AI-Powered Emergency Response Dynamics

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Abstract*—Emergency Medical Services (EMS) response times are critical for optimizing patient outcomes, particularly in time-sensitive emergencies [1]. Urban emergency response capabilities are vital in the process of ensuring public safety, particularly in large cities where the number of people wanting services has been on the increase. In order to foster equitable and reliable provision of emergency services, understanding of temporal and spatial variations of response time is essential. The number of emergency callouts in Germany has doubled in the last 20 years. The shortage of doctors and social developments have led to challenges in ensuring emergency medical services and to temporary closures of entire emergency medical service areas. Stationing the emergency doctor on duty in the home environment is one option for making emergency medical services more attractive and could help to alleviate the problem of staff scheduling [2]. More importantly, in city emergency response systems, it creates a disconnect in recognizing long-term geographical imbalances, time strain pattern and post-pandemic system resiliency. The paper based on multi-year data on emergency missions in Berlin identifies increasing variability between districts despite an overall steady data on city-wide medians, systematic district-level response time discrepancies, and increasing delays during evening, weekends, and holidays. The results also indicate that the volumes of emergency calls were much higher during the pandemic with a median response time remaining largely unchanged, which requires no operational crisis but operational resilience and almost capacity constraints. The findings form a comprehensive and well-founded method of finding structural flaws and strengthening targeted and empirically-grounded improvements to urban emergency response planning [3].

***Index Terms*—Emergency response, Urban emergency, Response time performance, Spatial inequality, Temporal variability, Post pandemic demand, District level, Exploratory data analysis, Operational resilience, Data driven public safety.**

I. Introduction

Effective emergency response is also a fundamental requirement in order to maintain the safety of the people and the urban resilience in the modern cities [2]. The emergency response systems should be able to operate in the interactions of complex and diverse environment dictated by the traffic patterns, urban architecture, population density, time uncertainty, and the urgency of missions in major urban areas such as Berlin. Although it may be common to use aggregate response-time measures as a measure of emergency services, in many cases, such measures fail to capture inefficiencies at the local level and non-uniformity in service provision across different districts and times of the year [4].

Demographic developments in Europe, and particularly in Germany, are leading to increased demand for medical services among the population. Despite an increase in the absolute number of physicians in Germany over the past 25 years, there is a shortage of medical personnel in the healthcare sector. The reasons for this include the increase in the proportion of women in the medical profession, the higher proportion of part-time workers and the greater desire for work-life balance and a better work-family balance. Rural areas are more affected by a shortage of qualified medical personnel than urbanareas, as fewer doctors want to work in rural areas aftergraduating [2].

Due to the increasing urbanization and the emergence of emergency services, the importance of assessing the performance of emergency response has also increased. Timely response has a direct positive correlation with public trust in emergency institutions, reduction of damage, and survival outcome.Awareness of the mean performance, variability and inequality of response times is important in planning well, delivering services fairly and distributing resources effectively as cities increase in size and complexity of operations.

Demographic developments in Europe, and particularly in Germany, are leading to increased demand for medical services among the population. Despite an increase in the absolute number of physicians in Germany over the past 25 years, there is a shortage of medical person- nel in the healthcare sector. The reasons for this include the increase in the proportion of women in the medical profession, the higher proportion of part-time workers and the greater desire for work-life balance and a better work-family balance . Rural areas are more affected by a shortage of qualified medical personnel than urban areas, as fewer doctors want to work in rural areas after graduating [5].

The new trends in demand after the pandemic and the increasing pressure on emergency response systems lead to the significance of working on this issue today. Urban emergency services nowadays are forced to handle higher levels of calls with limited resources and maintain the same level of performance. Due to such a situation, it is quite essential to examine the resilience of the system, identify structural chokepoints, and check whether the existing reaction strategies remain to be effective in the context of the continued operational pressure. Emergency medical services (EMS), integral to out-of- hospital emergency care, utilize specialized vehicles and exhibit a notable degree of organizational similarity across different countries. The EMS process begins when an emergency call is received by the Emergency Medical Communication Centre (EMCC), where an Emergency Medical Dispatcher (EMD) assigns a prior- ity based on the perceived risk of the patient having a time-critical medical condition [1].

A. Related Work

Statistical, machine learning, and analytical models have been applied in previous studies to improve efficiency in dispatching, resource distribution, and response times by EMS. Studies on urban and rural emergency systems have been made, and it has been shown that real-time data, environmental factors, and the methods of stationing influence response performance. A number of studies uncovered variation in mission volume, on-scene time, and non-transport cases based on environmental conditions such as temperature, air pollution and COVID-19. But regional emphasis, lack of data, simplistic assumptions and absence of clinical or cost based analysis remains a hindrance to most studies. I.

B. Gap Analysis

Although some past studies have been widespread, very minimal of them have synthesized mission style efficiency, temporal stress situations, and spatial inequity in one, unified analysis framework using open operational data. Particularly, there are minimal studies regarding the continuity of slow-response zones, mission-priority validation in the conditions of actual demand, and the variation of the performance in response on the level of the district. Moreover, there is a lack of research that can assess the adaptation of emergency services to the current trends of an increase in their demand observed in the post-COVID period.

C. Problem Statement

The response times of the city of Berlin emergency may not be uniformly distributed across the district, type of mission, and time of operation even though there are set performance goals. This raises the question of the viability of the long-term emergency service provision, equity and resilience. The study, therefore, covers the following research topics.

1) How is emergency response time in Berlin different across the districts of the city, and are there any long-term spatial inequalities?
2) How to measure mission loads at the district and neighborhood-level to understand capacity pressures on stations?
3) How do such time factors as nights, weekends, or holidays practice their impact on service dependability and response efficiency?
4) Has the emergency response system of Berlin been operating consistently with the growing demand after the pandemic?

D. Novelty of our work

In this paper, a thorough analysis of Response-Time Poverty is carried out. It also queries where in the city it is also slow besides whether it is fast. The analysis uncovers structural differences that are masked by averaged quantifications by