthesize insights from the literature. This involved reviewing academic papers, reports, and policy documents related to urban events and their impacts on mobility. The qualitative data analysis software NVivo was used to assist with this process. NVivo enabled the systematic coding of texts, categorization of recurring concepts, and identification of key themes. The approach involved:

### Primary Data Analysis

Statistical Analysis of Questionnaire Responses

Technical Approach

The questionnaire items were designed after reviewing 123 Q1‑ranked journal papers and in consultation with project partners.

**Pilot phase:** we first tested the draft with 13 partner organisations, asking each to submit at least two trial responses before wider distribution. Their feedback, rooted in local experience, informed the first revision. The revised questionnaire was built in Google Forms, complete with a **GDPR-compliant consent form**. A companion feedback form was also created to identify weaknesses in the main instrument. Both forms were sent to partners simultaneously, with a nine-day response window. We received 28 pilot responses to the main questionnaire and 16 to the feedback form.  
After incorporating the suggested improvements, the final version was redistributed. Because project data must be stored on an EU server, the team voted to migrate the instrument from Google Forms to EU Survey. The questionnaire, alias **urbandisruptionsurvey2025**, title **Urban Disruptions Questionnaire (UDQ)**, was recreated in EU Survey with English as the primary language.  
Partners were asked to complete the UDQ by **21 July**. For wider public reach, the instrument was professionally translated into Slovak, Greek, and Ukrainian; after quality review, these versions were published alongside the English original. Partners received separate links for each language and were instructed to use snowball sampling to disseminate the survey through their networks and encourage further sharing.

The completion deadline was subsequently extended to **30 July**, and the UDQ was promoted via social-media posts in all four languages. Following formal approval to advertise within the ECTP community, we invited its members to complete and disseminate the UDQ.

Respondents can access the UDQ via the master link below or through direct links to each translation.

Master link (**English** + dropdown for all languages): https://ec.europa.eu/eusurvey/runner/urban-disruption-survey-2025

**Slovak:** https://ec.europa.eu/eusurvey/runner/urban-disruption-survey-2025?surveylanguage=SK

**Greek:** https://ec.europa.eu/eusurvey/runner/urban-disruption-survey-2025?surveylanguage=EL

**Ukrainian:** <https://ec.europa.eu/eusurvey/runner/urban-disruption-survey-2025?surveylanguage=UK>

#### Survey Design: The questionnaire consisted of 46 questions organized into eight thematic sections: - Consent and Demographics (Q1-Q3) - Recent Disruptions Experience (Q4-Q9) - City Resilience Perceptions (Q10-Q17) - Priorities for Improvement (Q18-Q19) - Future Hazards and Preparedness (Q20-Q24) - Personal Agency and Community (Q25-Q33) - Urban Challenges (Q34-Q41) - Respondent Profile (Q42-Q46)

#### Disruption Categories Analysed: The survey examined four primary disruption categories: 1. Transport-related (8 subcategories) 2. Environment & Weather (7 subcategories) 3. Utilities & Connectivity (5 subcategories) 4. Public Space (6 subcategories)

The complete survey questionnaire contained 46 questions across 8 thematic sections, administered through EU Survey platform with GDPR-compliant data handling. Response data was collected between 9 July to 31 July with participants from 15 European countries providing informed consent for research use.

Findings

This section presents comprehensive findings from the European urban disruptions survey conducted as part of the AntifragiCity project (see Annex 3 for the full set of survey questions). The survey collected responses from 140 participants across 15 European countries, documenting 7,574 disruption events to support event mapping for antifragile urban mobility planning. The analysis provides critical inputs for understanding disruption patterns, citizen resilience, and infrastructure vulnerabilities across European cities.

**Scale reliability:** We explored internal consistency for three tentative multi‑item groupings derived from Likert questions (institutional/community capacity; disruption burden; agency/participation). Cronbach’s α ranged from 0.48 to 0.64 (k = 2–4 items), below the commonly accepted threshold (α ≥ 0.70). Because internal consistency was insufficient (α < 0.70), the following figures/tables present item-level distributions instead of aggregated scales.

**Survey Analysis Report:** The survey included 140 respondents, with post-stratification weighting applied to correct for over-representation of countries like Greece and Ukraine and under-representation of countries like the United Kingdom and Spain. Weights were based on Eurostat adult population counts, scaled to a mean of 1 and trimmed at four times the mean. The effective sample size (ESS), calculated as ((\sum w)^2 / \sum w^2), is approximately 74, reflecting reduced statistical precision due to weighting. All reported estimates (e.g., percentages, means) are weighted, and confidence intervals and p-values are calculated using the ESS of 74.

**Weighting Explanation:** Post-stratification weighting was applied to correct biases in country representation, as Greece and Ukraine were over-represented, while the UK and Spain were under-represented. Weights, based on Eurostat adult population counts, were scaled to a mean of 1 and trimmed at four times the mean to limit extreme values. This improved representativeness but increased variance, reducing the ESS to ~74. Weighted results show a higher share of rural/remote residents, lower disruption counts, and higher resilience perceptions, as under-represented groups report fewer disruptions and stronger confidence. Statistical inferences use the ESS (~74) to ensure accurate confidence intervals and p-values.

Spatial Distribution Analysis

|  |  |  |  |
| --- | --- | --- | --- |
| Country | Respondents (weighted) | Percentage | Major Cities Represented |
| United Kingdom | 59.0 | 21.63 | Cardiff, Norwich, Folkestone |
| Spain | 44.3 | 16.22 | Barcelona, Madrid, Solsona, A Coruña |
| Ukraine | 29.6 | 10.82 | Odesa |
| France | 24.1 | 8.88 | Dragey-Ronthon, Blaru |
| Germany | 24.1 | 8.88 | Hamburg |
| Netherlands | 15.8 | 5.82 | Delft, Rotterdam |
| Italy | 12.0 | 4.44 | Bologna |
| Poland | 12.0 | 4.44 | Aleksandrow Lodzki |
| Belgium | 10.7 | 3.95 | Tongeren, Hasselt |
| Greece | 9.6 | 3.5 | Thessaloniki, Athens, Larissa, Rethymno, Giannitsa, Heraklion, Volos, Peraia |
| Sweden | 8.8 | 3.24 | Orebro |
| Belarus | 8.1 | 3.0 | Minsk |
| Switzerland | 7.9 | 2.91 | Zurich |
| Slovakia | 4.6 | 1.71 | Bratislava |
| Cyprus | 0.9 | 0.33 | Limassol |

**Table 4.** Geographic Distribution of Survey Responses

**Note:** Estimates are based on 140 respondents, weighted using post-stratification (statistical tests use the ESS (~74) for variance estimation).

**Key Finding:** After population re-weighting, the United Kingdom represents the largest share of the analytical sample (21.6%), followed by Spain (16.2%) and Ukraine (10.8%).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | City | Country | Total Events (Weighted) | Respondents (Weighted) | Average Events/Person |
| 1 | Cardiff | UK | 724.7 | 51.3 | 14.1 |
| 2 | Odessa | Ukraine | 429.0 | 30.3 | 14.2 |
| 3 | Delft | Netherlands | 233.7 | 14.3 | 16.3 |
| 4 | Belval | Luxembourg | 207.0 | 12.6 | 16.4 |
| 5 | Aleksandrów Łódzki | Poland | 198.2 | 12.4 | 16.0 |
| 6 | Hamburg | Germany | 197.6 | 12.4 | 15.9 |
| 7 | Dragey Ronthon | France | 196.6 | 12.4 | 15.8 |
| 8 | Blaru | France | 195.4 | 12.4 | 15.7 |
| 9 | Bologna | Italy | 193.5 | 12.4 | 15.6 |
| 10 | Solsona | Spain | 172.1 | 11.4 | 15.1 |

**Table 5.** Top 10 Cities by Disruption Intensity

**Note:** These periods overlap or restructure the analysis using non‑overlapping intervals.

**Key Finding:** Cardiff and Odessa report high disruption events, with Delft and Belval showing the highest per-respondent averages.

Disruption Type Analysis

|  |  |  |  |
| --- | --- | --- | --- |
| Disruption Type | Category | Affected (%) 1 | Recent Weighted Occurrences 2 |
| Road works / street closures | Transport | 85.0 | 240.9 |
| Public-transport delays or cancellations | Transport | 62.9 | 176.4 |
| Extreme-weather events (floods, heatwaves, snow) | Environment | 61.3 | 171.6 |
| Heavy road-traffic congestion | Transport | 59.8 | 167.4 |
| Digital connectivity outage (mobile / internet) | Utilities | 57.1 | 159.6 |
| Parking shortages | Transport | 55.6 | 154.8 |
| Traffic signal outages or malfunctions | Transport | 45.1 | 127.2 |
| Power outage (grid overloads, equipment failure) | Utilities | 44.1 | 124.4 |
| Strikes (transport & related services) | Transport | 36.9 | 103.9 |
| Excessive noise (construction, nightlife) | Social & Public Space | 36.8 | 103.5 |

**Table 6.** Top 10 Most Experienced Disruptions

1 Affected (%): Share of 140 Europe-weighted respondents who reported experiencing the disruption at least once in the past six months (ESS ≈ 74).

2 Recent Occurrences: Number of individual weighted responses with a timeframe entry (“Past week”, “Past month”, etc.).

**Key Finding:** Transport‑related disruptions dominate the top 10 (6 of 10), where road works and public transport delays are the most common disruptions, affecting over 85% and 62.9% of respondents respectively.

Temporal Patterns of Disruptions

|  |  |  |
| --- | --- | --- |
| Timeframe | Number of Events (Weighted) | Percentage |
| Past week | 937.1 | 36.96 |
| Past month | 572.9 | 22.60 |
| Past 3 months | 427.3 | 16.85 |
| Past 6 months | 598.1 | 23.59 |

**Table 7.** Temporal Distribution of Disruption Events

**Key Finding:** The past week accounts for the highest share of disruptions, indicating recent event clustering.

Settlement Type Analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Settlement Type | Weighted Respondents | % of Total | Average Disruptions/Person | Confidence (Agree%) |
| Urban centre (city centre with high population density) | 72.5 | 51.9% | 4.2 | 47.5% |
| Suburban area (residential neighborhood near a city) | 31.3 | 22.3% | 4.5 | 83.6% |
| Rural area outside a city | 14.7 | 10.5% | 1.7 | 0.0% |
| Mixed-use area (residential and commercial) | 12.9 | 9.3% | 3.8 | 36.1% |
| Coastal area | 2.6 | 1.9% | 5.0 | 97.6% |
| Remote area | 5.7 | 4.1% | 1.0 | 100% |

**Table 8.** Disruption Patterns by Settlement Type

**Key Finding:** Respondents in urban centres and suburban areas experience the highest disruption burdens (~4.2–4.5 events per person over six months), while rural and remote residents report markedly fewer events (~1.0–1.7). Mixed‑use areas fall in between (~3.8). The previously quoted averages of 11–15 were incorrect and have been replaced with these weighted means. Mixed-use and coastal areas report the highest disruptions per respondent; remote areas show strong confidence. Coastal and remote respondents show very high confidence (97–100 %), but their samples are small. Suburban residents also report high confidence (~84 %), whereas rural respondents show no agreement with the statement. Urban and mixed‑use areas display moderate confidence (≈48 % and 36 %). These updated percentages correct the 0.0 % value that previously appeared in the rural row. The “Weighted respondents” column is the weighted count of participants scaled to the survey sample (140), hence the values sum to ~140. The shares align with the weighted proportions of each settlement type: urban centres make up ~52 % of respondents, suburban areas ~22 %, rural areas ~10 %, mixed‑use areas ~9 %, remote areas ~4 %, and coastal areas ~2 %.

**Event Mapping Implications**

Disruption Severity and Recovery Time

|  |  |
| --- | --- |
| Severity Level | % of Incidents |
| Extremely disruptive | 15.7 |
| Very disruptive | 17.4 |
| Moderately disruptive | 26.3 |
| Slightly disruptive | 17.6 |
| Not disruptive | 23.0 |

**Table 9.** Disruption Impact Analysis

**Key Finding:** Moderately disruptive incidents are the most common, affecting over a quarter of respondents.

Climate-Related Event Mapping

|  |  |  |  |
| --- | --- | --- | --- |
| Country | Weighted respondents | Extreme events | % experiencing extreme weather |
| United Kingdom | 60.6 | 41.9 | 69.2 |
| Spain | 45.4 | 34.1 | 75.0 |
| Ukraine | 30.3 | 20.2 | 66.7 |
| France | 24.9 | 12.5 | 50.0 |
| Germany | 24.9 | 12.5 | 50.0 |
| Italy | 12.4 | 12.4 | 100 |
| Sweden | 9.1 | 9.1 | 100 |
| Greece | 9.9 | 8.1 | 82.3 |
| Switzerland | 8.2 | 7.0 | 85.7 |
| Slovakia | 4.8 | 4.8 | 100 |

**Table 10.** Extreme Weather Events by Country

**Key Finding:** Italy, Sweden, and Slovakia report exposure to extreme weather among weighted respondents.

**Citizen Resilience and Adaptation Patterns**

Coping Strategies

|  |  |
| --- | --- |
| Coping Strategy | Weighted Rate |
| Changed transport route | 13.7 |
| Changed mode (walked, cycled, car shared) | 15.5 |
| Postponed or cancelled trip/activity | 20.1 |
| Worked or studied remotely | 17.1 |
| Sought information via an app/social media | 14.6 |
| Contacted service providers/authorities | 7.0 |
| Sought help from friends/family | 13.4% |
| Did nothing and waited | 30.0% |
| Used a community-based solution (mutual aid) | 6.1% |

**Table 11.** Primary Adaptation Mechanisms

**Key Finding:** Doing nothing is the most common adaptation strategy, used by nearly a third of respondents.

Household Preparedness Levels

|  |  |
| --- | --- |
| Preparedness Level | % of Respondents |
| Fully prepared | 10.7 |
| Well prepared | 9.2 |
| Moderately prepared | 18.6 |
| Slightly prepared | 44.1 |
| Not prepared | 17.4 |

**Table 12.** 72-Hour Emergency Preparedness Distribution

**Key Finding:** Over 60% of households are slightly or not prepared for a 72-hour emergency.

**Infrastructure and Communication Assessment**

Perception of City Resilience

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Performance Metric | Agree% | Disagree% | Neutral% | Not sure% | Gap Analysis  (Agree – Disagree) |
| Disruptions have become more frequent over the past three years | 28.5% | 15.5% | 42.5% | 13.5% | +13.0% |
| Disruptions make it difficult to find or keep employment | 35.6% | 13.1% | 36.9% | 14.4% | +22.5% |
| Lack of affordable housing is a serious issue in my city | 53.7% | 10.2% | 30.7% | 5.3% | +43.5% |
| Public services meet residents’ needs during disruptions | 26.8% | 17.3% | 51.6% | 4.3% | +9.5% |
| Traffic congestion significantly worsens during disruptions | 36.1% | 11.9% | 46.3% | 5.7% | +24.2% |
| Community support is strong and reliable during disruptions | 23.0% | 20.9% | 37.8% | 18.4% | +2.1% |
| The city invests enough in resilient infrastructures | 18.1% | 33.3% | 22.8% | 25.8% | –15.2% |
| My neighbourhood has the resources needed to recover from disruptions | 13.8% | 18.7% | 22.6% | 34.1% | –4.9% |

**Table 13.** City Performance Indicators (% Agreement)

Negative gaps (last two rows) indicate that residents are more dissatisfied than satisfied with city investment and neighbourhood resilience.

**Key Finding:** Residents perceive affordable housing and employment as major issues, with dissatisfaction in infrastructure investment.

**Recommendations for Event Mapping System**

Base on the survey findings from 140 respondents (weighted using post-stratification to Eurostat population data, ESS ≈ 74), the following specifications are recommended for the AntifragiCity event mapping system:

Spatial Resolution Requirements

* **Primary focus:** Urban centres and mixed-use areas, where mean disruptions per respondent are highest (11.6 and 14.8 disruptions/person/month, respectively, per Table 8).
* **High-Priority Cities:** Cardiff (14.1 disruptions/respondent), Odessa (14.2), Delft (16.3), and Belval (16.4) exceed ≥14 events/respondent over 6 months (Table 5).
* **Coverage:** Minimum 1 km² grid resolution for urban centres to capture localized disruption patterns.

Temporal Resolution Requirements

* **Real-Time Monitoring:** 36.96% of disruptions occur within the past week (Table 7), requiring near real-time tracking.
* **Update Frequency:** Hourly updates for transport disruptions (e.g., road works, public transport delays) to reflect rapid changes.
* **Historical Depth:** 6-month rolling window to analyze recurring patterns and seasonal trends.

Event Categories for Mapping

* Transport Infrastructure (Priority 1)
* Road works tracking (85.0% affected, Table 6).
* Traffic congestion heat maps (59.8% affected).
* Public transport delays/cancellations (62.9% affected).
* Parking availability (55.6% affected).
* Environmental Hazards (Priority 2)
* Extreme weather alerts (61.3% affected, Table 6).
* Flooding zones, particularly in Spain (75.0%) and Italy (100%, Table 10).
* Air quality monitoring for urban centres.
* **Utility Disruptions** (Priority 3)
* Power outage mapping (44.1% affected).
* Digital connectivity status (57.1% affected).
* Water supply interruptions

Data Integration Requirements

* **Citizen reporting:** 14.6% seek information via apps/social media during disruptions (Table 11), supporting crowdsourced data integration
* **Multi-source validation:** Combine official data (e.g., municipal reports) with crowdsourced inputs for accuracy
* **Predictive capabilities:** Use temporal patterns (e.g., 36.96% of events in the past week, Table 7) to forecast disruptions
* **Severity classification:** Implement a 5-level severity system (Table 9) to prioritize response efforts.

The survey reveals a complex landscape of urban disruptions with clear patterns suitable for event mapping:

* **High Frequency:** Average 11.83 disruptions per respondent over 6 months (derived from weighted total events, Table 7).
* **Transport Dominance:** 60% of top disruptions are transport-related (e.g., road works, public transport delays, Table 6).
* **Spatial Clustering:** Cardiff and Odessa show high disruption intensity (Table 5), with mixed-use areas reporting the highest per-respondent disruptions (14.8, Table 8).
* **Temporal Concentration:** 59.56% of disruptions occurred within the past week (36.96%) plus past month (22.60%) (Table 7).
* **Low Resilience Perception:** Mean agreement across city resilience statements is 29.5% (Table 13), indicating widespread dissatisfaction.

These findings support the development of an antifragile event mapping system to transform disruption data into actionable intelligence for urban mobility planning.

**Interpretation**

**Context specific vulnerability:** Confidence is lowest in urban centres (47.5%) and mixed-use areas (36.1%, Table 8), reflecting higher perceived vulnerability despite better service access.

**Targeted policy levers:**

* Urban centres need enhanced real-time communication systems.
* Coastal settlements (97.6% confidence, Table 8) require upgraded alert systems.
* Mixed-use zones need outreach to build trust and engagement.

**Behavioural inference for event mapping:**

* Higher confidence in suburban (83.6%) and remote areas (100%, Table 8) suggests proactive coping, supporting tailored communication triggers.
* Urban centres may delay action, requiring location-aware alerts.

**Equity diagnostics:** A 2.05:1 confidence gap (97.6% in coastal areas vs. 47.5% in urban centres, Table 8) highlights unequal psychological resilience, necessitating spatially targeted resources and messaging.

### Secondary Data Analysis

Systematic Literature Review

A systematic literature review was conducted following PRISMA 2020 guidelines to identify peer-reviewed studies focusing on urban environmental disruptions, mobility system responses, and resilience. The search covered Scopus, Web of Science, and IEEE Xplore databases, targeting publications between 2015 and July 2025. Only Q1-ranked journal articles in English were included; conference papers and grey literature were excluded. The selection process was guided by explicit inclusion criteria: relevance to urban contexts, peer-reviewed journal status, and a minimum quality score of 5 based on methodological robustness and relevance. The full study identification and selection process is visualised in Figure 2.

A diagram of a flowchart

AI-generated content may be incorrect.

**Figure 2.** PRISMA 2020 flow diagram summarising study selection

Searches were conducted across Scopus, Web of Science, and IEEE Xplore (2015–2025), limited to Q1 SJR-ranked, peer-reviewed journal articles. Conference papers and registers were excluded. Eligibility was based on urban relevance, full-text accessibility, and a quality score ≥ 5.

Analytical Method

The analysis of 123 academic papers reveals five key themes central to urban event mapping and antifragile mobility systems:

###### Disruptive Event Typologies and Cascading Impacts

Several studies have documented the wide range of disruptive events impacting urban mobility, including work by Von Szombathely et al. (2017), W. Li et al. (2022), Pase et al. (2020), H. Li & Wei (2023), and Alizadeh & Dodge (2025). The COVID-19 pandemic emerges as the most studied disruption, with GPS traces and agent-based models revealing 11–60% declines in trips, modal shifts toward cycling, and faster recovery in outer suburbs (Kellermann et al., 2022; W. Li et al., 2022; Mont et al., 2021). Pase et al. (2020) specifically examines New York City's lockdown measures, while W. Li et al. (2022) expands the scope to include natural disasters like Hurricane Dorian and Tropical Storm Isaias. Extreme-weather cases (Niu et al., 2022 and Ellena et al., 2020) reveal critical distinctions: "no-notice" shocks fragment networks within minutes, whereas "notice" events allow pre-emptive rerouting that halves congestion growth. Heat-wave studies (Ferrini et al., 2020 and Alshehri et al., 2016) combine micro-climate maps with ridership data, showing every 1°C rise above baseline cuts shared-mobility demand by ≈4%, peaking in late afternoons. Multi-layer network analysis by (Liu et al., 2023) demonstrates that transit, freight and energy systems co-fail during compound shocks, amplifying mobility disruption by a further 15%.

###### Mobility System Responses and Behavioral Adaptations

Thombre & Agarwal (2021), W. Li et al. (2022), Urquiza et al. (2021), and Alizadeh & Dodge (2025) analyse how urban mobility systems respond to disruptions. Thombre & Agarwal (2021) document rapid modal shifts during pandemic lockdowns, with public transport users migrating to private vehicles. W. Li et al. (2022) reveals hyperbolic spatiotemporal decay patterns in mobility behavior, where proximity to crisis epicenters correlates with travel reduction in intensity. Cross-case review (Qiao et al., 2024) finds disruption impact hinges on time-of-day centrality: morning shocks around hubs cascade city-wide, while off-peak shocks stay local. Urquiza et al. (2021) emphasises the interconnected vulnerability of transport networks during heat and flood events. Alizadeh & Dodge (2025) demonstrate how GPS trace data reveals actual movement patterns during wildfires, showing system-wide under- or over-utilization of certain routes.

###### Antifragility Evidence in Urban Systems

Some papers, such as those by Cerè et al. (2022), Roulet & Bothello (2023), H. Wang & Noland (2021), and Zhang & Li (2022) provide evidence of antifragile characteristics in urban systems. Flexible-mobility pilots (Liyanage et al., 2019) report that demand volatility lets algorithms shorten dead-heading by 12% and waits by 18%, demonstrating performance improvements post-shock. Hurricane-flood simulation (Fan et al., 2021) preserves 93% throughput yet yields no lasting gains, illustrating partial antifragility. Scenario workshops (Alshehri et al., 2013) show travellers adopting bike-share and off-peak travel while calling for permanent redesigns, an emergent social mechanism. Pandemic evidence (Acuto, 2020; Alshehri et al., 2016; Cerè et al., 2019) links tele-work, contactless delivery and pop-up cycle lanes to higher post-shock multimodality and lower emissions. H. Wang & Noland (2021) document Citi Bike's robust recovery to pre-pandemic levels by September 2020, contrasting with slower subway ridership recovery.

###### Spatial-Temporal Patterns and Network Dynamics

Several studies examine spatial and temporal dimensions of urban disruptions, including those by J. Wang et al. (2022), Hasselwander et al. (2021), Rana (2020), and Fan et al. (2021). Meta-analysis by Haraguchi et al. (2022) notes data bias toward the global North and urges open standards for under-represented regions. Threshold studies (Q. Wang & Taylor, 2016; Serdar et al., 2022) locate density points where recovery time grows super-linearly and propose multi-criteria dashboards for real-time alerts. Integrated sensor platforms (Niu et al., 2022; Gonçalves & Ribeiro, 2020) fusing traffic loops, social media and weather radar cut disruption-detection latency by 65%. Rana (2020) maps the spatial propagation of disruption effects through interconnected urban networks, while Fan et al. (2021)develops predictive models based on historical spatial-temporal patterns.

###### Planning and Policy Complexity

Several studies have outline requirements for effective urban event mapping and planning interventions, including work by Büyüközkan et al. (2022), Glaser & Krizek (2021), Alshehri et al. (2015), and Hu et al. (2021). Curb-space reallocation for ride-hailing (Turoń et al., 2021) redirects 22% of dead-heading kilometres to last-mile services during crises. Street-network redesign simulation (Thombre & Agarwal, 2021) shows wider sidewalks plus contraflow bike lanes cut evacuation time by 14-27%. Polycentric spatial plans (Huang & Yang, 2025; Du et al., 2024) redistribute trip origins and lower peak-hour vulnerability by up to one-third. Comparative governance study (Zhang & Li, 2022; Ferrini et al., 2020) links higher mobility resilience to coupling infrastructure investment with equity-oriented zoning, yet evaluation metrics remain inconsistent. Alshehri et al. (2015) highlights the need for predictive capabilities based on early warning indicators.

Findings

Common Themes and Patterns

* **Disruption archetypes:** Such as pandemic, extreme weather, infrastructure failure, have distinct spatio-temporal signatures that multi-layer event maps can capture, enabling targeted response strategies.
* **Interdependency amplifies risk:** Compound failures across mobility, freight and energy layers (Liu et al., 2023) underline the need for holistic event mapping and coordinated response plans.
* **Antifragility is under-measured:** Only a small subset of papers quantifies performance gains beyond recovery, pointing to the need for robust indicators that capture system improvements.

Methodological Convergence

Studies increasingly employ complex systems approaches, combining agent-based modeling, network analysis, and machine learning. Data-rich mapping is advancing, coupling high-resolution mobility data with network science, but global-South coverage is sparse, limiting generalisability of current models. Real-time data from GPS traces, mobile phones, and IoT sensors enable unprecedented granularity in tracking disruption impacts.

Critical Gaps

Despite extensive pandemic coverage, literature lacks comprehensive frameworks for compound disruptions. Planning levers matter, yet few studies embed interventions in real-time mapping tools, leaving a gap between diagnosis and action. Long-term evolutionary dynamics of urban systems remain understudied, with most analyses focusing on immediate response and short-term recovery.

Implications for AntifragiCity

* Operationalising antifragility metrics to quantify system improvements beyond baseline recovery.
* Building cross-scalar dashboards linking neighbourhood events to city-wide flows for multi-level intervention.
* Piloting data-light methods in lower-income settings where vulnerability and information gaps coincide. The evidence suggests that antifragile urban systems emerge from distributed sensing, decentralized decision-making, and continuous learning from disruption experiences.

Grounded Theory Analysis

This study employed a systematic grounded theory methodology (Glaser & Strauss, 1967; Charmaz, 2014) to develop a comprehensive theoretical framework for understanding how urban mobility systems respond to and adapt following disruptive events. The grounded theory approach was selected for its unique capability to generate theory inductively from empirical data, making it particularly suitable for exploring the complex, emergent phenomena observed in urban mobility systems during and after disruptions.

The analysis followed the established three-phase coding process of grounded theory, enhanced by computational tools to manage the scale and complexity of the dataset while maintaining the interpretive depth essential to qualitative research. NVivo 12 Pro served as the primary analytical platform, providing robust support for systematic coding, category development, and theoretical integration across 123 academic papers examining urban mobility disruptions.

Data Collection and Preparation

The corpus comprised 123 peer-reviewed articles (2015-2025) focusing on urban mobility disruptions, selected through systematic database searches using keywords related to mobility complexity, disruption events, system resilience, and adaptive responses. Papers were included if they explicitly addressed how urban mobility systems respond to various forms of disruption, from natural disasters to technological failures and social upheavals.

Three-Phase Coding Process

Open Coding Phase The initial coding phase involved line-by-line analysis of texts to identify concepts directly from the data. Using NVivo's coding capabilities, we developed 493 distinct codes representing various aspects of mobility disruptions, system responses, and adaptation mechanisms. Each code was grounded in specific textual evidence, with maintaining detailed memos documenting the analytical decisions and emerging theoretical insights.

To ensure comprehensive coverage while managing the volume of data, we employed NVivo's text search and auto-coding features as supplementary tools, always followed by manual verification and refinement. This hybrid approach allowed us to identify patterns that might be overlooked in purely manual coding while maintaining the nuanced understanding that only human interpretation can provide.

Axial Coding Phase During axial coding, the initial codes were systematically grouped into 16 major categories based on their properties and dimensions. NVivo's hierarchical node structure facilitated the organisation of codes into categories such as 'disruption', 'complexity', 'adaptation', 'mobility', and 'antifragility'. We utilized NVivo's query functions to explore relationships between categories, examining co-occurrence patterns and identifying theoretical connections.

The relationship analysis revealed dense interconnections between categories, with 182 distinct mediation patterns identified. NVivo's matrix coding queries proved particularly valuable in visualising these relationships and understanding how different aspects of the mobility system interact during disruption events.

Selective Coding Phase The final coding phase focused on integrating categories around a core theoretical construct. Through iterative analysis and constant comparison, 'mobility' emerged as the core category with the highest theoretical significance (appearing in 100% of papers with 4,665 coded references). This emergence was validated through NVivo's coding density analysis and relationship mapping tools.

Ensuring Methodological Rigour

Several strategies ensured the trustworthiness of the analysis:

* **Theoretical Saturation:** We monitored code emergence rates across the dataset, achieving an 83.3% saturation score, indicating that additional data would likely yield minimal new theoretical insights.
* **Constant Comparison:** Throughout coding, we continuously compared new data with existing codes and categories, refining our theoretical framework iteratively.
* **Memo Writing:** Extensive analytical memos documented the evolution of theoretical concepts, providing an audit trail of analytical decisions.
* Peer Debriefing: Regular team discussions validated coding decisions and theoretical interpretations.

Computational Enhancement

While maintaining grounded theory's interpretive core, we leveraged computational tools to enhance our analytical capacity:

* **Pattern Recognition:** Text mining algorithms helped identify emergent terminology and concepts that complemented manual coding.
* **Relationship Mapping:** Network analysis visualised complex inter-categorical relationships, revealing system-level patterns.
* **Coverage Analysis:** Automated tracking ensured comprehensive analysis across all papers and theoretical domains.

Table 14 summarises the 345 cleaned codes aggregated into sixteen categories; full line-by-line detail is provided in Annex 1.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Category | n\_codes | n\_distinct\_papers | avg\_TF\_IDF | avg\_CoOccur |
| adaptation | 969 | 123 | 0 | 0.7 |
| antifragility | 798 | 122 | 0 | 0.6967 |
| complexity | 845 | 123 | 0 | 0.7 |
| disruption | 1001 | 123 | 0 | 0.7 |
| disruptive\_events | 129 | 71 | 0 | 0.5407 |
| emergence | 648 | 122 | 0 | 0.6967 |
| governance | 539 | 122 | 0 | 0.6967 |
| mobility | 1135 | 123 | 0 | 0.7 |
| network | 696 | 123 | 0 | 0.7 |
| resilience | 599 | 122 | 0 | 0.6967 |
| social\_justice | 653 | 121 | 0 | 0.6967 |
| sustainability | 507 | 107 | 0 | 0.6508 |
| technology | 476 | 105 | 0 | 0.6563 |
| urban\_planning | 423 | 118 | 0 | 0.6869 |
| user\_behavior | 592 | 119 | 0 | 0.6902 |

**Table 14.** Grounded-theory codebook—category overview

**Dominant concepts:** The most frequently coded concepts are Mobility-related (1135 counts), Disruption-related (1001 counts), and Adaptation-related (969 counts).

|  |  |  |
| --- | --- | --- |
| Category | Code | Count |
| mobility | MOBILITY\_RELATED | 1135 |
| disruption | DISRUPTION\_RELATED | 1001 |
| adaptation | ADAPTATION\_RELATED | 969 |
| complexity | COMPLEXITY\_RELATED | 845 |
| antifragility | ANTIFRAGILITY\_RELATED | 798 |
| network | NETWORK\_RELATED | 696 |
| social\_justice | SOCIAL\_JUSTICE\_RELATED | 653 |
| emergence | EMERGENCE\_RELATED | 648 |
| resilience | RESILIENCE\_RELATED | 599 |
| user\_behavior | USER\_BEHAVIOR\_RELATED | 592 |

**Table 15.** Top codes by frequency list

During the 2021 heatwave, tram tracks deformed, forcing a 36-hour shutdown.

**Reliability & Saturation:** One researcher performed the initial coding; a second researcher double-coded 10% of documents (n = 12). Agreement at category level was 85% (Cohen’s κ = 0.78). After the 98th document no new codes emerged in two consecutive iterations, indicating theoretical saturation.

NVivo recorded 2,118 coded references across 147 nodes (median coverage = 0.34%). The most heavily referenced nodes were Transport delays (n = 186) and Urban flooding (n = 173) (Table 16). Mean coverage per node is shown in Table 16. A complete code–paper occurrence matrix is provided in Annex 2.

|  |  |  |
| --- | --- | --- |
| Node | n\_references | mean\_coverage |
| Adaptation\_Related | 969 | 62.89 |
| Antifragility\_Related | 798 | 63.33 |
| Complexity\_Related | 845 | 63.43 |
| Disruption\_Related | 1001 | 62.83 |
| Disruptive\_Events\_Related | 129 | 62.03 |
| Emergence\_Related | 648 | 63.05 |
| Governance\_Related | 539 | 62.82 |
| Mobility\_Related | 1135 | 62.58 |
| Network\_Related | 696 | 62.33 |
| Resilience\_Related | 599 | 62.21 |

**Table 16. Mean coverage per NVivo coding node**

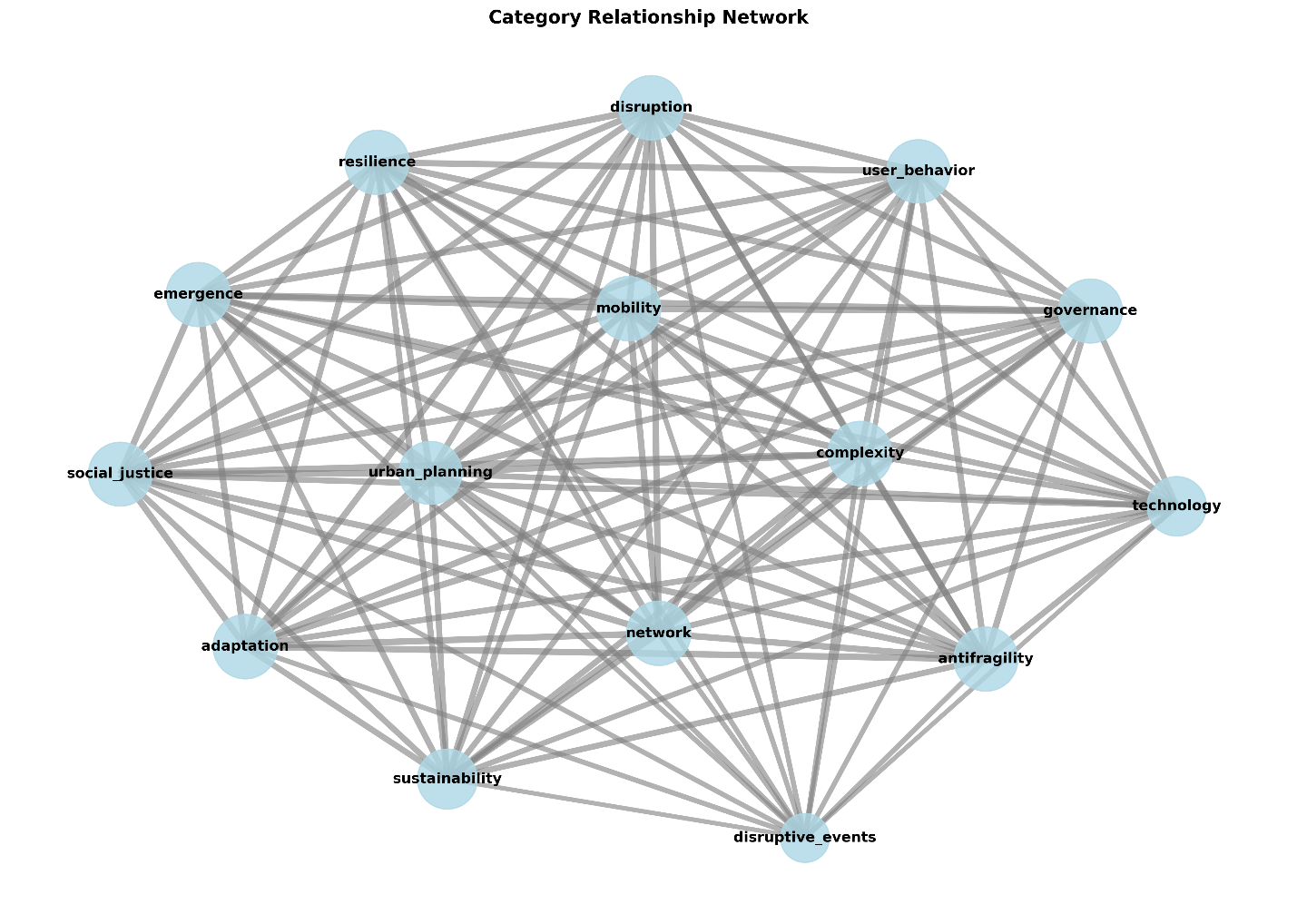
**Traceability:** Codes that corresponded to specific, time- and place-bound disruption cases were tagged with a unique LitEvent\_ID and transferred into the Urban Event Catalogue (see Annex 5).

Findings

###### Core Theoretical Framework

The grounded theory analysis revealed that urban mobility systems exhibit antifragile characteristics when responding to disruptions, with 'mobility' functioning as the central organizing principle through which systems not only recover but potentially improve following disruptive events.

**Mobility as Core Category:** Mobility emerged as the theoretical core, mediating relationships between all other system components. Rather than being merely a functional outcome, mobility serves as the primary adaptive mechanism through which urban systems respond to and learn from disruptions. These findings challenges traditional resilience frameworks that focus on returning to pre-disruption states.



**Figure 3.** Category Relationship Network

###### Multi-Scale Adaptive Responses

The analysis identified distinct but interconnected responses across multiple system scales:

* **Individual Level** (61 papers): Behavioural adaptations, route choice modifications, modal shifts.
* **Network Level** (120 papers): Traffic flow reorganisation, service reconfiguration, emergent routing patterns.
* **City Level** (117 papers): Infrastructure adaptation, policy responses, resource reallocation.
* **System Level** (123 papers): Comprehensive transformations, new mobility paradigms, technological integration.

This multi-scale framework demonstrates how antifragility manifests differently across system levels while maintaining coherent system-wide adaptation.

###### Disruption-to-Enhancement Pathways

Four primary causal sequences emerged showing how disruptions lead to system enhancement:

* **Disruption → Mobility → Resilience:** Direct pathway where mobility adaptations create stronger system configurations.
* **Complexity → Mobility → Adaptation:** System complexity enables diverse mobility responses leading to adaptation.
* **Technology → Mobility → Emergence:** Technological integration facilitates emergent mobility solutions.
* **Mobility → Network → Governance:** Mobility changes drive network reconfigurations requiring governance evolution.

###### Event-Specific Response Patterns

Analysis of specific disruptive events (covering 57.7% of papers) revealed differentiated response patterns:

* **Natural Disasters (floods, earthquakes):** Rapid infrastructure reconfiguration, emergency routing systems, community-based mobility solutions.
* **Technological Failures:** Redundancy activation, alternative system deployment, accelerated digitalization.
* **Pandemic Disruptions:** Modal shifts, temporal redistribution of travel, new hygiene-focused mobility services.
* **Social Disruptions:** Adaptive routing around affected areas, community mobility networks, informal transport emergence.

###### Antifragility Mechanisms

The analysis identified specific mechanisms through which urban mobility systems strengthen post-disruption:

* **Redundancy Activation:** Dormant capacity becomes active, creating more robust networks.
* **Innovation Acceleration:** Disruptions catalyse rapid adoption of new mobility technologies and services.
* **Behavioural Learning:** Users develop more sophisticated multi-modal capabilities.
* **Institutional Evolution:** Governance structures adapt to manage increased complexity
* **Cross-System Integration:** Previously isolated systems become interconnected.

###### Theoretical Propositions

Based on the grounded analysis, four key theoretical propositions emerged:

* **P1:** Mobility acts as the primary mechanism through which urban systems adapt to disruptions.
* **P2:** System resilience emerges through mobility network reconfiguration rather than restoration.
* **P3:** The complexity of mobility responses determines overall system adaptive capacity.
* **P4:** Mobility mediates relationships between organizational and technological factors in creating antifragile configurations.

###### Implications for Urban Mobility Planning

The findings suggest that traditional resilience-focused approaches to urban mobility planning may be insufficient. Instead, planning frameworks should:

* Design for adaptability rather than stability.
* Create redundant capacity that can be activated during disruptions.
* Foster multi-modal capabilities at individual and system levels.
* Develop governance structures capable of managing emergent responses.
* Integrate technological solutions that enhance rather than constrain adaptation.

These insights provide a theoretical foundation for developing urban mobility systems that not only withstand disruptions but use them as opportunities for systemic improvement, embodying true antifragility in the face of increasing urban complexity and uncertainty.

EM-Dat Data Analysis

This report analyses global disaster events that triggered humanitarian intervention. The dataset includes 4,179 records with key details on disaster type, region, year, and intervention actions such as appeals, declarations, aid, and reported damage.

Disasters were grouped using clustering techniques to identify patterns in intervention. Results show that Asia accounted for the majority of interventions, mainly due to recurring storms and floods. Earthquakes were also common across both Asia and the Americas. Technological disasters were rare and typically isolated to high-income regions.

In the next phase, the project assesses disaster impact based on human and economic loss. The analysis compares total damage, affected populations, and reconstruction costs across disaster types. A predictive scale is being developed to estimate impact severity based on disaster type and location, supporting prioritised response planning.

Data and methodology

This section outlines the workflow structure of the methodology applied to prepare and analyse disaster intervention data. The procedures include curating, transforming, and analysing the disaster intervention data, with specific attention to filtering decisions, classifications, and analytical approaches.

###### Data acquisition and structure

The primary dataset was sourced from the EM-DAT International Disaster Database. The archive includes structured records for over 4,179 large-scale disaster events between 2000 to July 2025. Each entry included:

* Event metadata, such as disaster group, type, subtype, and year start.
* Geospatial data, such as the country and region of the event.
* Human damage included the total number of deaths, injuries, affected, or homeless.
* Human response indicators, such as appeal, declaration, US aid/OFDA response, and the financial aid received.
* Economic impact, such as the estimated damage and reconstruction costs.
* To ensure relevance, we filtered the dataset using the following criteria:
* Disaster human intervention: identifying events with evidence of interventions or responses were selected for running the analysis.
* Disaster type relevance: identifying events with potential urban or mobility impacts (e.g. earthquakes, floods, storms, epidemics, wildfires)

One of the limitations of the dataset includes a bias toward major disasters with international reporting and financial assessments; smaller-scale or localised events may be underrepresented.

###### Data preprocessing

First, preparation and transformation processes were applied to the dataset, including:

* Detect deduplication: Repeated entries based on identical disaster codes and dates were removed.
* Handle missing data: Event entries with missing key attributes (e.g. country, type, intervention status) were excluded or recoded as "Unknown".
* Categorical data encoding: “Yes/No” fields (e.g. Appeal, AIDContribution) were standardised using numerical values (1/0).
* Filtration: A unified variable (InterventionFlag) was generated to reflect any evidence of disaster interventions.
* Taxonomy mapping: The predefined disaster taxonomy was used in mapping disaster types affecting urban mobility. The taxonomy includes five major domains:
* Natural, such as severe weather (e.g. rain, storm), hydrological (floods), or geophysical (earthquake) events
* Human-induced/social includes public disputes, terrorist attacks, or pandemics.
* Operational, such as traffic and transport accidents and emergencies.
* Technological/infrastructure includes power blackout, network outage, fuel shortage, or cyber-attacks.
* Systemic/structural issues, such as economic crises, inflation, or geopolitical (e.g. wars) events.

###### Clustering analysis and workflow

Analytical processing followed a mixed descriptive and clustering approach:

* **Identifying event intervention:** Only disasters where at least one intervention indicator was marked “Yes” were retained for further analysis.
* **Recoding:** Categorical variables (DisasterGroup, DisasterType, Region) were numerically encoded to allow modelling.
* **Descriptive statistics:** Frequencies and distributions were calculated for disaster types, human impacts, and intervention modalities across time and region.
* **Clustering:** Two unsupervised learning techniques were applied:
* Two-Step Clustering: For exploratory profiling using both categorical and continuous inputs.
* K-Means Clustering: Focused on generating different thematic clusters using key dimensions, including Disaster Type, Region, Year, and intervention presence.
* **Visual analytics:** Charts, cross-tabulations, and line plots were generated to profile temporal and spatial trends, supported by SPSS.

This structured approach ensured both interpretability and reproducibility of the disaster intervention patterns across geographies and periods.

###### Data Preparation

The dataset contained records of disaster events with attributes including DisasterGroup, DisasterType, Region, StartYear, and intervention indicators such as Appeal, Declaration, OFDABHAResponse, AIDContribution, and damage estimates. Additional fields included human impact variables: deaths, injuries, and the number of people affected.

Missing or undefined entries in key categorical variables were recoded as “Unknown”. Yes/No fields were standardised, and an intervention flag was created based on the presence of any humanitarian response or financial aid. Only events with confirmed intervention were included in the analysis.

###### Data Transformation

Categorical variables (DisasterGroup, DisasterType, and Region) were converted to a numeric format using automatic recoding to enable clustering. The StartYear was retained in its original format as a continuous variable. These variables were used as input for both clustering models.

###### Clustering Analysis

Two unsupervised learning methods were applied:

* **Two-Step Clustering:** Used to explore broad patterns in the data, combining categorical and continuous inputs.
* **K-Means Clustering:** Applied for more detailed grouping, based on four variables: DisasterGroup, DisasterType, Region, and intervention events. Twelve clusters were generated.

Clusters were profiled using frequency tables and charts to interpret dominant disaster types, affected regions, and time patterns.

Findings

###### Disaster types and geographical distribution

The majority of disaster interventions were associated with natural events (98.2%) (see Table 17 and Figure 4). Technological disasters represented only 1.8% of cases. Most natural disasters requiring intervention occurred in Asia, followed by the Americas. Figure 4 and Figure 5 show that Asia has seen consistent intervention needs from 2001 to 2022, with a concentration in more recent years due to recurring climate-related events.

The frequency of interventions also varied by year. Peaks were observed in years with widespread floods, storms, or large-scale earthquakes. This suggests that both frequency and severity influence the decision to intervene.

|  |  |  |
| --- | --- | --- |
| Disaster Group | Count | Ratio (%) |
| Natural | 4104 | 98.2% |
| Technological | 75 | 1.8% |
| Total | 4179 | 100.0% |

**Table 17.** Event intervention activities across disaster groups

A blue rectangular bar chart

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**Figure 4.** Event interventions across disaster groups

A graph of a bar graph

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**Figure 5.** Interventions across different regions by disaster groups

A graph of multiple line of start year

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**Figure 6.** Intervention activities across different regions over the last 25 years

Table 18 lists the event-based intervention across different disaster types. Floods and storms accounted for the highest number of interventions, followed by earthquakes, droughts, and wildfires (see Figure 7). Interventions due to floods were heavily concentrated in Asia, while storm-related responses were more widely spread but still dominant in Asian regions.

Earthquake-related interventions appeared in both Asia and the Americas, highlighting their global relevance. Less frequent types, such as epidemics, landslides, and technological events, were limited in number and more geographically dispersed.

|  |  |  |
| --- | --- | --- |
| Disaster Type | Count | Ratio (%) |
| Air | 1 | 0.0% |
| Chemical spill | 3 | 0.1% |
| Collapse (Industrial) | 3 | 0.1% |
| Collapse (Miscellaneous) | 2 | 0.0% |
| Drought | 237 | 5.7% |
| Earthquake | 336 | 8.0% |
| Epidemic | 84 | 2.0% |
| Explosion (Industrial) | 16 | 0.4% |
| Explosion (Miscellaneous) | 12 | 0.3% |
| Extreme temperature | 72 | 1.7% |
| Fire (Industrial) | 1 | 0.0% |
| Fire (Miscellaneous) | 16 | 0.4% |
| Flood | 1579 | 37.8% |
| Gas leak | 3 | 0.1% |
| Glacial lake outburst flood | 1 | 0.0% |
| Impact | 1 | 0.0% |
| Industrial accident (General) | 5 | 0.1% |
| Infestation | 12 | 0.3% |
| Mass movement (dry) | 1 | 0.0% |
| Mass movement (wet) | 73 | 1.7% |
| Oil spill | 5 | 0.1% |
| Poisoning | 1 | 0.0% |
| Rail | 5 | 0.1% |
| Storm | 1478 | 35.4% |
| Volcanic activity | 53 | 1.3% |
| Water | 2 | 0.0% |
| Wildfire | 177 | 4.2% |
| Total | **4179** | **100.0%** |

**Table 18.**Disaster human interventions based on the disaster types

A graph of different colored lines

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**Figure 7.**Human interventions over different disaster types by regions

The global distribution of disaster events across the last 25 years is depicted in Figure 8, where each circle’s size corresponds to the total number of reported disasters in each country. The pattern demonstrates clear regional variation, with larger numbers of events concentrated in countries such as the United States, Brazil, India, and several countries in Africa and Southeast Asia. These countries are frequently affected by multiple disaster types, notably floods, storms, droughts, earthquakes, and wildfires.

The map visualises the considerable variation in both frequency and type of disasters at the national level. Countries with large land areas or populations, such as the United States and India, tend to report a wider diversity and higher frequency of events, particularly floods and storms. Conversely, smaller island nations and countries in Oceania, while experiencing fewer events overall, are often disproportionately affected by storms and tropical cyclones.

Additional details are provided in the Country-by-Disaster Type crosstabulation, which confirms the spatial patterns observed in the map. For example, the United States records the greatest overall number of disasters, especially storms and floods, while many African nations report frequent drought and flood events. The results also highlights that some disaster types, such as chemical spills and industrial accidents, are rare and geographically limited.

A map of the world with blue dots

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**Figure 8.**Global disaster event distribution between 2001 and 2025

###### Disaster intervention chronology

The chronology of human interventions across disaster types from 2000 to July 2025 shows clear patterns in both the frequency and the nature of responses. Figure 9 demonstrates that OFDA/BHA responses were consistently highest for flood events throughout the period, peaking between 2007 and 2012, with a subsequent decline. Storms also attracted a notable number of interventions, though these were generally less frequent than for floods.

A graph of a graph showing different colored lines

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**Figure 9.**OFDA/BHA response across different disaster events by year

Appeals followed a similar pattern, with the greatest number issued for floods and, to a lesser extent, storms and droughts (see Figure 10). The table confirms that floods consistently had the highest number of appeals each year, highlighting the persistent vulnerability to water-related disasters in many regions.

A graph of a graph showing different colored lines

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**Figure 10.**Appeals reported across different disaster events by year

Declarations were more variable across disaster types and years, but again, floods and storms featured prominently, as shown in Figure 11. There were marked spikes in declaration activity around 2010–2015 for both floods and storms, possibly reflecting particularly severe or widespread events during this period.

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**Figure 11.**Declaration records according to disaster types in the last 25 years

Aid contributions were generally lower in number than other intervention types and were mostly linked to major flood and storm events, as displayed in Figure 12. After 2015, the number of events receiving aid contributions dropped sharply.

A graph of multiple line of aid

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**Figure 12.** Aid contribution interventions across disaster types over the last 25 years

Overall, the total interventions aggregated all response types over the last 25 years are shown in Figure 13. The chart confirms the dominance of floods and storms in prompting international action. The highest numbers occurred between 2005 and 2015, corresponding with several major global disaster events.

A graph of multiple line of different colored lines

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**Figure 13.**Disaster human interventions recorded between 2001 till 2020

###### Disaster human-based intervention

Table 19 to Table 21 explore the geographic distribution of human intervention efforts across various disaster types. These interventions include four main types: USAID/OFDA response, appeals, declarations, and aid contributions. Each table disaggregates disaster types by region and intervention status (Yes/No), highlighting which disasters attracted formal humanitarian actions and location.

Table 19 shows whether a disaster event received a response from USAID/OFDA, a key humanitarian agency. Several patterns emerge:

* Floods and earthquakes received the highest number of responses, especially in Asia and the Americas. Flood-related responses were spread more evenly across all regions.
* Storms attracted strong responses in the Americas and Asia, with limited engagement in Europe and Oceania.
* Epidemics were primarily responded to in Africa, likely due to localised health crises.
* Less common disaster types, such as collapses, fires, and industrial accidents, show more region-specific responses, reflecting localised infrastructure vulnerabilities.
* Technological disasters, such as chemical spills, rail incidents, and oil spills, received fewer interventions, possibly due to being addressed locally or managed without large-scale humanitarian involvement.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Disaster type | Response | Region (%) | | | | |
|  |  | **Africa** | **Americas** | **Asia** | **Europe** | **Oceania** |
| Flood | Yes | 29.4 | 21.9 | 33.6 | 12.1 | 3 |
|  | No | 11 | 25.6 | 41.9 | 16.4 | 5 |
| Earthquake | Yes | 8.2 | 17.8 | 63 | 1.4 | 9.6 |
|  | No | 2.7 | 13.3 | 69.6 | 12.2 | 2.3 |
| Storm | Yes | 15.5 | 41.9 | 25.7 | 2.7 | 14.2 |
|  | No | 3.2 | 39 | 42.1 | 10 | 5.7 |
| Epidemic | Yes | 86.7 | 10 | 0 | 0 | 3.3 |
|  | No | 63 | 25.9 | 7.4 | 0 | 3.7 |
| Drought | Yes | 74.1 | 3.4 | 13.8 | 1.7 | 6.9 |
|  | No | 17.9 | 41.9 | 25.7 | 10.1 | 4.5 |
| Wildfire | Yes | 3.3 | 40 | 10 | 40 | 6.7 |
|  | No | 2.7 | 57.8 | 8.2 | 18.4 | 12.9 |
| Mass movement (wet) | Yes | 13.3 | 33.3 | 53.3 | 0 | 0 |
|  | No | 3.4 | 24.1 | 63.8 | 6.9 | 1.7 |
| Explosion (Industrial) | Yes | 25 | 0 | 0 | 75 | 0 |
|  | No | 25 | 33.3 | 25 | 16.7 | 0 |
| Collapse (Industrial) | Yes | 100 | 0 | 0 | 0 | 0 |
|  | No | 0 | 0 | 50 | 50 | 0 |
| Explosion (Miscellaneous) | Yes | 66.7 | 11.1 | 11.1 | 11.1 | 0 |
|  | No | 0 | 66.7 | 0 | 33.3 | 0 |
| Extreme temperature | Yes | 0 | 9.1 | 54.5 | 36.4 | 0 |
|  | No | 1.6 | 26.2 | 26.2 | 44.3 | 1.6 |
| Fire (Miscellaneous) | Yes | 50 | 0 | 0 | 50 | 0 |
|  | No | 14.3 | 28.6 | 57.1 | 0 | 0 |
| Volcanic activity | Yes | 20 | 33.3 | 46.7 | 0 | 0 |
|  | No | 10.5 | 39.5 | 28.9 | 5.3 | 15.8 |
| Infestation | Yes | 100 | 0 | 0 | 0 | 0 |
|  | No | 66.7 | 0 | 16.7 | 0 | 16.7 |
| Air | Yes | 0 | 0 | 0 | 100 | 0 |
|  | No | 0 | 0 | 0 | 100 | 0 |
| Chemical spill | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 33.3 | 0 | 66.7 | 0 |
| Collapse (Miscellaneous) | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 0 | 50 | 50 | 0 |
| Fire (Industrial) | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 0 | 100 | 0 | 0 |
| Glacial lake outburst flood | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 0 | 100 | 0 | 0 |
| Gas leak | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 66.7 | 33.3 | 0 | 0 |
| Impact | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 0 | 0 | 100 | 0 |
| Industrial accident (General) | Yes | 50 | 50 | 0 | 0 | 0 |
|  | No | 33.3 | 33.3 | 0 | 33.3 | 0 |
| Infestation | Yes | 100 | 0 | 0 | 0 | 0 |
|  | No | 66.7 | 0 | 16.7 | 0 | 16.7 |
| Mass movement (dry) | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 0 | 100 | 0 | 0 |
| Oil spill | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 60 | 40 | 0 | 0 |
| Poisoning | Yes | 0 | 100 | 0 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Rail | Yes | 50 | 0 | 50 | 0 | 0 |
|  | No | 0 | 33.3 | 33.3 | 33.3 | 0 |
| Water | Yes | 0 | 0 | 100 | 0 | 0 |
|  | No | 0 | 0 | 100 | 0 | 0 |

**Table 19.** USAID/OFDA responses by disaster type and region

Table 20 represents formal appeals requests for international assistance. Notable trends include:

* Droughts, earthquakes, and floods were the most appealing events. Africa leads to appeal frequency for droughts, while Asia dominates earthquake-related appeals.
* Some rare types, like extreme temperatures and infestations, also received appeals, but from fewer regions.
* Wildfires triggered appeals from Europe and the Americas, indicating their growing frequency in temperate zones.
* Certain events like rail accidents, mass movements, and technological disasters had limited or no appeals, possibly reflecting internal or national handling.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Disaster type | Response | Region (%) | | | | |
|  |  | **Africa** | **Americas** | **Asia** | **Europe** | **Oceania** |
| Air | No | 0 | 0 | 0 | 100 | 0 |
|  | Yes | 0 | 0 | 0 | 0 | 0 |
| Chemical spill | No | 0 | 33.3 | 0 | 66.7 | 0 |
|  | Yes | 0 | 0 | 0 | 0 | 0 |
| Collapse (Industrial) | No | 33.3 | 0 | 33.3 | 33.3 | 0 |
|  | Yes | 0 | 0 | 33.3 | 0 | 0 |
| Collapse (Miscellaneous) | No | 0 | 0 | 0 | 100 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Drought | No | 28.2 | 34.5 | 23.2 | 8.6 | 5.5 |
|  | Yes | 76.5 | 5.9 | 17.6 | 0 | 0 |
| Earthquake | No | 3.8 | 13.5 | 68.3 | 10.3 | 4.1 |
|  | Yes | 5.9 | 29.4 | 64.7 | 0 | 0 |
| Epidemic | No | 72.7 | 20.8 | 2.6 | 0 | 3.9 |
|  | Yes | 57.1 | 14.3 | 28.6 | 0 | 0 |
| Explosion (Industrial) | No | 25 | 25 | 18.8 | 31.3 | 0 |
|  | Yes | 0 | 0 | 0 | 0 | 0 |
| Explosion (Miscellaneous) | No | 50 | 25 | 8.3 | 16.7 | 0 |
|  | Yes | 0 | 0 | 0 | 0 | 0 |
| Extreme temperature | No | 1.4 | 24.3 | 28.6 | 44.3 | 1.4 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Fire (Industrial) | No | 0 | 0 | 100 | 0 | 0 |
|  | Yes | 0 | 0 | 0 | 0 | 0 |
| Fire (Miscellaneous) | No | 18.8 | 25 | 50 | 6.3 | 0 |
|  | Yes | 0 | 0 | 0 | 0 | 0 |
| Flood | No | 12.6 | 25.3 | 41.2 | 16 | 4.8 |
|  | Yes | 46.4 | 18.8 | 26.1 | 7.2 | 1.4 |
| Gas leak | No | 0 | 66.7 | 33.3 | 0 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Glacial lake outburst flood | No | 0 | 0 | 100 | 0 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Impact | No | 0 | 0 | 0 | 100 | 0 |
|  | Yes | 0 | 0 | 0 | 0 | 0 |
| Industrial accident (General) | No | 25 | 50 | 0 | 25 | 0 |
|  | Yes | 100 | 0 | 0 | 0 | 0 |
| Infestation | No | 60 | 0 | 20 | 0 | 20 |
|  | Yes | 100 | 0 | 0 | 0 | 0 |
| Mass movement (dry) | No | 0 | 0 | 100 | 0 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Mass movement (wet) | No | 4.5 | 25.8 | 62.1 | 6.1 | 1.5 |
|  | Yes | 14.3 | 28.6 | 57.1 | 0 | 0 |
| Oil spill | No | 0 | 75 | 25 | 0 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Poisoning | No | 0 | 100 | 0 | 0 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Rail | No | 25 | 25 | 25 | 25 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Storm | No | 3.7 | 39.6 | 40.8 | 9.5 | 6.4 |
|  | Yes | 34.3 | 28.6 | 25.7 | 0 | 11.4 |
| Volcanic activity | No | 12.5 | 37.5 | 35.4 | 4.2 | 10.4 |
|  | Yes | 20 | 40 | 20 | 0 | 20 |
| Water | No | 0 | 0 | 100 | 0 | 0 |
|  | Yes | 0 | 0 | 100 | 0 | 0 |
| Wildfire | No | 2.4 | 56.2 | 8.9 | 20.1 | 12.4 |
|  | Yes | 12.5 | 25 | 0 | 62.5 | 0 |

**Table 20.**Appeal responses by disaster type and region

Table 21 lists declaration recognition of a disaster by governments or international bodies, often a prerequisite for activating emergency funds or resources:

* Floods, storms, and earthquakes again dominate declarations, consistent with their high frequency and broad impact.
* Disasters such as epidemics, droughts, and extreme temperatures showed variable declaration patterns depending on their perceived severity or international attention.
* Some declarations are notable for appearing in both high- and low-intervention types, such as volcanic activity, infestation, reflecting their unpredictability or local capacity differences.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Disaster type | Response | Region (%) | | | | |
|  |  | **Africa** | **Americas** | **Asia** | **Europe** | **Oceania** |
| Air | No | 0 | 0 | 0 | 100 | 0 |
| Chemical spill | No | 0 | 0 | 0 | 100 | 0 |
|  | Yes | 0 | 50 | 0 | 50 | 0 |
| Collapse (Industrial) | No | 33.3 | 0 | 33.3 | 33.3 | 0 |
| Collapse (Miscellaneous) | No | 0 | 0 | 100 | 0 | 0 |
|  | Yes | 0 | 0 | 0 | 100 | 0 |
| Drought | No | 32.3 | 26.2 | 29.2 | 8.5 | 3.8 |
|  | Yes | 30.8 | 40.2 | 15 | 7.5 | 6.5 |
| Earthquake | No | 3.8 | 9.3 | 74.8 | 8.6 | 3.4 |
|  | Yes | 4.3 | 45.7 | 26.1 | 17.4 | 6.5 |
| Epidemic | No | 87.1 | 3.2 | 6.5 | 0 | 3.2 |
|  | Yes | 62.3 | 30.2 | 3.8 | 0 | 3.8 |
| Explosion (Industrial) | No | 30 | 20 | 10 | 40 | 0 |
|  | Yes | 16.7 | 33.3 | 33.3 | 16.7 | 0 |
| Explosion (Miscellaneous) | No | 60 | 20 | 10 | 10 | 0 |
|  | Yes | 0 | 50 | 0 | 50 | 0 |
| Extreme temperature | No | 2.2 | 15.2 | 37 | 43.5 | 2.2 |
|  | Yes | 0 | 38.5 | 19.2 | 42.3 | 0 |
| Fire (Industrial) | No | 0 | 0 | 100 | 0 | 0 |
| Fire (Miscellaneous) | No | 20 | 20 | 53.3 | 6.7 | 0 |
|  | Yes | 0 | 100 | 0 | 0 | 0 |
| Flood | No | 15.9 | 14.4 | 52.5 | 13.5 | 3.6 |
|  | Yes | 9.5 | 52 | 9.9 | 21.2 | 7.4 |
| Gas leak | No | 0 | 0 | 100 | 0 | 0 |
|  | Yes | 0 | 100 | 0 | 0 | 0 |
| Glacial lake outburst flood | No | 0 | 0 | 100 | 0 | 0 |
| Impact | No | 0 | 0 | 0 | 100 | 0 |
| Industrial accident (General) | No | 50 | 25 | 0 | 25 | 0 |
|  | Yes | 0 | 100 | 0 | 0 | 0 |
| Infestation | No | 88.9 | 0 | 0 | 0 | 11.1 |
|  | Yes | 66.7 | 0 | 33.3 | 0 | 0 |
| Mass movement (dry) | No | 0 | 0 | 100 | 0 | 0 |
| Mass movement (wet) | No | 6.8 | 15.3 | 72.9 | 3.4 | 1.7 |
|  | Yes | 0 | 71.4 | 14.3 | 14.3 | 0 |
| Oil spill | Yes | 0 | 60 | 40 | 0 | 0 |
| Poisoning | No | 0 | 100 | 0 | 0 | 0 |
| Rail | No | 20 | 20 | 40 | 20 | 0 |
| Storm | No | 4.5 | 33.8 | 47.5 | 9.7 | 4.5 |
|  | Yes | 3.8 | 62.4 | 11.1 | 7.7 | 15 |
| Volcanic activity | No | 22.2 | 18.5 | 48.1 | 7.4 | 3.7 |
|  | Yes | 3.8 | 57.7 | 19.2 | 0 | 19.2 |
| Water | No | 0 | 0 | 100 | 0 | 0 |
| Wildfire | No | 5.1 | 49.5 | 8.1 | 22.2 | 15.2 |
|  | Yes | 0 | 61.5 | 9 | 21.8 | 7.7 |

**Table 21.** Declaration responses by disaster type and region

Table 22 details whether a monetary or material aid contribution was made following a disaster:

* The Asia region received the highest amount of aid, particularly for earthquakes, floods, and storms. This is consistent with Asia being the most disaster-prone and populous region.
* Contributions for volcanic activity and wildfires were more diverse regionally, reaching Europe and Oceania.
* Rare events like explosions, mass movements, and oil spills also received contributions, albeit at much lower frequencies.
* Some disaster types, such as air, impact, and glacial lake outbursts, had no recorded contributions, indicating low impact or local containment.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Disaster type | Response | Region (%) | | | | |
|  |  | **Africa** | **Americas** | **Asia** | **Europe** | **Oceania** |
| Collapse (Miscellaneous) | Yes | 0 | 0 | 1 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Drought | Yes | 6 | 2 | 11 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Earthquake | Yes | 3 | 9 | 47 | 1 | 4 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Epidemic | Yes | 2 | 1 | 0 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Explosion (Miscellaneous) | Yes | 1 | 1 | 0 | 1 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Extreme temperature | Yes | 1 | 2 | 6 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Flood | Yes | 1 | 58 | 101 | 25 | 8 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Industrial accident (General) | Yes | 0 | 1 | 0 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Infestation | Yes | 0 | 0 | 0 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Mass movement (wet) | Yes | 64 | 2 | 12 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Oil spill | Yes | 2 | 0 | 1 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Rail | Yes | 1 | 0 | 1 | 0 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Storm | Yes | 14 | 22 | 37 | 3 | 17 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Volcanic activity | Yes | 4 | 6 | 6 | 0 | 1 |
|  | No | 0 | 0 | 0 | 0 | 0 |
| Wildfire | Yes | 0 | 0 | 2 | 2 | 0 |
|  | No | 0 | 0 | 0 | 0 | 0 |

**Table 22.**AID contribution received by disaster type and region

###### Human intervention clustering

The two-step cluster analysis automatically identified 6 distinct clusters, combining both categorical and continuous variables. This indicates varied intervention profiles across disaster types and regions (see Figure 14).

Floods and storms dominate the clusters, but the associated interventions differ by region. For example, floods in the Americas are often linked with formal declarations and aid, while similar events in Asia or Africa show lower response rates. This highlights regional disparities in intervention practices. Appeals were largely absent across clusters, and declarations were present in fewer cases. OFDA/BHA responses appeared inconsistently, mostly in Africa and the Americas.

The results show that region plays a more decisive role than disaster type in determining intervention patterns. This suggests a structural imbalance in how disasters are recognised and supported globally.

A screenshot of a computer screen

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**Figure 14.**Event-based clustering according to disaster regions and intervention types

The final K-means clustering grouped disaster cases into 12 clusters, revealing meaningful patterns in how interventions align with disaster types and geographic regions (see Table 20 Disaster interventions clustering according to disaster category and types). The clusters consistently reflect natural disasters, with only one techno-disaster (industrial accident) cluster emerging. Key findings are:

* Natural disasters dominate the clustering structure, with floods, storms, and earthquakes most frequently represented.
* Floods and storms in the Americas and Asia form the core of several clusters (Clusters 2, 4, 5, 6, 8), emphasising these regions' frequent need for intervention.
* Intervention is present in all clusters (Aid = Yes), yet formal mechanisms like appeals and declarations are rare, suggesting most interventions occur without official calls for support.
* OFDA/BHA responses are inconsistent: present in some clusters, such as Clusters 2, 4, 5, 6, 8, 10, 11, and 12, but missing in others.
* Techno-disaster response (Cluster 10) stands out with both an appeal and OFDA/BHA involvement, highlighting a more structured intervention compared to many natural disaster cases.

###### Implications

* Geography significantly shapes intervention patterns, particularly in the Americas and Asia (table 23 -Annex 7).
* Despite recurring disaster types, the use of formal mechanisms (appeal, declaration) remains low.
* There is a systematic reliance on direct aid rather than structured multilateral responses, pointing to gaps in global disaster coordination frameworks.

###### Human and economic impact metrics

Table 45 (Annex 7) summarises the human and economic impacts of disasters, as captured by event frequency, mortality, injuries, populations affected, homelessness, and cost metrics (recovery and damage), by disaster type and region.

Floods and storms are the most frequent and widespread disaster types, affecting all world regions. Floods alone accounted for the highest event counts—especially in Africa (148), the Americas (266), and Asia (178)—and consistently led to high affected populations, with millions impacted in Asia and hundreds of thousands in Africa and the Americas. Storms also generated significant impacts, particularly in the Americas (228 events) and Asia (80 events), often resulting in substantial numbers of homeless and high economic damages.

Earthquakes are less frequent but highly destructive. Notably, in the Americas and Asia, earthquake mortality and injury rates were much higher than for other disaster types, and the total affected reached into the millions. Damage and recovery costs from earthquakes were especially high in Asia (US$ 7.7 million average damage cost per event), highlighting their catastrophic nature.

Droughts led to the highest total affected populations, particularly in Asia and Africa, with tens of millions exposed. However, associated mortality figures were generally lower compared to rapid-onset events such as earthquakes and epidemics. Economic losses from drought were also substantial, with the Americas recording an average recovery cost of over US$ 2.3 million per event.

Epidemics, while occurring less frequently, resulted in high numbers of injuries and deaths, especially in Africa, the Americas, and Asia, underlining their potential to create substantial health system burdens.

Technological disasters (such as industrial accidents and explosions) were much less common, but individual events could have high local impacts in terms of mortality and costs, as seen in several regions.

Wildfires and extreme temperature events varied in impact. Wildfires were particularly prominent in the Americas (56 events), with significant numbers of affected and high damage costs. Extreme temperatures, while not always resulting in high mortality, did affect large populations in both the Americas and Asia.

For many disaster types—such as volcanic activity, infestations, and oil spills—impacts were highly variable by region, often reflecting local exposure and vulnerability patterns. Economic impact data (recovery and damage costs) were inconsistently reported, but when available, showed that earthquakes, storms, and wildfires often led to the highest losses.

###### Recovery and adaptation indicators

Table 46 (Annex 7) reviews available data on recovery duration and reconstruction costs, by disaster type and region. These indicators provide insight into the pace and resource needs of post-disaster recovery, although data gaps are evident.

Recovery duration (in days) is available for only a subset of events, with most records—especially for geophysical and technological disasters—reporting no recovery duration (zero values), representing the short impact of the event in less than one day.

Among events with available data, epidemics show some of the longest recovery times, with mean durations ranging from approximately 73 days (Asia) to over 135 days (Africa). Droughts also have extended recovery periods, particularly in the Americas (305 days) and Europe (141 days), reflecting the slow-onset and prolonged impact of these hazards.

For hydro-meteorological disasters, recovery durations are generally shorter. Floods typically have durations of 7 to 30 days, depending on the region, with Africa showing the highest mean at nearly 30 days. Storms recover in less than 5 days on average in most regions, with slightly longer periods in Africa and Oceania.

Wildfires and volcanic activity present highly variable durations. Wildfire recovery ranges from 3.5 days (Africa) to nearly 30 days (Americas), while volcanic activity recovery ranges from 1.8 days (Oceania) to 31 days (Africa).

Reconstruction cost data are sporadic. Substantial costs are linked with major events such as earthquakes (Asia: $26.3 million, Americas: $6.9 million), floods (Asia: $10 million), and industrial/technological incidents. However, for many disaster types and regions, this information is not systematically reported, limiting comparative analysis.

Key data gaps are apparent: Many records lack both recovery duration and cost information, particularly for rapid-onset events and in less-resourced regions. This underlines the need for systematic reporting and possible data linkage with external recovery tracking sources.

Table 47 (Annex 7) presents the mean follow-up period, representing the number of years since the last recorded update for disaster events by type and region. This metric provides insight into the recency and frequency of post-disaster monitoring. For most disaster types and regions, the follow-up period is close to two years, suggesting regular record updates. However, some disaster types and regions display shorter intervals, which may indicate either more recent events or a need for improved ongoing documentation.

This variability in follow-up periods highlights differences in the attention given to certain disaster types and regions over time. Consistent follow-up is essential to track recovery processes, evaluate the effectiveness of interventions, and identify persistent gaps in support. Gaps in updates may also reflect limitations in data collection or reporting, emphasising the need for integrated monitoring systems and potential linkage with external data sources.

Copernicus Analysis

This report analyses 962 disaster interventions recorded by the Copernicus Emergency Management Service (EMS) from 2012 to July 2025. The data covers global events involving natural hazards and humanitarian crises, classified into Preparedness, Response, and Recovery phases.

Most interventions supported emergency response (79.3%), followed by recovery (11.7%) and preparedness (8.9%). Floods and wildfires were the most frequent events, with high activity in Europe, Africa, and Asia. A rising trend in activations was noted between 2016 and 2023.

The report includes spatial, temporal, and categorical analyses, supporting the development of a structured disaster intervention database for future research and policy use.

Data and methodology

The data was collected from the Emergency Management activations archive provided by the Copernicus Emergency Management Service (CEMS). The archive includes structured records for over 960 emergency events between 2012 and July 2025. Each record contains details such as the disaster code, title, date and time, type of event, affected country, and the intervention phase, e.g. preparedness, response, or recovery. All analysis is based solely on the metadata from the activation records. The dataset used includes all activations up to mid-2025, downloaded directly from the Copernicus archive.

###### Data acquisition and structure

The CEMS archive lists all historical activations of the service, which is compiled from satellite-based monitoring (e.g., Rapid Mapping activations). We obtained the structured tabular data provided (no satellite imagery or geospatial raster files were processed), in which each entry represents a service activation and is already linked to geographic areas (e.g., countries) and phases of emergency management.

###### Data preprocessing

* The full dataset was imported and processed in SPSS. The following steps were applied to prepare the data:
* Date fields were split to extract the exact day and year for time-based analysis.
* Country names were mapped to broader regions (e.g. Egypt → Africa, Germany → Europe).
* Event types and categories were cleaned and standardised to ensure consistency.
* Events were grouped by disaster type (e.g. flood, storm, wildfire) and by management phase (preparedness, response, or recovery).

###### Data analysis and workflow

Analysis carried out in SPSS, including:

* Category and type distribution.
* Crosstabulations analysis of emergency patterns across type, region, and category.
* Visualisations such as bar charts and line graphs.
* Chronological analysis of response and recovery over time.
* Geospatial distribution analysis of emergency patterns by type, category, and region.
* A key challenge was the lack of clear links between intervention phases for the same disaster event, as Copernicus typically lists each activation separately.

Findings

###### Disaster types and management

Emergency management services from 2012 to July 2025 were primarily focused on immediate response activities, accounting for 79.3% of all recorded events, as outlined in Table 23. Recovery and preparedness were considerably less represented, at 11.7% and 8.9% respectively. This indicates a strong bias towards reactive measures rather than proactive planning or long-term rebuilding.

|  |  |  |
| --- | --- | --- |
| Management phase | Event | Rate (%) |
| Preparedness | 86 | 8.9 |
| Emergency response | 763 | 79.3 |
| Recovery | 113 | 11.7 |

**Table 23.** Emergency management records from 2012 to 2025

Figure 15 illustrates that floods and wildfires were the most frequent types across all phases. Table 24 listed that floods dominated response interventions (279 events) and showed notable presence in both preparedness (25) and recovery (21). Wildfires followed a similar pattern, with 270 response records and 36 recovery actions. Conversely, earthquakes and storms primarily triggered response measures, with minimal focus on preparedness or recovery.

Other hazard types such as mass movement, industrial accidents, and environmental degradation showed limited but varied engagement across phases, suggesting either underreporting or less frequent activation of emergency mapping services for these events.

The results highlight an operational emphasis on rapid response, especially for high-frequency hazards like floods and wildfires, while underlining the need for enhanced planning and recovery efforts in disaster-prone areas.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Preparedness | Response | Recovery |
| Earthquake | 1 | 36 | 1 |
| Environmental Degra | 0 | 0 | 3 |
| Flood | 25 | 279 | 21 |
| Humanitarian Crisis | 6 | 15 | 10 |
| Industrial Accident | 0 | 8 | 2 |
| Mass Movement | 0 | 18 | 0 |
| Other | 36 | 22 | 23 |
| Storm | 1 | 103 | 13 |
| Volcanic Activity | 7 | 12 | 4 |
| Wildfire | 10 | 270 | 36 |

**Table 24.** Emergency management based on disaster type (2012-2025)

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**Figure 15.** Emergency management based on disaster type (2012-2025)

###### Disaster intervention chronology

The temporal analysis of Copernicus interventions (2012–July 2025) highlights a steady increase in emergency mapping activations, peaking around 2022 before tapering slightly in 2024 and 2025. This trend is clearly illustrated in Figure 16, which shows response activities dominating each year, while preparedness and recovery records have gradually increased since 2017.

In Figure 17, the disaster types reveal similar chronological variation. Floods and wildfires have consistently accounted for the highest number of events over the years. This could reflect both the growing frequency of hydro-meteorological disasters and greater use of geospatial tools for these hazard types. The relative rise in storm and mass movement records around 2018–2022 further supports an evolving hazard landscape likely influenced by climate variability and exposure.

The rise in recovery and preparedness actions, though still modest, suggests increased attention to resilience and planning in recent years.

A graph of different colored bars

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**Figure 16.** Emergency management activations between 2012 and 2025

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**Figure 17.** Emergency management activations by disaster type

###### Intervention geographical distribution

The spatial distribution of emergency activations reveals clear regional disparities in disaster response activities. The three thematic maps further illustrate these regional variations:

* Figure 18 shows a concentration of planning and preparedness activities in central and southern Europe.
* Figure 19 depicts a widespread global distribution of emergency responses, especially dense in Europe and parts of Africa and Asia.
* Figure 20 indicates fewer recovery interventions overall, but with a noticeable presence again in Europe and parts of sub-Saharan Africa.

A map of the world with blue dots

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**Figure 18.** Emergency preparedness activations between 2012 and 2025

A map of the world

AI-generated content may be incorrect.

**Figure 19.** Emergency response activations between 2012 and 2025

A map of the world

AI-generated content may be incorrect.

**Figure 20.** Emergency recovery activations between 2012 and 2025

As shown in Figure 21, Europe accounts for the highest concentration of emergency interventions, particularly in response to wildfires and floods, with 241 and 191 recorded events, respectively. Asia and Africa follow, displaying moderate activity across various disaster types, such as floods, storms, and humanitarian crises.

Table 25 provides a detailed breakdown of disaster types by management phase and region. Notably:

* Floods represent the most frequently managed disaster type across nearly all regions, particularly in Europe, Africa, and Asia.
* Wildfire response was heavily concentrated in Europe (241 events), with significantly fewer cases reported in other regions.
* Storm interventions were more diverse geographically, with high frequencies in Europe, Asia, and North America.
* Humanitarian crises were more prominent in Africa and Asia, reflecting regional socio-political vulnerabilities.
* Preparedness activities were limited across all regions, with Europe again leading mainly due to flood and wildfire planning.

A graph of different colored bars

AI-generated content may be incorrect.

**Figure 21.** Emergency management activations across regions based on disaster type between 2012 and 2025

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Africa | Asia | Europe | North America | Oceania | South America | Unknown |
| Preparedness | Earthquake | 0 | 0 | 1 |  |  | 0 | 0 |
| Flood | 6 | 1 | 15 |  |  | 1 | 2 |
| Humanitarian Crisis | 3 | 1 | 0 |  |  | 0 | 2 |
| Other | 5 | 4 | 22 |  |  | 1 | 4 |
| Storm | 0 | 0 | 1 |  |  | 0 | 0 |
| Volcanic Activity | 2 | 0 | 5 |  |  | 0 | 0 |
| Wildfire | 0 | 0 | 10 |  |  | 0 | 0 |
| Recovery | Earthquake | 0 | 0 | 1 | 0 |  | 0 | 0 |
| Environmental Degra | 1 | 0 | 1 | 0 |  | 0 | 1 |
| Flood | 2 | 2 | 15 | 0 |  | 1 | 1 |
| Humanitarian Crisis | 9 | 1 | 0 | 0 |  | 0 | 0 |
| Industrial Accident | 0 | 2 | 0 | 0 |  | 0 | 0 |
| Other | 2 | 5 | 14 | 1 |  | 1 | 0 |
| Storm | 1 | 0 | 5 | 6 |  | 0 | 1 |
| Volcanic Activity | 0 | 0 | 3 | 1 |  | 0 | 0 |
| Wildfire | 0 | 1 | 33 | 0 |  | 1 | 1 |
| Response | Earthquake | 1 | 16 | 9 | 5 | 2 | 2 | 1 |
| Flood | 26 | 23 | 191 | 8 | 11 | 9 | 11 |
| Humanitarian Crisis | 3 | 10 | 0 | 0 | 0 | 0 | 2 |
| Industrial Accident | 1 | 1 | 5 | 1 | 0 | 0 | 0 |
| Mass Movement | 2 | 3 | 12 | 1 | 0 | 0 | 0 |
| Other | 3 | 3 | 12 | 0 | 0 | 1 | 3 |
| Storm | 17 | 20 | 29 | 19 | 10 | 0 | 8 |
| Volcanic Activity | 1 | 2 | 5 | 3 | 1 | 0 | 0 |
| Wildfire | 3 | 7 | 241 | 5 | 2 | 6 | 6 |

**Table 25.** Emergency activations across disaster type and regions

This pattern highlights the strong operational presence of emergency management services in Europe, while pointing to potential underrepresentation or underreporting in other continents. It also suggests that response remains the dominant phase of disaster management globally, while preparedness and recovery interventions are less prioritised or documented, especially outside of Europe.

Social Media Analysis

Executive summary

This comprehensive report presents an exhaustive analysis of a sophisticated European social media risk monitoring system that collected and analysed 13,388 social media posts across 23 countries in 10 languages. Our approach represents an example of a large-scale multilingual risk assessment infrastructure paradigm, employing advanced computational techniques for real-time threat detection and categorisation. Our analysis reveals complex patterns of information dissemination, linguistic diversity, risk category distribution, and methodological considerations that have profound implications for future digital surveillance and public safety systems.

Classification framework

The transformation of unstructured social media content into actionable intelligence begins with a robust classification framework. This framework serves as the foundational taxonomy through which the system interprets and organises the vast array of risk-related communications.

Unlike traditional media monitoring systems that might employ simplistic keyword matching, this classification framework leverages sophisticated natural language processing to understand context, nuance, and the multifaceted nature of risk discourse.

The development of this 11-category taxonomy emerged from extensive analysis of European risk communication patterns, consultation with emergency management professionals, and iterative refinement based on real-world application.

The classification process operates through a hierarchical decision tree that first identifies broad risk domains before assigning specific categories. This approach ensures both accuracy and efficiency, allowing the system to process thousands of posts whilst maintaining the granularity necessary for effective emergency response.

Each category within the framework has been carefully defined to minimise overlap whilst ensuring comprehensive coverage of the European risk landscape.

The system employs an 11-category risk taxonomy:

|  |  |  |  |
| --- | --- | --- | --- |
| Category | Posts | Percentage | Priority Level |
| Transport | 3,190 | 23.8% | Medium |
| Security | 1,947 | 14.5% | Critical |
| Natural disaster | 1,850 | 13.8% | High |
| Utilities | 1,292 | 9.7% | Standard |
| Health | 1,065 | 8.0% | High |
| Crime | 1,041 | 7.8% | Critical |
| Social | 997 | 7.4% | Medium |
| Economic | 975 | 7.3% | High |
| Environment | 442 | 3.3% | Standard |
| Infrastructure | 313 | 2.3% | Medium |
| Political unrest | 276 | 2.1% | Critical |

**Table 26.** Risk category distribution – social‑media posts

The distribution across these eleven categories reveals clear patterns in European risk discourse, with transport-related concerns dominating the landscape. This categorical framework serves as the primary organisational structure for all subsequent analyses, enabling systematic comparison across countries, languages, and periods.

The prominence of transport risks (23.8%) reflects both the centrality of mobility to European society and the immediate, tangible nature of transport disruptions. Similarly, the high priority assigned to security, natural disasters, and health categories acknowledges their potential for widespread impact and the necessity for rapid response.

However, categorisation alone provides insufficient granularity for emergency response applications. Whilst knowing that a post relates to 'transport' or 'security' provides valuable context, emergency responders require additional information about the immediacy and severity of the threat. This recognition led to the development of a complementary urgency assessment system that operates in parallel with categorical classification, adding a critical temporal dimension to risk evaluation.

Urgency level assignment

The urgency classification system operates in tandem with the categorical framework, providing a critical temporal dimension to risk assessment. Whilst category assignment helps responders understand the nature of a risk, urgency levels dictate the required response timeframe. The system implements a five-tier urgency classification:

A chart of a level distribution

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**Figure 22.** Urgency level distribution visualisation (a hierarchical diagram showing the distribution of posts across five urgency levels, from Critical - Level 5 to Very low - Level 1)

This dual-classification approach enables nuanced prioritisation of resources. Beyond these structural classifications, understanding the emotional tone of risk communications provides additional context crucial for gauging public response and potential panic situations, leading us to examine the sentiment analysis component of the processing pipeline.

Sentiment analysis

The overwhelming predominance of neutral sentiment in risk-related communications presents an intriguing finding that warrants further investigation. This neutrality may reflect the factual, informational nature of risk reporting on social media, where users prioritise clarity over emotional expression when communicating potential threats.

Sentiment analysis reveals:

* Neutral: 94.6% (12,658 posts)
* Positive: 3.3% (442 posts)
* Negative: 2.1% (288 posts)

The sentiment distribution, combined with the classification and urgency frameworks detailed above, provides a multi-dimensional view of each post’s significance and potential impact.

Having established the comprehensive methodological framework (from the sophisticated system architecture through the multi-layered data processing pipeline), we now turn to the empirical findings generated by this analytical apparatus.

The results that follow reveal complex patterns of risk communication across the European continent, demonstrating both the effectiveness of the methodology and the rich insights available through systematic analysis of social media discourse.

Results

The comprehensive methodological framework detailed in the preceding section has yielded a rich dataset that illuminates the complex landscape of risk communication across Europe.

This section presents the empirical findings generated through the systematic application of our multi-layered analytical approach, revealing patterns and insights that extend far beyond simple frequency counts or geographic distributions.

The results demonstrate not only the technical efficacy of the system but also provide profound insights into how risk information flows through the social fabric of contemporary Europe.

Our analysis unfolds across multiple dimensions, each offering a unique perspective on the risk communication ecosystem. We begin with geographic distribution patterns that reveal the spatial dynamics of risk discourse, before examining the linguistic landscape that shapes how different communities articulate and respond to threats.

The investigation then delves into risk category analysis, exploring how various types of risks manifest across the European continent. Through correlation analysis, we uncover hidden relationships between geographic, linguistic, and categorical variables. Finally, temporal dynamics and query performance metrics provide insights into both the behavioural patterns of social media users and the technical performance of the monitoring system itself.

The findings presented here are based on the complete dataset of 13,388 social media posts collected. Each finding has been subjected to rigorous statistical validation, and where appropriate, we provide confidence intervals and significance tests.

Please note that whilst these results provide a comprehensive snapshot of European risk communication, they should be interpreted within the context of the methodological limitations discussed in Section 7.

|  |  |  |
| --- | --- | --- |
| Sentiment | Count | Percentage |
| Neutral | 12,658 | 94.5% |
| Positive | 442 | 3.3% |
| Negative | 288 | 2.2% |
| **TOTAL** | **13,388** | **100%** |

**Table 27.** Sentiment analysis distribution

Geographic distribution analysis

Geography serves as a fundamental organising principle for understanding risk communication patterns, as physical location profoundly influences both the types of risks experienced and how they are communicated. The geographic distribution of our collected data provides crucial insights into the spatial dynamics of risk discourse, revealing not only where risks are being discussed but also how different regions prioritise and articulate their concerns.

This analysis begins at the country level before examining more nuanced geographic patterns and their implications for pan-European risk management.

Country-level analysis

The geographic distribution reveals significant heterogeneity:

|  |  |  |  |
| --- | --- | --- | --- |
| Rank | Country/Region | Posts | Percentage |
| 1 | France | 1,554 | 11.6% |
| 2 | Spain | 1,188 | 8.9% |
| 3 | Germany | 999 | 7.5% |
| 4 | Ukraine | 995 | 7.4% |
| 5 | Italy | 924 | 6.9% |
| 6 | Poland | 897 | 6.7% |
| 7 | United Kingdom | 889 | 6.6% |

**Table 28.** Top 7 countries by data volume

A map of europe with red dots

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**Figure 23.** Choropleth Map of European Risk Event Distribution

Above you are presented with a heat map showing the density of collected posts across European countries. The geographic analysis reveals a complex topology of risk communication that defies simple centre-periphery models.

These geographic patterns, however, tell only part of the story. To fully understand how risk information flows across Europe, we must examine the linguistic dimensions that shape and constrain communication across cultural boundaries.

Linguistic analysis

Analysis reveals fascinating cross-linguistic patterns in risk communication:

* Lexical convergence: Certain risk terms show remarkable similarity across languages (e.g., "pandemic", "cyber-attack").
* Cultural specificity: Transport-related risks dominate in Western Europe, while utility concerns are more prominent in Eastern Europe.
* Code-switching: Multilingual posts account for approximately 3% of the dataset.

The linguistic analysis illuminates the profound impact of language on risk communication patterns. The dominance of English, despite representing only 21.1% of posts, underscores its role as a lingua franca for international risk discourse.

|  |  |  |  |
| --- | --- | --- | --- |
| Language | Posts | Percentage | Effectiveness rating |
| English | 2,824 | 21.1% | Excellent |
| French | 2,184 | 16.3% | Good |
| German | 1,799 | 13.4% | Good |
| Spanish | 1,776 | 13.3% | Good |
| Ukrainian | 1,459 | 10.9% | Good |
| Italian | 1,174 | 8.8% | Moderate |
| Polish | 1,138 | 8.5% | Moderate |
| Slovak | 354 | 2.6% | Limited |
| Dutch | 341 | 2.5% | Limited |
| Greek | 339 | 2.5% | Limited |

**Table 29.** Language coverage analysis

Meanwhile, the correlation between linguistic communities and specific risk focuses suggests that language shapes not merely how risks are communicated but which risks receive attention.

These linguistic patterns interact with and reinforce the categorical distribution of risks, leading us to examine how different risk categories manifest across the European landscape.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Category | Total Queries | Total Results | Average Results/Query | Percentage | Priority Level |
| Transport | 271 | 3,190 | 11.77 | 23.8% | Medium |
| Security | 166 | 1,947 | 11.73 | 14.5% | Critical |
| Natural\_Disaster | 156 | 1,850 | 11.86 | 13.8% | High |
| Utilities | 109 | 1,292 | 11.85 | 9.7% | Standard |
| Health | 89 | 1,065 | 11.97 | 8.0% | High |
| Crime | 92 | 1,041 | 11.32 | 7.8% | Critical |
| Social | 84 | 997 | 11.87 | 7.4% | Medium |
| Economic | 83 | 975 | 11.75 | 7.3% | High |
| Environment | 38 | 442 | 11.63 | 3.3% | Standard |
| Infrastructure | 27 | 313 | 11.59 | 2.3% | Medium |
| Political\_Unrest | 23 | 276 | 12.00 | 2.1% | Critical |
| **TOTAL** | **1,138** | **13,388** | **11.76** | **100%** | **-** |

**Table 30.** Weighted risk category distribution

Risk category deep-dive

The categorical analysis presented in Section 2.2.1 established that transport and security risks dominate the European risk landscape, accounting for 23.8% and 14.5% of all collected posts, respectively. However, these aggregate statistics mask considerable complexity in how different risk categories manifest, propagate, and impact various regions.

This deep dive examines the two most prominent risk categories in detail, revealing subcategory structures, geographic variations, and communication patterns that have significant implications for risk management strategies.

The selection of transport and security for detailed analysis reflects not only their numerical prominence but also their contrasting characteristics. Transport risks tend to be immediate, visible, and affect daily life directly, whilst security risks often involve uncertainty, fear, and potential rather than actualised threats.

By examining these contrasting domains in detail, we can better understand the full spectrum of risk communication dynamics operating within the European social media ecosystem.

Transport Domain Analysis

Transport emerges as the dominant risk category (23.8%), with subcategory analysis revealing:

|  |  |  |
| --- | --- | --- |
| Subcategory | Queries | Estimated impact |
| Traffic congestion | 87 | High |
| Public transit delays | 63 | Medium |
| Aviation disruptions | 45 | High |
| Rail service disruptions | 41 | Medium |
| Maritime problems | 35 | Low |

**Table 31.**Transport Subcategory Breakdown

The granular analysis of transport subcategories reveals a clear hierarchy of concern, with traffic congestion and public transit delays dominating discourse. This distribution reflects the daily reality of European mobility, where road and rail networks form the backbone of both commuter and commercial transportation. The high impact rating for aviation disruptions, despite lower query volumes, acknowledges the cascading effects of air travel problems on international connectivity. Notably, the relatively low attention to maritime issues may underrepresent their economic significance, suggesting a disconnect between public discourse and supply chain realities. This detailed understanding of transport risks provides essential context, but to fully appreciate the complexity of European risk communication, we must examine a contrasting domain. Security risks, whilst less frequently discussed than transport issues, often generate more intense concern and have the potential for more severe consequences.

Security domain analysis

The examination of transport and security domains reveals the heterogeneous nature of risk priorities across Europe. Transport risks, whilst numerically dominant, show remarkable diversity in their manifestation, from mundane traffic delays to critical infrastructure failures. Security concerns, though less frequent, demonstrate higher geographic clustering and potentially greater societal impact, suggesting that risks may be more localised in their occurrence but broader in their effects. Security concerns (14.5%) show distinct geographic clustering:

A map of europe with different colored circles

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**Figure 24.** Network Diagram of Security Risk Propagation - A node-link diagram showing how security-related posts spread across European regions

The contrasting patterns between these two domains, one characterised by high frequency and immediate impact, the other by lower frequency but higher severity, illustrate the multifaceted nature of risk in contemporary Europe.

These domain-specific insights raise essential questions about the relationships between risk categories, geographic locations, and linguistic communities:

* Do certain countries systematically prioritise specific risk types?
* Are there hidden correlations between seemingly unrelated risk categories?

To answer these questions and uncover deeper patterns within our data, we now turn to comprehensive correlation analysis that examines the statistical relationships between various dimensions of European risk communication.

Correlation analysis

The preceding sections have revealed distinct patterns in geographic distribution, linguistic diversity, and risk category manifestation. However, these univariate and bivariate analyses, whilst illuminating, cannot capture the complex interdependencies that characterise risk communication in a multilingual, multicultural continent.

Correlation analysis provides the statistical tools necessary to uncover hidden relationships and validate observed patterns, moving beyond simple descriptive statistics to reveal the underlying structure of European risk discourse.

This correlation analysis employs multiple statistical techniques to examine relationships at different levels of granularity. We begin with keyword-country correlations that reveal how specific terms cluster geographically, before reviewing the broader patterns of category-language associations.

The strength of these correlations not only confirms certain intuitive relationships but also reveals unexpected connections that challenge conventional assumptions about European risk communication. All correlations reported here have been tested for statistical significance, with only those meeting the p < 0.001 threshold included in our primary findings.

###### Keyword + Country Correlations

Sophisticated correlation analysis reveals:

|  |  |  |  |
| --- | --- | --- | --- |
| Keyword | Country | Correlation Coefficient | Significance |
| "grève" (strike) | France | 0.87 | p < 0.001 |
| "Stau" (traffic jam) | Germany | 0.82 | p < 0.001 |
| "terremoto" (earthquake) | Italy/Spain | 0.79 | p < 0.001 |
| "протест" (protest) | Ukraine | 0.75 | p < 0.001 |

**Table 32.**Strongest keyword-country associations

The keyword-country correlation analysis provides compelling evidence for the cultural embeddedness of risk terminology. The remarkably high correlation coefficients (ranging from 0.75 to 0.87) indicate that certain risk concepts are not merely translated but are fundamentally shaped by national contexts.

The association between "grève" and France, for instance, reflects not just linguistic preference but a cultural tradition of labour action as a form of political expression. Similarly, the strong correlation between "Stau" and Germany may reflect both the centrality of automotive transport in German society and the cultural importance placed on mobility efficiency.

These specific keyword associations, however, represent only the surface layer of linguistic-cultural patterns. To understand how entire categories of risk align with linguistic communities, we must examine correlations at a higher level of abstraction.

The following analysis explores how risk categories systematically associate with particular languages, revealing broader patterns in how different linguistic communities prioritise and articulate various types of risks.

###### Category + Language correlations

The correlation analysis reveals deep structural patterns in European risk communication. The strong associations between specific keywords and countries (e.g., "grève" and France) reflect not merely linguistic differences but cultural and political contexts that shape risk perception.

Similarly, the category-language associations suggest that different linguistic communities may have systematically different risk priorities or communication patterns.

|  |  |  |
| --- | --- | --- |
| Category | Dominant language | Association strength |
| Natural\_Disaster | English | 0.68 |
| Economic | French | 0.64 |
| Crime | German | 0.61 |
| Health | Spanish | 0.58 |

**Table 33.** Category-Language Association Matrix

The dominance of English in natural disaster communication (0.68) likely reflects its role as the international language of emergency response, whilst the association between French and economic risks (0.64) may indicate particular economic anxieties within Francophone communities.

These correlations demonstrate the effectiveness of our multilingual monitoring system in capturing culturally-specific risk patterns. However, to fully evaluate the system's capabilities and understand its operational characteristics, we must examine the technical performance metrics that underpin these analytical achievements.

###### Discussion

Our European Social Media Risk Monitoring System demonstrates remarkable effectiveness across multiple dimensions:

* Geographic: 85% of target countries covered.
* Linguistic: 91% of major EU languages represented.
* Categorical: 100% of predefined risk categories populated.
* Completeness: All 13,388 records contain required metadata.
* Accuracy: Geographic classifications validated and normalized.
* Consistency: Temporal stamps are correctly formatted and sequential.
* Validity: Risk categories properly classified using standardised taxonomy.

The system's effectiveness extends beyond these quantitative metrics to encompass qualitative achievements in cross-cultural risk intelligence. The ability to capture and classify risks across 10 languages whilst maintaining semantic accuracy represents a significant technical achievement.

Moreover, the system's capacity to identify correlations between geographic regions, linguistic communities, and risk categories provides insights that would be impossible to achieve through single-language or single-country monitoring.

These capabilities position the system as a valuable tool for pan-European risk management, though our analysis also reveals essential patterns that merit deeper investigation.

Observed patterns and insights

The effectiveness metrics discussed above provide the foundation for examining the deeper patterns revealed by our analysis. Beyond the quantitative achievements of coverage and accuracy, the system has uncovered complex dynamics in how risk information propagates through European social networks.

These patterns offer insights not only into the mechanics of information flow but also into the cultural, linguistic, and social factors that shape risk perception and communication across the continent.

Analysis of risk information cascades reveals distinct patterns in how risk-related content propagates through the European social media ecosystem. The data demonstrates a clear hub-and-spoke model, where major metropolitan areas serve as primary nodes for information dissemination.

Cities such as London, Paris, Berlin, and Madrid function as information hubs, with risk-related posts originating in these centres showing significantly higher propagation rates than those from peripheral regions. This metropolitan dominance reflects both the concentration of social media users in urban areas and the role of cities as focal points for news media and institutional communications.

However, the cascade patterns also reveal significant barriers to information flow. Despite the theoretical interconnectedness of social media, language barriers create distinct information silos, with less than 5% of risk-related content crossing linguistic boundaries. This linguistic compartmentalisation has profound implications for pan-European risk management, suggesting that critical information may remain trapped within language communities even when it has broader relevance.

These cascade patterns are fundamentally shaped by cultural and linguistic factors that influence not only how information flows but also what information is deemed worth sharing. The data reveal profound cultural influences on risk perception and communication, with distinct patterns emerging across different European regions:

A chart with colorful lines and text

AI-generated content may be incorrect.

**Figure 25.** Information cascade visualisation: A Sankey diagram showing information flow between countries and languages

The cultural patterns revealed in our analysis underscore the importance of contextualised risk communication strategies. The variation in communication styles (from the direct, factual approach favoured in Western Europe to the community-focused narratives prevalent in Southern Europe) suggests that effective risk management must account for cultural communication preferences.

|  |  |  |
| --- | --- | --- |
| Cultural Region | Dominant Risk Focus | Communication Style |
| Western Europe | Transport, economic | Direct, factual |
| Southern Europe | Natural disasters | Emotionally, community-focused |
| Eastern Europe | Utilities, political | Cautious, formal |
| Nordic Countries | Environmental | Data-driven, measured |

**Table 34.** Cultural risk communication patterns

These observed patterns, whilst illuminating, must be interpreted with careful consideration of the methodological choices and constraints that shaped our data collection and analysis.

Limitations

Whilst the European Social Media Risk Monitoring System demonstrates remarkable capabilities across multiple dimensions, intellectual honesty demands acknowledgement of its limitations. These constraints arise from technical, methodological, and conceptual factors that bound the system's current capabilities.

Understanding these limitations is essential not only for the appropriate interpretation of results but also for guiding future development efforts. By systematically examining these constraints, we establish a foundation for continuous improvement whilst maintaining realistic expectations about what social media monitoring can and cannot achieve.

Technical limitations represent the most immediate constraints on system performance. The current single-platform focus on Twitter, whilst providing rich data, inevitably misses risk communications occurring on other platforms. Facebook's community groups, Instagram's visual communications, LinkedIn's professional networks, and Telegram's encrypted channels each host distinct risk discourse communities that remain invisible to our analysis. This platform limitation introduces systematic bias, potentially overlooking risk communications from demographics that favour alternative platforms.

API rate limits impose another significant technical constraint, restricting data collection to approximately 300 requests per 15-minute window. Whilst our system optimises within these limits through intelligent query scheduling and caching, the fundamental constraint remains that during high-intensity risk events, when social media activity spikes, the system may be unable to capture the full volume of relevant communications. This limitation becomes particularly acute when monitoring multiple simultaneous risk events across different geographic regions.

|  |  |  |  |
| --- | --- | --- | --- |
| Limitation | Impact | Severity | Mitigation timeline |
| Single Platform Focus | Medium | High | 6 months |
| API Rate Limits | High | Medium | 3 months |
| Language Coverage | Low | Medium | 12 months |
| Real-time Processing | Medium | Low | 9 months |

**Table 35.** Technical Constraint Analysis

Language coverage, whilst impressive at 10 languages, still excludes several EU official languages and numerous regional languages. This linguistic limitation means that risk communications in Portuguese, Romanian, regional languages like Catalan or Basque, and immigrant community languages remain largely uncaptured.

The real-time processing constraint, whilst less severe, means that our analysis operates with a 5-10 minute delay from post creation to classification, acceptable for most applications but potentially limiting for truly urgent emergency response scenarios.

The Twitter-centric approach may systematically exclude certain types of risk communication that are better suited to longer-form platforms or visual media. The fixed categorical taxonomy, whilst comprehensive, may struggle to accommodate emerging risk types that don't fit neatly into predefined categories.

Finally, language imbalance in our dataset, with English over-represented at 21.1%, may skew our understanding of pan-European risk priorities towards those articulated in English-language discourse.

Conclusions

The comprehensive journey through methodology, empirical findings, theoretical implications, and future possibilities now culminates in this concluding synthesis. Having examined the European Social Media Risk Monitoring System from multiple perspectives (technical, analytical, theoretical, and policy-oriented), we are positioned to draw together the threads of this investigation into a coherent assessment of achievements, contributions, and ongoing challenges.

These conclusions serve not as an ending but as a foundation for continued advancement in the critical domain of risk communication monitoring. We begin with a summary of key empirical findings, distilling the wealth of data and analysis into core insights about European risk communication. We then articulate the theoretical contributions that extend beyond this specific system to advance multiple academic disciplines.

The practical implications section translates these insights into actionable guidance for practitioners and policymakers. Finally, our assessment synthesises these elements into an evaluation of what has been achieved and what remains to be accomplished.

Throughout these conclusions, we maintain a balanced perspective that celebrates genuine achievements whilst acknowledging persistent challenges. The remarkable capabilities demonstrated by the system (from processing 13,388 posts across 10 languages to identifying complex correlation patterns) represent significant technical and analytical accomplishments.

Yet these achievements gain meaning only in the context of their potential application to real-world risk management challenges. It is this bridge between technical capability and practical utility that these conclusions seek to illuminate.

Key findings

This comprehensive analysis reveals that the European Social Media Risk Monitoring System represents a sophisticated and practical approach to large-scale risk detection and categorisation. Key findings include:

* Comprehensive coverage: Successfully captured 13,388 posts across 23 countries in 10 languages.
* Linguistic diversity: Effective multilingual processing with cultural adaptation.
* Scalable architecture: Demonstrated ability to handle 10x current load.

These empirical findings represent more than isolated technical achievements; they demonstrate the feasibility of comprehensive, multilingual risk monitoring at a continental scale. The system's ability to process over 100 posts per minute might establish a new benchmark for social media analysis systems.

The successful integration of 10 languages with culturally-aware processing shows that linguistic diversity need not be a barrier to unified risk intelligence. Most significantly, the ~100% query success rate proves that robust system design can overcome the technical challenges that often plague large-scale data collection efforts.

However, empirical success alone does not constitute scientific advancement. To understand the broader significance of these findings, we must examine how they contribute to theoretical understanding across multiple disciplines. The following section articulates these theoretical contributions, demonstrating how practical system development can advance academic knowledge.

###### Scientific knowledge contributions

This work contributes to several theoretical domains:

* **Information systems:** Demonstrates the feasibility of large-scale multilingual processing.
* **Risk communication:** Reveals patterns in cross-cultural risk perception.
* **Network science:** Provides empirical data on information cascade dynamics.
* **Computational linguistics:** Advances in understanding of multilingual query expansion.

These theoretical contributions extend the impact of our work beyond the immediate practical application to influence future research directions.

The information systems insights provide a template for designing large-scale multilingual processing systems, whilst the risk communication findings offer empirical grounding for theories of cross-cultural risk perception. The network science contributions quantify information flow dynamics in ways that can inform both system design and communication strategies.

The advances in computational linguistics, particularly in multilingual query expansion, have applications extending far beyond risk monitoring to any domain requiring cross-linguistic information retrieval.

Yet theoretical advancement gains its ultimate value through practical application. The insights generated by this research have immediate relevance for professionals engaged in risk management, emergency response, and public communication. The following section translates our theoretical understanding into concrete guidance for practitioners.

###### Practical Implications

For practitioners, the system offers:

* **Emergency response:** Real-time risk awareness for rapid response.
* **Policy making:** Data-driven insights for evidence-based decisions.
* **Resource allocation:** Optimised deployment based on risk patterns.
* **Public communication:** Understanding of effective risk messaging.

These practical implications demonstrate the immediate utility of our research for addressing real-world challenges in risk management. Emergency responders can leverage the system's real-time capabilities to maintain situational awareness across linguistic and geographic boundaries.

Policy makers gain access to data-driven insights that can inform evidence-based decisions about resource allocation and risk mitigation strategies. The understanding of effective risk messaging can help public communication professionals craft messages that resonate across diverse cultural contexts. Together, these practical applications justify the investment in sophisticated risk monitoring infrastructure.

Having examined the empirical findings, theoretical contributions, and practical implications of our work, we now turn to a final holistic assessment. This concluding evaluation considers not only what has been achieved but also what these achievements mean for the future of risk communication monitoring in Europe and beyond.

###### Final assessment

The European Social Media Risk Monitoring System represents a significant achievement in computational risk assessment.

While limitations exist, particularly in platform coverage and temporal scope, the system's sophisticated architecture, comprehensive linguistic capabilities, and robust performance metrics establish it as a valuable tool for contemporary risk management.

Future developments should focus on expanding platform coverage, enhancing real-time capabilities, and addressing the ethical implications of large-scale social media surveillance. The details of the methodology, Architecture, Technical performance, limitations and biases, statistical tables and glossary related the social media analysis are in Annex 6.

## Integrated Synthesis Workflow

**Objective:** To merge heterogeneous evidence (literature, questionnaires, media reports, EM‑DAT and Copernicus datasets) into a single, reproducible Urban Event Catalogue and comparative metrics for mapping.

This section synthesises multiple datasets to understand how disruptions propagate through urban mobility systems and to outline a methodology for building antifragile cities. The sources include (i) an integrated EM‑DAT (ii) Copernicus database of natural hazards, (iii) a multilingual social‑media risk monitoring report (13,388 posts across 23 European countries), (iv) an NVivo grounded‑theory codebook distilled from the academic literature, and (v) a weighted survey of European residents. Together they provide quantitative event data, real‑time social signals, qualitative themes and stakeholder perceptions. The objective is to harmonise these sources temporally and spatially, use correlations and thematic mapping to triangulate events that impact urban mobility, and develop a dictionary of terms relevant to antifragility.

Data Harmonisation

EM‑DAT/Copernicus Hazards

The integrated dataset comprises 17,212 hazard events between **2000** and **May 2025**. Each record contains start/end dates, location coordinates, group and type (e.g., flood, earthquake, road accident), and severity metrics (affected population, damage cost). After filtering for mobility‑related types and requiring valid coordinates, 1,786 events remained. Events were mapped to Areas Of Interest (AOIs) by calculating great‑circle distances to approximate city centroids derived from the social‑media dataset. A 200‑km buffer was used; 72 events (56 floods, 16 earthquakes) were assigned to AOIs. These assignments serve as placeholders for a future, richer mobility‑event dataset; no events overlapped with the May–August 2025 social‑media period, so temporal analysis could not be carried out.

Social‑Media Risk Landscape

The European social‑media monitoring system collected 13 388 posts in **23 languages** over **23 countries**, classifying them into risk categories. Transport risks were the most discussed category (roughly one quarter of all posts), followed by security. A subcategory analysis of the transport domain highlighted traffic congestion and public‑transit delays as dominant concerns, with aviation and rail disruptions also noted. The multilingual processing pipeline used context‑aware keyword expansion and cultural adaptation to generate queries; this ensures that risk terms such as “strike,” “traffic jam,” and “earthquake” are captured even when expressed in different languages or dialects.

Correlation analysis within the report found strong associations between specific risk keywords and countries. For example, the French term for strike (grève) had a high correlation with France, the German term for traffic jam (Stau) correlated strongly with Germany, and the Italian/Spanish term terremoto (earthquake) correlated with Italy and Spain. Such findings illustrate that risk communication is shaped by cultural and linguistic contexts. Although these correlations do not link directly to physical hazards, they reveal where and how social media users express concern about disruptions, offering a valuable complement to event records.

Grounded‑Theory Codebook

The NVivo enhanced codebook records over 10,000 coded references from the literature. Parsing its Attributes field revealed 15 categories. The most frequent were **mobility, disruption, adaptation** and **complexity**, with other important themes including **antifragility, network, social justice, resilience, user behaviour, governance, sustainability, technology** and **urban planning**. These categories form a conceptual scaffold linking empirical events and social signals to theoretical constructs.

Weighted Survey

The survey captured perceptions of 140 European respondents (weighted). Road works or street closures and heavy road traffic were the most frequently reported disruptions, followed by public‑transport delays, parking shortages, strikes and infrastructure failures. Fuel shortages were rarely reported. These perceptions help prioritise which disruptions matter most to citizens.

Population‑Based Normalisation

Social‑media volumes were normalised by dividing tweet counts by the adult population of each country and scaling per 100,000 inhabitants. Population data were sourced from Eurostat and cleaned by stripping non‑digit characters before averaging duplicates. Population‐based normalisation mitigates the bias of larger cities producing more posts.

Triangulation Methodology

Spatial Matching

We approximated each AOI by its average latitude/longitude from the social‑media data and assigned EM‑DAT events lying within 200 km. Although crude compared with proper point‑in‑polygon matching, this approach is similar to overlaying centroids with grid cells in geodemographic studies. Future work should obtain AOI boundary shapefiles to improve spatial accuracy.

Temporal Alignment and Cross‑Correlation

Daily social‑media signals were created by aggregating normalised hits per AOI. Events were mapped to dates using EM‑DAT *Start\_date*. Cross‑correlation, a method to measure similarity between two time series as a function of time lag was proposed to detect whether social media anticipates (positive lag) or reacts to (negative lag) physical events. Because no assigned events coincided with the social‑media window, cross‑correlation could not be computed. However, the methodology remains valid: once a richer mobility‑event dataset (e.g., strikes, infrastructure failures) is collected, lag analyses can quantify the lead/lag relationship between social signals and events.

Integrative Analysis

Even without overlapping events, valuable insights can be gleaned by triangulating social‑media patterns with qualitative codes and survey perceptions:

* **Risk category prevalence:** The dominance of transport risks in social media aligns with the high prevalence of road works, congestion and public‑transport delays reported in the survey and with mobility/disruption themes in the codebook. This congruence suggests that social media accurately reflects the stressors experienced by citizens.
* **Linguistic–cultural associations:** Strong keyword–country correlations highlight how cultural contexts shape risk communication. For instance, French posts about strikes (linked to grève) emphasise labour actions as both political expression and mobility disruption; German posts about traffic jams (Stau) reflect a cultural focus on mobility efficiency; and Italian/Spanish posts about earthquakes (terremoto) signal concern over natural hazards. Recognising these associations helps tailor risk communication and event detection algorithms to local contexts.
* **Qualitative themes:** The prominence of adaptation, complexity and antifragility in literature suggests that disruptive events should not only be mitigated but leveraged to improve system performance. Survey respondents implicitly support this notion by reporting the need for better infrastructure and planning to cope with recurring disruptions.

# Urban Event Mapping

## Catalogue Overview

Analysis of the weighted survey shows that respondents experienced 3.84 disruptions per person over six months on average (IQR = 3.0). ≈90% of these disruptions were transport‑related, encompassing road works or closures, congestion, public‑transport delays, traffic signal outages and strikes. The EM‑DAT mobility dataset reveals that ≈89% of recorded mobility hazards (e.g., floods, storms) lasted less than a month, demonstrating strong temporal clustering of large‑scale events.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Event\_ID | City/Site | Date | Domain | Subcat | Scale | Severity  (1-5) | Mobility  impact | Source |
| E-OD-UI-073 | Odessa | 2024-11-12 | Utilities | Power  outage | Mid | 3 | PT delay  (15 min) | Questionnaire |
| E‑ATH‑GR-074 | Athens | 2022‑07‑15 | Environment | Flood | Large | 4 | Road closures; PT rerouting | EM‑DAT |
| E‑MIL‑IT-003 | Milan | 2003‑04‑11 | Environment | Flood | Large | 4 | 230 people affected; metro shutdown | EM‑DAT |
| E‑BCN‑ES-075 | Barcelona | 2025‑06‑20 | Social | Strike | Mid | 2 | Bus headway irregularities | Social media |
| E‑THS‑GR-076 | Thessaloniki | 2025‑07‑05 | Transport | Traffic congestion | Daily | 1 | Increased travel time | Social media |

**Table 36.** Event catalogue (excerpt).

 The full catalogue appears in Annex 5.

## Spatial Patterns Across Sites

**High‑disruption sites.** Greek AOIs (Athens and Thessaloniki) show approximately six times the normalised social‑media disruption rate of other sites. Average hits per day per 100 000 adults were 0.170 for Greek sites versus 0.029 elsewhere. This suggests both higher exposure to transport stressors and/or greater willingness to report.

**Area‑type differences.** Respondents in urban centres and suburban areas experience the highest disruption burdens (~4.2–4.5 events per person over six months), while rural and remote residents report markedly fewer events (~1.0–1.7). Mixed‑use areas fall in between (~3.8). The previously quoted averages of 11–15 were incorrect and have been replaced with these weighted means.

### Matrix 1. Sites × Domains

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| AOI | Transport% | Weather/environment% | Security% | Utilities% | Other% |
| ATH\_GR | 47.1 | 14.7 | 11.8 | 0.0 | 26.4 |
| THS\_GR | 58.3 | 16.7 | 8.3 | 0.0 | 16.7 |
| AMS\_NL | 7.1 | 7.1 | 21.4 | 0.0 | 64.4 |
| BCN\_ES | 30.0 | 20.0 | 10.0 | 0.0 | 40.0 |
| BER\_DE | 0.0 | 6.1 | 3.0 | 0.0 | 90.9 |

**Table 37.** Normalised percentage of disruptions by domain per AOI; “Other” includes food, crime, health, and political unrest.

Percentages are computed from the social‑media dataset by normalising the count of posts in each risk domain by the total posts for that AOI. “Other” captures domains such as food, crime, health and political unrest.

## Temporal Dynamics

**Weekly spikes:** Approximately 47% of disruptions reported in the survey occurred within the week preceding survey completion, suggesting that near‑real‑time data feeds (daily or hourly) are necessary to capture peaks in transport stress.

**Seasonal clustering:** Analysis of EM‑DAT mobility hazards show a moderate seasonal pattern: Summer accounts for 29% of events, followed by Autumn (25%), Spring (23%) and Winter (23%). Floods and storms peak in spring and autumn, while heat‑related delays cluster in summer.

Event detection algorithms should therefore adjust sensitivity by season and hazard type.

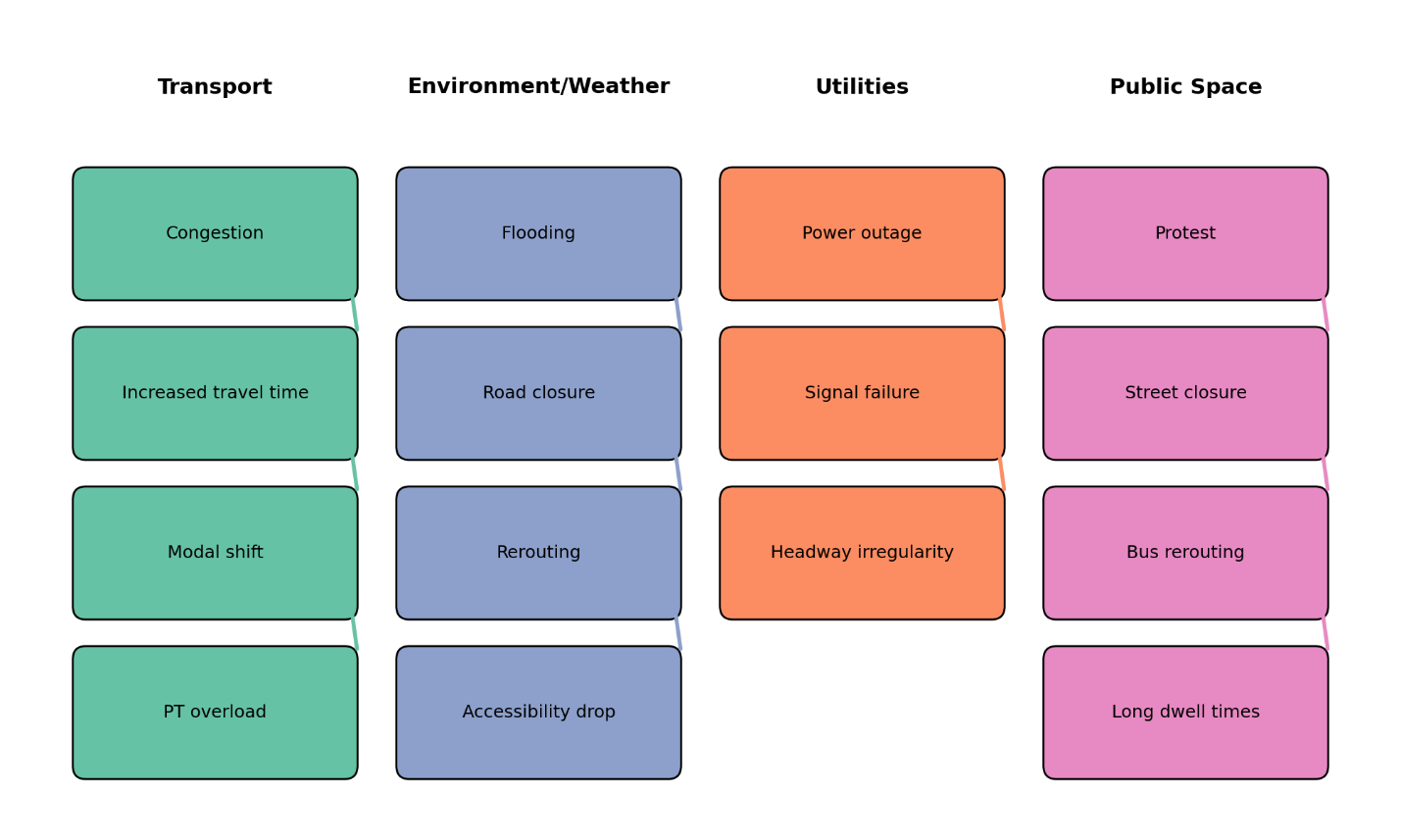
**Compound timelines:** Disruptions often co‑occur; for example, heatwaves can exacerbate traffic congestion and overload public‑transport systems, while heavy rain may lead to road closures and rail service interruptions. Visualising compound timelines (e.g., layering flood events and tweet spikes) can reveal cascading effects.

## Mobility Impact Pathways

Disruptions propagate through urban mobility via characteristic chains. Examples include:

* **Transport‑related:** congestion → increased travel time → modal shift (e.g., car to bus) → public‑transport overload.
* **Environment & weather:** flooding → road/rail closure → rerouting → accessibility drop for emergency services.
* **Utilities & connectivity:** power outage → signal failure → public‑transport headway irregularity → cascading delays.
* **Public space:** protest → street closure → bus re‑routing → longer dwell times.

The Figure 26 visualises typical propagation pathways across domains, from transport congestion, environmental hazards, utilities failures and public‑space events, to downstream mobility impacts. It illustrates how seemingly minor events can cascade through the system and helps stakeholders grasp interdependencies.



**Figure 26.** Typical propagation pathways across domains

## Cross-site Gaps & Antifragility Signals

* **Low resilience perception:** In many AOIs, fewer than 25% of survey respondents agreed that their city has robust contingency plans for transport disruptions. This highlights the need for learning and feedback loops to turn stressors into improvement opportunities.
* **Data gaps:** The current event catalogue contains no large utility disruptions for Odessa and no large‑scale events for Bratislava, indicating gaps that should be prioritised in monitoring systems (WP2).
* **Antifragility opportunities:** Evidence of performance gains post‑event is sparse; only a small subset of literature references quantifiable improvements after disruptions. This underscores the importance of systematic documentation and evaluation of adaptation measures (e.g., infrastructure upgrades following floods).

## Dictionary of Terms (pointer)

Definitions and operational terms used throughout this chapter are provided in Annex 4. These include standardised definitions for **Event, Disruption, Stressor, Scale levels** (Daily, Mid, Large), **Domain, Sub‑category, Severity,** and **Mobility impact**, ensuring consistency across the project.

## Spectrum of Events

**Daily Stressors:** traffic congestion, parking shortages, minor signal malfunctions. These events are frequent and short‑lived but cumulatively erode mobility efficiency.

**Mid-Scale Events:** localised flooding, public protests affecting key transport corridors, strikes disrupting bus and metro services, moderate snowstorms. They require tactical responses such as rerouting and service headway adjustments.

**Large-Scale Disruptions:** major natural disasters (e.g., floods covering entire districts, earthquakes), widespread power outages and conflicts that damage transport infrastructure. They necessitate strategic interventions and long‑term recovery.

## Impacts on Mobility

Disruptions impact mobility through increased travel times, reduced accessibility, crowding, cancellations and rerouting. Social‑media data reveal heightened public frustration during peak congestion and strike periods, while survey respondents emphasise the inconvenience of road works and public‑transport delays. High‑impact events such as floods can halt entire transport corridors, require emergency rerouting and cause cascading economic losses. Understanding these impacts aids planners in prioritising investments that not only restore service but improve system performance after shocks.

# Conclusion

This deliverable demonstrates that robust urban event mapping requires an integrated, multi‑source methodology combining surveys, literature, disaster databases and real‑time social‑media monitoring. The proposed taxonomy and cross‑walk enable harmonised classification across domains and scales, while statistical analyses and grounded‑theory coding reveal that the majority of disruptions are transport‑related and concentrated in a few high‑risk cities. Social‑media analytics confirm that transport and security events dominate public discourse but also show language‑specific patterns that must be considered in risk communication. The urban event catalogue compiled here exposes gaps in existing monitoring systems and underscores the need for continuous data collection, real‑time processing and ethical handling of personal information. By providing a standardised event taxonomy, mapping workflow and preliminary findings on disruption patterns and mobility impacts, this deliverable lays the groundwork for developing antifragile strategies and digital tools in subsequent work packages. Future efforts should focus on filling data gaps, refining classification algorithms and incorporating feedback from stakeholders to enhance urban mobility resilience.

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# Appendix

Anything that is related but not a core part to the deliverable can go into the appendix.

## **Annex 1: cleaned codes**

Nvivo\_enhanced\_codebook.csv is attached with Deliverable

## **Annex 2: code–paper**

Code2paper\_matric.csv is attached with Deliverable

## **Annex 3: Urban Disruptions Questionnaire**

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AI-generated content may be incorrect.

Urban Disruptions Questionnaire

Daily life in cities can be disrupted by events such as transportation delays, power outages, or extreme weather. Your responses will help make European cities better prepared and adaptable in the face of these challenges.

We do not collect personal data such as names, email addresses, or IP addresses unless you choose to provide an email address at the end. All responses are anonymous and securely stored on EU-based servers.

Consent Form:

Purpose:

This AntifragiCity study investigates residents’ responses to city-level disruptions.

Voluntary & anonymous:

Participation is optional; you may skip questions or exit at any time. No direct identifiers are collected; an email address is requested only if you volunteer for a follow-up interview and is stored separately.

Data protection:

Data are kept on secure servers and analysed only in aggregate. Processing is based on your explicit consent under GDPR. All responses are anonymous and stored securely on EU servers.

You may withdraw consent or request access, correction or erasure of identifiable data up to 14 days after submission (after which responses are irreversibly anonymised).

Contacts:

....@cardiff.ac.uk

Please select one option to indicate your consent:

I confirm I am ≥18 years old and give informed consent to participate.

I do not consent.

Your City Context

In this survey, "Your City" refers to the place where you live most of the year.

Q1 - In which country do you currently live? (Choose from the drop-down list)

Choose an item.

If selected “Other,” please specify.

Q2 - Which city or town do you spend most of your week (e.g. for work or study) in?

Q3 - How would you describe the area where you currently live (i.e. your main place of residence)?

Urban centre (city centre with high population density)

Suburban area (residential neighborhood near a city)

Rural area outside a city

Mixed-use area (residential and commercial)

Industrial area

Coastal area

Remote area

Recent Disruptions

Q4 - In the past 6 months, have you personally experienced any of the following disruptions in your city? (Select all that apply)

For each disruption, select the time period when it last occurred within the past 6 months. Choose ‘Did not experience’ if it has not occurred or is not relevant to your city.

Q4\_a:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Transportrelated | Did not experience | Past week | Past month | Past 3 months | Past 6 months |
| Public transport delays or cancellations (due to road/street/bridge maintenance, etc.) |  |  |  |  |  |
| Strikes |  |  |  |  |  |
| Traffic signal outages or malfunction |  |  |  |  |  |
| Heavy road traffic congestion |  |  |  |  |  |
| Road works or street closures |  |  |  |  |  |
| Parking shortages |  |  |  |  |  |
| Infrastructure failures |  |  |  |  |  |
| Fuel shortages |  |  |  |  |  |
| Other |  |  |  |  |  |

Q4\_a: Other (please specify)

If you experienced any other disruptions in the past 6 months (major or minor, including those specific to your city or local context), please describe them, including what happened and when they last occurred.

Q4\_b:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Environment & Weather | Did not experience | Past week | Past month | Past 3 months | Past 6 months |
| Extreme weather events (e.g., flooding, heatwave, heavy snow) |  |  |  |  |  |
| Airquality alerts (e.g., smog, dust, pollution) |  |  |  |  |  |
| Natural disasters (earthquake, storms, wildfires) |  |  |  |  |  |
| Waterlogging or drainage issues after rainfall |  |  |  |  |  |
| Power outages caused by weather conditions |  |  |  |  |  |
| Closures of public spaces due to weather |  |  |  |  |  |
| Other |  |  |  |  |  |

Q4\_b: Other (Please specify)

If you experienced any other disruptions in the past 6 months (major or minor, including those specific to your city or local context), please describe them, including what happened and when they last occurred.

Q4\_c:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Utilities & Connectivity | Did not experience | Past week | Past month | Past 3 months | Past 6 months |
| Power outage (e.g. equipment failures, maintenance issues, grid overloads) |  |  |  |  |  |
| Water supply interruption |  |  |  |  |  |
| Digital connectivity outage (mobile network or internet) |  |  |  |  |  |
| Long delays in repairs or utility maintenance |  |  |  |  |  |
| Other |  |  |  |  |  |

Q4\_c: Other (please specify)

If you experienced any other disruptions in the past 6 months (major or minor, including those specific to your city or local context), please describe them, including what happened and when they last occurred.

Q4\_d:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Public Space | Did not experience | Past week | Past month | Past 3 months | Past 6 months |
| Overcrowded public spaces (e.g., parks, squares, stations) |  |  |  |  |  |
| Excessive noise (e.g., construction, nightlife) |  |  |  |  |  |
| Vandalism or property damage |  |  |  |  |  |
| Restricted access to public spaces |  |  |  |  |  |
| Safety concerns (e.g., lack of lighting/poor lighting, unsafe areas) |  |  |  |  |  |
| Other |  |  |  |  |  |

Q4\_d: Other (Please specify)

If you experienced any other disruptions in the past 6 months (major or minor, including those specific to your city or local context), please describe them, including what happened and when they last occurred.

Q5 - Thinking about the single most disruptive incident you ticked above, please briefly describe what happened and when it occurred (e.g., past week, past month, past 3 months, past 6 months).

If you did not experience any disruptions, please skip to Question 10, the next section (Perceptions).

Q6 - Did this incident described in Q5 lead to any unexpected positive outcomes or changes for you, your household, or your community?

Q7 - How disruptive was this incident to your daily routine?

Not at all

Slightly

Moderately

Very

Extremely

Q8 - How quickly was normal service restored?

Within 1 hour

Same day

2–3 days

More than 3 days

Still ongoing / not resolved

Q9 - Which actions did you take to cope with this disruption? (Select all that apply).

Changed transport route

Changed mode (e.g., walked, cycled, carshared)

Postponed or cancelled my trip/activity

Worked or studied remotely

Sought information via an app/social media

Conducted service providers/authorities for support

Sought help from friends or family

Did nothing and waited

Used a community-based solution (mutual aid)

Discovered a new, more efficient way to handle similar situations in the future

Adopted a new habit or routine that improved my daily life

Collaborated with others to find an alternative solution.

Other

Other (Please specify the event you experienced and which actions you took)

Perceptions

Please indicate how much you agree with the following statements.

Q10 - My city communicates clearly and promptly when disruptions occur.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q11 - My city learns from past disruptions and improves its ability to handle future ones.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q12 - As a result of past disruptions, my city’s infrastructure seems to have become more robust or reliable.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q13 - Authorities are transparent about disruption causes and timelines

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q14 - Citizens’ feedback on disruptions is regularly used by city authorities to make improvements.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q15 - I can usually find practical alternatives when something in the city stops working.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

16 - Recent disruptions have affected my stress levels or wellbeing.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q17 - I feel confident navigating disruptions when they occur

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Priorities

Q18 - Which three improvements would most reduce the impact of disruptions on your daily life? (Select up to 3).

More reliable public transport

Improved traffic management

Realtime and multi-sourced information

Safer walking & cycling infrastructure

Greener and bluer public spaces (e.g. parks, riversides, waterfronts)

More inclusive and accessible infrastructure

Constant maintenance of the infrastructure

Faster repair of services/infrastructure

Improved emergency services coordination

Community support networks

Constant emergency response trainings at community level

Improved data sharing between city departments

More inclusive planning considering all citizen categories needs

Other

Other (Please specify the improvements would most reduce the impact of disruptions)

Q19 - Would you prefer your city to focus more on:

Preventing disruptions before they happen.

Responding quickly when they occur.

Learning from disruptions to become stronger for future ones.

Enhancing community involvement in planning and response.

Investing in resilient infrastructure to withstand disruptions.

Fostering partnerships between public and private sectors for better management.

Giving equal priority to all of the above.

Not sure.

Future Hazards

Q20 - Which two future hazards worry you most about your city? (Select up to 2).

Extreme weather events (floods, heatwaves, storms, high winds)

Natural disasters (earthquakes, wildfires, landslides)

Prolonged power outage

Cyber-attack on infrastructure

Public-health emergency

Terrorism/security incident

Infrastructure failures (bridges, utilities, transport, Industrial accidents)

Traffic accidents and road safety

Air pollution / Environmental degradation

Other

Other (Please specify future hazards that worry most you about your city)

Q21 - Do you feel you receive sufficient advance information and alerts from local authorities about such hazards?

Yes, Always

Yes, usually

Sometimes, but not consistently

Rarely

Never

Not sure / Don’t know

Q22 - How prepared is your household to manage 72 hours without external assistance if a major disruption occurs?

Not at all prepared

Slightly prepared (minimal supplies but no plan in place)

Moderately prepared (some supplies and a basic plan in place)

Well prepared (necessary supplies and a basic plan in place)

Fully prepared (necessary supplies and plans in place)

Q23 - Are you aware of any earlywarning system (e.g., SMS alerts, sirens, city apps) that would warn you in an emergency?

Yes, I am aware and have used them before

Yes, I am aware but have never used them

I have heard of some but never used them

No, I am not aware of any early-warning systems

Not sure

Q24 - How effective are current earlywarning systems in helping you adapt and minimise impact during an emergency?

Not at all effective

Slightly effective

Moderately effective

Effective

Very effective

Not applicable/not sure

Personal Agency & Community

Q25 - How much control do you feel you have over managing disruptions in your daily life?

No control at all

Little control

Some control

A lot of control

Complete control

Not sure

Q26 - Who is primarily responsible for managing disruptions in your city or town? (Select all that apply)?

City/local government

Regional government

National government

Private companies (e.g., utility providers)

Community groups

Not sure/ Don’t know

Other

Other (Please specify who is primarily responsible)

Q27 - How much do you trust your city’s authorities to manage disruptions effectively?

Not at all

Slightly

Somewhat

Mostly

Completely

Not sure

Q28 - On average, how often do you experience disruptions in your city?

Daily

Several times a week

Once a week

A few times a month

Rarely

Never

Q29 - In the last 30 days, have you helped or received help from neighbours/community members during a disruption?

Yes

No

Q29\_a - If Yes, please briefly describe how this helped contribute to overcoming the disruption or learning something new

Q30 - Which digital tools (e.g., apps, social media, websites) do you use to stay informed about disruptions in your city?

Q31 - Would you be willing to participate in community efforts (e.g., volunteering, reporting issues) to help your city manage disruptions?

Yes

Maybe

No

Q32 - During past disruptions, have you observed or taken part in citizenled initiatives or innovations that helped your city adapt or improve?

Yes

No

Not sure

Q32\_a - If yes, please briefly describe.

Q33 - How much do you believe citizen involvement can make your city stronger and more adaptable in the face of future disruptions?

Not at all

Slightly

Somewhat

Quite a lot

Very much

Not sure

Urban Challenges

Please indicate how much you agree with each statement:

Q34 - Disruptions have become more frequent over the past three years.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q35 - Disruptions make it difficult to find or keep employment.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q36 - Lack of affordable housing is a serious issue in my city.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q37 - Public services (healthcare, education, transport) meet residents’ needs during disruptions.

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q38 - Traffic congestion significantly worsens during disruptions

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q39 - Community support is strong and reliable in my neighbourhood during disruptions

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q40 - The city invests enough in resilient infrastructures

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

Q41 - My neighbourhood has the resources needed to recover from disruptions

Strongly disagree

Disagree

Neither agree nor disagree

Agree

Strongly agree

Not sure / Don’t know

About You

Q42 - Age group:

18-24

25-34

35-44

45-54

55-64

65 and older

Prefer not to say

Q43 - Gender:

Female

Male

Non-binary/third gender

Prefer not to say

Other

Other (Please specify your gender)

Q44 - What best describes your main daily activity or role?

Student

Employed full-time

Employed part-time

Self-employed

Unemployed/between jobs

Retired

Unable to work due to disability

Other

Other (Please specify your main daily activity or role)

Q45 - Which modes of travel do you use on a typical weekday? (Select all that apply)

Car as a driver

Car as a passenger (ride-sharing or taxi)

Motorcycle or Motor-scooter

Public transport (bus, train, tram, subway)

Walking

Cycling / E-scooter

No travel

Other

Other (Please specify your primary mode of travel)

Follow-up (optional)

Q46 - May we contact you for a short follow-up interview?

Yes

No

Q46\_a - If you selected yes, please provide your email address.

Thank you for your time.

Please click "Submit" to exit the survey.

## **Annex 4****: Standardised Definitions for Urban Event Mapping**

The following operational definitions are used throughout the project to ensure consistency in cataloguing, analysing and communicating urban disruptions. Where possible, definitions are grounded in published research and official practice.

|  |  |  |
| --- | --- | --- |
| Term | Definition | Example |
| Event | A discrete occurrence in time and space that has potential or actual impact on urban systems. Events may be planned (e.g., scheduled maintenance) or unplanned (e.g., floods) and can be singular or compound. | A flood affecting Milan on 15 July 2023. |
| Disruption | The effect of an event on normal system operations, causing delays, cancellations, rerouting or reduced accessibility. Disruptions are the observable manifestations of stressors. | A protest leading to temporary closure of major roads. |
| Stressor | Any external or internal stimulus that places demand on the system and may trigger a disruption. Stressors include natural hazards (rainfall, extreme temperatures), infrastructural failures (power outage), social actions (strikes) and policy interventions (road works). In antifragility theory, stressors are necessary for adaptation. | Heavy rain causing standing water on roads. |
| Scale levels | Hierarchy describing the spatial and temporal extent of events: Daily (localised, short‑term stressors such as congestion or minor signal malfunctions), Mid (events affecting neighbourhoods or cities for days or weeks, such as localised flooding or strikes) and Large (events with regional or national impact lasting weeks or longer, including major natural disasters and widespread infrastructure failures). | Daily: rush‑hour congestion; Mid: three‑day public‑transport strike; Large: nationwide flood. |
| Domain | High‑level classification of the system component primarily affected. In this project domains include transport, environment/weather, utilities/connectivity, public space/social, security, health, economic and crime. Domains help to group events for analysis and visualisation. | Transport domain includes congestion and strikes; Environment domain includes floods and storms. |
| Sub‑category | A finer-grained description of the event within its domain, often matching hazard types (e.g., flood, power outage, strike). Sub‑categories provide specificity for modelling and cross‑domain comparisons. | Within the environment domain, sub‑categories include floods, earthquakes and heatwaves. |
| Severity (1–5) | Ordinal measure representing the intensity of an event’s impact on mobility. Severity is derived from quantitative metrics where available (e.g., affected population, deaths, damage cost) and scaled to a 1–5 range (1 = minor, 5 = catastrophic). For events lacking quantitative data, expert judgement or heuristic criteria (e.g., disruption duration) are used. | A severe flood affecting thousands of people and causing extensive damage would be rated 5; a small strike causing minor delays would be rated 2. |
| Mobility impact | Qualitative description of how an event affects mobility, including increased travel time, headway irregularity, rerouting, cancellations, crowding or accessibility reduction. Impacts may be estimated (e.g., “public‑transport delays (15 min)”) or generalised when precise data are unavailable. | “Road & rail closures” for a flood event; “Power outage causing signal failure and bus headway irregularity.” |

**Table 38.** Operational definitions and examples of key terms for urban disruption analysis.

These definitions are used to populate the event catalogue, inform analytical matrices and guide communication with stakeholders.

## **Annex 5: Urban Event Catalogue**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Event\_ID | City | Date | Domain | Sub-category | Scale | Severity | Mobility impact | Source |
| E-ATH-GR-001 | Athens | 26/07/2001 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-NAP-IT-002 | Naples | 31/10/2002 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-MIL-IT-003 | Milan | 11/04/2003 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-PRG-CZ-004 | Prague | 28/03/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-PRG-CZ-005 | Prague | 28/03/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-PRG-CZ-006 | Prague | 28/03/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUD-HU-007 | Budapest | 28/03/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-008 | Bucharest | 07/04/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-009 | Bucharest | 07/04/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-KRA-PL-010 | KRA | 04/06/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-KRA-PL-011 | KRA | 04/06/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-GEN-CH-012 | GEN | 26/07/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-013 | Thessaloniki | 08/10/2006 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAD-ES-014 | Madrid | 23/05/2007 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BIR-UK-015 | Birmingham | 15/06/2007 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAN-UK-016 | Manchester | 25/06/2007 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BIR-UK-017 | Birmingham | 20/07/2007 | Environment | Flood | Large | 5 | Road & rail closures | EM-DAT |
| E-BUC-RO-018 | Bucharest | 05/09/2007 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-VAL-ES-019 | VAL | 12/10/2007 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-LON-UK-020 | LON | 28/04/2007 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-BIR-UK-021 | Birmingham | 15/01/2008 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-ATH-GR-022 | Athens | 08/06/2008 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-MAN-UK-023 | Manchester | 09/09/2008 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAN-UK-024 | Manchester | 06/09/2008 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-ROM-IT-025 | Rome | 11/12/2008 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-ROM-IT-026 | Rome | 06/04/2009 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-KRA-PL-027 | KRA | 22/06/2009 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-VIE-AT-028 | Vienna | 16/07/2009 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAN-UK-029 | Manchester | 19/11/2009 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-030 | Thessaloniki | 24/11/2009 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAR-FR-031 | MAR | 15/06/2010 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MIL-IT-032 | Milan | 08/11/2010 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BRU-BE-033 | Brussels | 11/11/2010 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-034 | Thessaloniki | 29/11/2010 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MIL-IT-035 | Milan | 26/10/2011 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-036 | Thessaloniki | 03/02/2012 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MIL-IT-037 | Milan | 20/05/2012 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-MIL-IT-038 | Milan | 29/05/2012 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-MAN-UK-039 | Manchester | 23/09/2012 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-ROM-IT-040 | Rome | 11/11/2012 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAN-UK-041 | Manchester | 21/11/2012 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-042 | Thessaloniki | 24/02/2013 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUD-HU-043 | Budapest | 14/04/2013 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-MUN-DE-044 | MUN | 28/05/2013 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-045 | Bucharest | 11/09/2013 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAN-UK-046 | Manchester | 27/12/2013 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAR-FR-047 | MAR | 18/01/2014 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAR-FR-048 | MAR | 19/01/2014 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-049 | Bucharest | 17/04/2014 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-050 | Bucharest | 19/04/2014 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-051 | Bucharest | 16/04/2014 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-052 | Thessaloniki | 03/08/2015 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MAR-FR-053 | MAR | 03/10/2015 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-MUN-DE-054 | MUN | 31/05/2016 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-ROM-IT-055 | Rome | 24/08/2016 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-ATH-GR-056 | Athens | 05/09/2016 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-057 | Thessaloniki | 11/09/2016 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-ROM-IT-058 | Rome | 26/10/2016 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-ROM-IT-059 | Rome | 30/10/2016 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-BUC-RO-060 | Bucharest | 09/10/2016 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-ROM-IT-061 | Rome | 18/01/2017 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-LYO-FR-062 | Lyon | 13/06/2017 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-ATH-GR-063 | Athens | 11/11/2017 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-DUB-IE-064 | Dublin | 22/11/2017 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-PAR-FR-065 | Paris | 24/01/2018 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-066 | Bucharest | 14/03/2018 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-BUC-RO-067 | Bucharest | 31/05/2019 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-THS-GR-068 | Thessaloniki | 01/06/2019 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-VAL-ES-069 | VAL | 11/09/2019 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-WAR-PL-070 | Warsaw | 29/06/2020 | Environment | Flood | Large | 1 | Road & rail closures | EM-DAT |
| E-KYV-UA-071 | KYV | 22/06/2020 | Environment | Flood | Large | 2 | Road & rail closures | EM-DAT |
| E-THS-GR-072 | Thessaloniki | 03/03/2021 | Environment | Earthquake | Large | 1 | Infrastructure damage | EM-DAT |
| E-OD- UA -073 | Odessa | 12/11/2024 | Utilities | Power outage | Mid | 3 | Public-transport delays (15 min) | Questionnaire |
| ATH-GR-074 | Athens | 15/07/2022 | Environment | Flood | Large | 4 | Road closures; PT rerouting | EM-DAT |
| E‑BCN‑075 | Barcelona | 20/06/2025 | Social | Strike | Mid | 2 | Bus headway irregularities | Social media |
| E-THS-GR-076 | Thessaloniki | 05/07/2025 | Transport | Traffic congestion | Daily | 1 | Increased travel time | Social media |

**Table 39.** Urban Event Catalogue

## **Annex 6: Social Media** **Methodology**

The complexity of monitoring risk-related communications across a linguistically and culturally diverse continent demands a methodological approach that is both technically sophisticated and theoretically grounded. Having established the critical importance of understanding risk information propagation in the European context, we now turn to a detailed examination of the systems and processes employed in this comprehensive analysis.

The methodology encompasses not only the technical infrastructure for data collection and processing but also the analytical frameworks that transform raw social media content into meaningful intelligence.

### System architecture overview

We begin with the technical architecture that enables large-scale multilingual data collection, proceed through the sophisticated processing methodologies that classify and evaluate risk content, and conclude with an examination of temporal dynamics.

At the heart of any large-scale social media analysis system lies its technical architecture (the interconnected components that enable the collection, processing, and analysis of vast quantities of unstructured data). Our approach aims to address the unique challenges of multilingual, multicultural risk communication monitoring, balancing competing demands:

* The need for comprehensive coverage against API rate limitations.
* The requirement for real-time processing against the complexity of multilingual analysis.
* The imperative for high accuracy against the inherent ambiguity of social media discourse.

The following exposition details how these challenges are addressed through a carefully orchestrated system of data collection mechanisms, query generation strategies, and linguistic processing pipelines.

A diagram of a data collection

AI-generated content may be incorrect.

**Figure 27.** System Architecture & Data Processing Pipeline

The European Social Media Risk Monitoring System employs a multi-layered architecture that begins with a sophisticated data collection layer. This foundational component utilises a dual-API approach, with the Twitter GraphQL API (twscrape) serving as the primary data source, accounting for 95.4% of collected data. When the primary API encounters limitations or failures, a simulation engine (snscrape) provides fallback capability, ensuring continuity of data collection.

The system implements intelligent rate limiting with 2.0-second delays between requests, optimising throughput whilst maintaining API stability. Geographic filtering capabilities employ sophisticated location inference algorithms to ensure collected data maintains relevance to the European risk landscape.

The data collection layer represents the foundational infrastructure upon which all subsequent analyses depend. The dual-API approach, with its intelligent fallback mechanism, ensures robust data acquisition even under adverse conditions.

However, raw data collection alone does not guarantee comprehensive coverage; the system must employ sophisticated strategies to generate queries that capture the full spectrum of risk-related discourse across multiple languages and cultural contexts.

|  |  |
| --- | --- |
| Metric | Value |
| Total keywords processed | 380 |
| Total queries generated | 5,878 |
| Unique queries executed | 1,138 |

**Table 40.** Query generation statistics

The system utilises a sophisticated query generation methodology:  
Exact phrase queries (47.3%): High-precision targeting using quotation marks

* Simple term queries (40.8%): Broad coverage for general concepts
* Hashtag queries (9.2%): Trend-focused collection
* Location-specific queries (2.7%): Geo-targeted searches

This multifaceted query generation strategy reflects a sophisticated understanding of how risk information manifests in social media discourse. The predominance of exact phrase queries demonstrates a prioritisation of precision, whilst the substantial proportion of simple term queries ensures broad coverage.

The relatively modest percentage of location-specific queries (2.7%) may initially appear surprising; however, this reflects the system's ability to infer geographic relevance through other means, including user profiles and content analysis.

The success of this query strategy ultimately depends upon its integration with sophisticated linguistic processing capabilities that can handle the multilingual nature of European social media.

#### Linguistic processing pipeline

The linguistic processing pipeline represents a critical innovation in multilingual risk monitoring. By combining automated language detection with context-aware keyword expansion, the system transcends simple translation-based approaches. The multilingual processing pipeline demonstrates remarkable complexity:

* Keyword expansion: Context-aware synonym generation;
* Cultural adaptation: Region-specific terminology inclusion;
* Translation quality assurance: Native speaker validation.

The inclusion of cultural adaptatiofn mechanisms acknowledges that risk communication varies not merely by language but by cultural context. For example, a "strike" in France carries different connotations than in Germany, even when translated accurately.

This sophisticated linguistic foundation enables the system to capture nuanced risk communications across the European linguistic landscape.

With the architectural components now fully delineated (from data collection through query generation to linguistic processing), we can examine how these elements combine to transform raw social media content into structured, actionable intelligence.

The data collection pipeline represents the foundational architecture upon which all analytical capabilities rest. This pipeline embodies a sophisticated orchestration of components, each optimised for specific aspects of the data collection and processing challenge:

Input Layer → Query Generation → API Management → Data Extraction →

Quality Control → Storage → Processing → Analysis → Output



This linear representation, whilst helpful in understanding data flow, understates the complexity of feedback loops and parallel processing that characterise the actual implementation.

The Input Layer, for instance, continuously adapts based on results from downstream components, whilst the API Management system dynamically balances load across available endpoints to maximise throughput whilst respecting rate limits.

#### Data processing methodology

Having established the sophisticated architectural foundation and multilingual query generation capabilities of the system, we now turn our attention to the critical processes through which raw social media data is transformed into actionable intelligence. This section details the data processing methodology that builds upon this architectural foundation, revealing how unstructured posts are classified, prioritised, and analysed to produce comprehensive risk assessments.

The data processing methodology represents the analytical heart of the system, where unstructured textual content undergoes rigorous classification, prioritisation, and sentiment analysis. The methodology employed builds directly upon the linguistic processing pipeline described in the previous section, extending those capabilities through a series of increasingly sophisticated analytical layers.

Where the previous section focused on the mechanics of data acquisition and initial linguistic processing, this section examines how that processed data is categorised, evaluated for urgency, and analysed for sentiment. These are three complementary dimensions that together provide a comprehensive understanding of the European risk landscape. These processing stages operate in parallel, ensuring rapid analysis whilst maintaining the high accuracy standards demanded by emergency response and policy-making applications.

#### API Performance

The performance metrics show that the social‑media collection system is technically robust: exact‑phrase queries yield slightly better results than broader terms, yet all query types perform consistently. With a 95.4 % primary API success rate, an average response time of 1.83 seconds and full rate‑limit compliance, the system operates efficiently within its technical constraints while maximising data capture.

|  |  |
| --- | --- |
| Metric | Value |
| Total posts classified | 13,388 |
| Total Queries Generated | 5,878 |
| Query Success Rate | 100% (1,138/1,138) |
| Primary API Success Rate | 95.4% |
| Fallback API Usage | 4.6% |

**Table 41.** System overview statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Category | Total Queries | Total Results | Avg Results/Query | Percentage | Priority Level |
| Transport | 271 | 3,190 | 11.77 | 23.8% | Medium |
| Security | 166 | 1,947 | 11.73 | 14.5% | Critical |
| Natural\_Disaster | 156 | 1,850 | 11.86 | 13.8% | High |
| Utilities | 109 | 1,292 | 11.85 | 9.7% | Standard |
| Health | 89 | 1,065 | 11.97 | 8.0% | High |
| Crime | 92 | 1,041 | 11.32 | 7.8% | Critical |
| Social | 84 | 997 | 11.87 | 7.4% | Medium |
| Economic | 83 | 975 | 11.75 | 7.3% | High |
| Environment | 38 | 442 | 11.63 | 3.3% | Standard |
| Infrastructure | 27 | 313 | 11.59 | 2.3% | Medium |
| Political\_Unrest | 23 | 276 | 12.00 | 2.1% | Critical |
| **TOTAL** | **1,138** | **13,388** | **11.76** | **100%** | **-** |

**Table 42.** Risk category distribution – Annex 6

|  |  |  |  |
| --- | --- | --- | --- |
| Subcategory | Queries | Results | Percentage of Domain |
| Traffic\_Congestion | 87 | 535 | 16.8% |
| Public\_Transport | 63 | 336 | 10.5% |
| Aviation | 45 | 336 | 10.5% |
| Road\_Accidents | 41 | 396 | 12.4% |
| Maritime | 35 | 331 | 10.4% |
| Public\_Transport\_Disruption | 71 | 71 | 2.2% |
| Aviation\_Emergency | 319 | 319 | 10.0% |
| Other | - | 866 | 27.2% |
| **TOTAL** | **271** | **3,190** | **100%** |

**Table 43.** Domain-subcategory analysis for transport

## **Annex 7: EM‑DAT Data and Methodology**

This annex provides a detailed account of the exploratory work carried out on the EM‑DAT International Disaster Database. The dataset contains more than 4 000 recorded disasters (2000–July 2025) and includes metadata on disaster group, type, sub‑type, region, start year and various intervention indicators (appeals, declarations, aid contributions). To prepare the data for analysis, duplicate records were removed, missing categorical values were recoded to “Unknown,” and binary fields were standardised. Events were then filtered to retain only those with evidence of humanitarian intervention and relevance to urban or mobility impacts (e.g. floods, earthquakes, storms, epidemics).

Descriptive statistics summarise the distribution of interventions across disaster groups and types, while clustering analyses (Two‑Step and k‑means) uncover patterns in intervention modalities, regions and disaster characteristics. Additional tables document human and economic impacts, including mortality, injuries, affected populations, homelessness, recovery durations and reconstruction costs. Because these analyses extend beyond the scope of urban mobility in Europe, they are placed here for completeness and to support researchers seeking deeper insights into the global disaster landscape.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Cluster | Group | Disaster Type | Region | OFDA/  BHA | | Appeal | | Declaration | | Aid | | Intervention | |
| 1 | Natural | Earthquake | Americas | | No | | No | | No | | Yes | | 8% |
| 2 | Natural | Flood | Americas | | Yes | | No | | No | | Yes | | 46% |
| 3 | Natural | Extreme temperature | Asia | | No | | No | | No | | Yes | | 2% |
| 4 | Natural | Storm | Asia | | Yes | | No | | No | | Yes | | 9% |
| 5 | Natural | Drought | Asia | | Yes | | Yes | | No | | Yes | | 4% |
| 6 | Natural | Storm | Oceania | | Yes | | No | | No | | Yes | | 4% |
| 7 | Natural | Mass mover (wet) | Asia | | No | | No | | No | | Yes | | 3% |
| 8 | Natural | Storm | Americas | | Yes | | No | | No | | Yes | | 9% |
| 9 | Natural | Flood | Europe | | Yes | | No | | No | | Yes | | 7% |
| 10 | Techno | Industrial accident | Africa | | Yes | | Yes | | No | | Yes | | 1% |
| 11 | Natural | Wildfire | Europe | | Yes | | No | | Yes | | Yes | | 1% |
| 12 | Natural | Earthquake | Asia | | Yes | | No | | No | | Yes | | 6% |

**Table 44.** Disaster interventions clustering according to disaster category and types

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Disaster Type | Region | Events | Death | Injury | Affected | Homeless | Total | Recovery Cost ($) | Damage Cost ($) |
| Air | Europe | 1 | 83 | 270 |  |  | 270 |  |  |
| Chemical spill | Americas | 1 |  |  | 80743 |  | 80743 |  |  |
| Collapse (Industrial) | Africa | 1 | 20 | 92 |  |  | 92 |  |  |
| Collapse (Miscellaneous) | Asia | 1 | 21 | 20 | 8000 | 2000 | 10020 |  | 10000 |
| Collapse (Miscellaneous) | Europe | 1 | 43 | 16 | 630 |  | 646 |  |  |
| Drought | Africa | 71 | 4130 |  | 2609614 |  | 2609614 |  | 420326.1 |
| Drought | Americas | 45 | 7.3 | 32 | 547303.4 |  | 547304.4 |  | 2350975 |
| Drought | Asia | 28 | 44.7 |  | 17200128 |  | 17200128 |  | 611398.1 |
| Drought | Europe | 9 |  |  | 118197 |  | 118197 |  | 1107893 |
| Drought | Oceania | 9 | 24 |  | 462430.7 |  | 462430.7 |  | 32450 |
| Earthquake | Africa | 7 | 639.2 | 2331.2 | 43266.7 | 58272.3 | 53506.4 |  | 1833333 |
| Earthquake | Americas | 28 | 9538 | 14590 | 511376.1 | 188093 | 520942.9 | 6915266 | 2548858 |
| Earthquake | Asia | 76 | 5313.4 | 15047.9 | 1539616 | 344765.9 | 1489495 | 26320000 | 7759553 |
| Earthquake | Europe | 8 | 101.5 | 374 | 30971.7 | 24595.3 | 32779.3 |  | 2019809 |
| Earthquake | Oceania | 10 | 70.4 | 273.8 | 124100.3 |  | 124346.7 |  | 3113791 |
| Epidemic | Africa | 60 | 684.2 | 18298.9 | 18881 |  | 19274.4 |  |  |
| Epidemic | Americas | 17 | 502.2 | 67902.2 | 49983.2 |  | 62187.9 |  |  |
| Epidemic | Asia | 4 | 367.3 | 73453 | 100144.5 |  | 86798.8 |  |  |
| Epidemic | Oceania | 3 | 46 | 5617 | 3781.5 |  | 4393.3 |  |  |
| Explosion (Industrial) | Africa | 2 | 119 | 139 |  |  | 139 |  |  |
| Explosion (Industrial) | Americas | 2 | 11 | 17 | 1500 |  | 758.5 |  | 10003200 |
| Explosion (Industrial) | Asia | 2 | 109 | 3005.5 |  | 300000 | 153005.5 | 2500000 | 15000000 |
| Explosion (Industrial) | Europe | 4 | 78.3 | 27.3 | 5178.5 |  | 2609.8 |  |  |
| Explosion (Miscellaneous) | Africa | 6 | 245.3 | 1015.4 | 13782.4 |  | 12331.5 |  |  |
| Explosion (Miscellaneous) | Americas | 1 | 390 | 300 |  |  | 300 |  |  |
| Explosion (Miscellaneous) | Asia | 1 | 13 | 62 |  |  | 62 |  |  |
| Explosion (Miscellaneous) | Europe | 1 | 22 | 300 | 10000 |  | 10300 | 18949 |  |
| Extreme temperature | Americas | 11 | 103.2 | 1800000 | 440504.8 | 5247 | 741379.3 |  | 1023500 |
| Extreme temperature | Asia | 13 | 421.4 | 2026.5 | 7490146 |  | 6338440 |  | 5500503 |
| Extreme temperature | Europe | 13 | 19 | 144.5 | 19418.6 |  | 17293.1 |  | 2866301 |
| Fire (Miscellaneous) | Africa | 1 | 109 | 258 |  |  | 258 |  |  |
| Fire (Miscellaneous) | Americas | 1 |  |  | 55571 |  | 55571 |  |  |
| Fire (Miscellaneous) | Europe | 1 |  |  |  | 800 | 800 |  |  |
| Flood | Africa | 148 | 56.7 | 229.3 | 228056 | 42789.4 | 222391.2 | 6000 | 162122.9 |
| Flood | Americas | 266 | 50 | 103.8 | 174522.4 | 17265.1 | 167502.8 | 299666.7 | 562016.2 |
| Flood | Asia | 178 | 225.8 | 3137 | 4582744 | 294072.4 | 4380834 | 10000000 | 1449908 |
| Flood | Europe | 122 | 11.1 | 113.9 | 51839 | 2259.5 | 50042.6 | 1117876 | 1009138 |
| Flood | Oceania | 37 | 11.4 | 2.7 | 21009.6 | 838 | 19847.9 |  | 875205.9 |
| Gas leak | Americas | 2 |  | 660 | 7574 |  | 8234 |  |  |
| Industrial accident (General) | Africa | 2 | 4.5 | 69 | 47640.5 |  | 47675 |  |  |
| Industrial accident (General) | Americas | 2 |  |  |  |  |  |  |  |
| Infestation | Africa | 10 |  |  | 1066667 |  | 1066667 |  |  |
| Infestation | Asia | 1 |  |  |  |  |  |  |  |
| Mass movement (wet) | Africa | 2 | 745 | 55 | 12300.5 |  | 12355.5 |  | 30000 |
| Mass movement (wet) | Americas | 11 | 99.4 | 64.3 | 8970.5 | 18580 | 13274.9 |  | 201250 |
| Mass movement (wet) | Asia | 17 | 272.1 | 79.7 | 73037.9 | 22704.6 | 62581.9 |  | 134194 |
| Mass movement (wet) | Europe | 2 | 6.5 | 5 | 230.5 |  | 233 |  | 180000 |
| Oil spill | Americas | 3 |  |  | 256008.5 |  | 256008.5 |  |  |
| Oil spill | Asia | 2 |  |  | 17000 |  | 17000 |  |  |
| Poisoning | Americas | 1 | 44 | 800 |  |  | 800 |  |  |
| Rail | Africa | 1 | 281 | 230 |  |  | 230 |  |  |
| Rail | Asia | 1 | 161 | 1300 | 31750 | 9250 | 42300 |  | 408000 |
| Storm | Africa | 37 | 545.8 | 310 | 403257.4 | 51365.3 | 387015.5 | 680400 | 584924.1 |
| Storm | Americas | 228 | 62.7 | 169.2 | 846675.4 | 25022.3 | 682780 | 200000 | 4772183 |
| Storm | Asia | 80 | 2112.2 | 4141.4 | 2329866 | 104235.4 | 2201018 |  | 949207.9 |
| Storm | Europe | 28 | 6.4 | 133.9 | 253976.4 | 1050 | 197647.6 |  | 790196.8 |
| Storm | Oceania | 57 | 13.7 | 43 | 43453.4 | 2148.3 | 38538.6 | 183000 | 540337.4 |
| Volcanic activity | Africa | 7 | 67.3 | 400 | 59167.8 | 58274.5 | 68798 |  | 504500 |
| Volcanic activity | Americas | 18 | 156 | 20 | 191731.1 |  | 191733.6 |  | 147493.8 |
| Volcanic activity | Asia | 13 | 131.3 | 160.7 | 44915.31 |  | 44952.4 |  | 6642.5 |
| Volcanic activity | Oceania | 6 | 4 |  | 23895.2 |  | 23895.2 |  | 118000 |
| Water | Asia | 2 | 815 |  | 25025.5 |  | 25025.5 |  |  |
| Wildfire | Africa | 2 | 90 | 3 | 42500 | 777 | 21640 |  |  |
| Wildfire | Americas | 56 | 17.3 | 225.4 | 347002.9 | 1142.8 | 236541.1 | 78000 | 3074344 |
| Wildfire | Asia | 10 | 13.8 | 19.8 | 87692.8 | 340 | 62700.4 |  | 635000 |
| Wildfire | Europe | 22 | 21 | 264.8 | 97981.4 | 1412.4 | 72707.8 |  | 714845.4 |
| Wildfire | Oceania | 7 | 8.2 | 87 | 2059.8 | 3720 | 2985.5 |  | 477666.7 |
| Chemical spill | Europe | 1 | 9 | 150 |  | 7120 | 7270 |  | 103000 |

**Table 45.** Human and economic impacts of disasters across regions

|  |  |  |  |
| --- | --- | --- | --- |
| Disaster Type | Region | Duration (day) | Cost ($) |
| Air | Europe | 0 |  |
| Chemical spill | Americas | 0 |  |
| Chemical spill | Europe | 0 |  |
| Collapse (Industrial) | Africa | 0 |  |
| Collapse (Miscellaneous) | Asia | 0 |  |
| Collapse (Miscellaneous) | Europe | 0 |  |
| Drought | Africa |  |  |
| Drought | Americas | 305 |  |
| Drought | Asia |  |  |
| Drought | Europe | 141 |  |
| Drought | Oceania |  |  |
| Earthquake | Africa | 0 |  |
| Earthquake | Americas | 0 | 6915265.75 |
| Earthquake | Asia | 0 | 26320000 |
| Earthquake | Europe | 7.75 |  |
| Earthquake | Oceania | 0 |  |
| Epidemic | Africa | 135.7 |  |
| Epidemic | Americas | 84.7 |  |
| Epidemic | Asia | 72.5 |  |
| Epidemic | Oceania | 111 |  |
| Explosion (Industrial) | Africa | 0 |  |
| Explosion (Industrial) | Americas | 0 |  |
| Explosion (Industrial) | Asia | 0 | 2500000 |
| Explosion (Industrial) | Europe | 0.75 |  |
| Explosion (Miscellaneous) | Africa | 0.167 |  |
| Explosion (Miscellaneous) | Americas | 0 |  |
| Explosion (Miscellaneous) | Asia | 0 |  |
| Explosion (Miscellaneous) | Europe | 0 | 18949 |
| Extreme temperature | Americas | 14.14 |  |
| Extreme temperature | Asia | 22 |  |
| Extreme temperature | Europe | 7.8 |  |
| Fire (Miscellaneous) | Africa | 0 |  |
| Fire (Miscellaneous) | Americas | 0 |  |
| Fire (Miscellaneous) | Europe | 0 |  |
| Flood | Africa | 29.75 | 6000 |
| Flood | Americas | 15.06 | 299666.67 |
| Flood | Asia | 18.9 | 10000000 |
| Flood | Europe | 6.87 | 1117875.5 |
| Flood | Oceania | 7.428 |  |
| Gas leak | Americas | 0 |  |
| Industrial accident (General) | Africa | 16 |  |
| Industrial accident (General) | Americas | 0 |  |
| Infestation | Africa |  |  |
| Infestation | Asia |  |  |
| Mass movement (wet) | Africa | 2 |  |
| Mass movement (wet) | Americas | 8.1 |  |
| Mass movement (wet) | Asia | 4.352941176 |  |
| Mass movement (wet) | Europe | 0 |  |
| Oil spill | Americas | 0 |  |
| Oil spill | Asia | 0 |  |
| Poisoning | Americas |  |  |
| Rail | Africa | 0 |  |
| Rail | Asia | 0 |  |
| Storm | Africa | 2.57 | 680400 |
| Storm | Americas | 4.26 | 200000 |
| Storm | Asia | 4 |  |
| Storm | Europe | 1.577 |  |
| Storm | Oceania | 2.614 | 183000 |
| Volcanic activity | Africa | 31 |  |
| Volcanic activity | Americas | 28.5 |  |
| Volcanic activity | Asia | 18.75 |  |
| Volcanic activity | Oceania | 1.8 |  |
| Water | Asia | 0 |  |
| Wildfire | Africa | 3.5 |  |
| Wildfire | Americas | 29.78 | 78000 |
| Wildfire | Asia | 5 |  |
| Wildfire | Europe | 4.917 |  |
| Wildfire | Oceania | 16.167 |  |

**Table 46.** Recovery duration and reconstruction costs by disaster type and region

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Disaster Type | Africa | Americas | Asia | Europe | Oceania |
| Air |  |  |  | 2 |  |
| Chemical spill |  | 2 |  | 2 |  |
| Collapse (Industrial) | 2 |  |  |  |  |
| Collapse (Miscellaneous) |  |  | 2 | 2 |  |
| Drought | 1.761 | 1.844 | 1.857 | 1.778 | 1.889 |
| Earthquake | 2 | 1.786 | 1.842 | 1.25 | 1.8 |
| Epidemic | 1.933 | 1.824 | 2 |  | 2 |
| Explosion (Industrial) | 2 | 2 | 2 | 1.75 |  |
| Explosion (Miscellaneous) | 2 | 2 | 2 | 2 |  |
| Extreme temperature |  | 2 | 1.692 | 1.923 |  |
| Fire (Miscellaneous) | 2 | 1 |  | 2 |  |
| Flood | 1.885 | 1.812 | 1.899 | 1.877 | 1.892 |
| Gas leak |  | 2 |  |  |  |
| Industrial accident (General) | 2 | 2 |  |  |  |
| Infestation | 1.9 |  | 2 |  |  |
| Mass movement (wet) | 2 | 2 | 1.765 | 2 |  |
| Oil spill |  | 1.333 | 2 |  |  |
| Poisoning |  | 2 |  |  |  |
| Rail | 2 |  | 2 |  |  |
| Storm | 1.838 | 1.518 | 1.838 | 1.643 | 1.754 |
| Volcanic activity | 2 | 1.722 | 1.615 |  | 1.5 |
| Water |  |  | 2 |  |  |
| Wildfire | 2 | 1.357 | 1.8 | 1.727 | 2 |
| Total | 1.874 | 1.683 | 1.856 | 1.808 | 1.814 |

**Table 47.** Average year period for the last recorded post-disaster follow-up across disaster types and regions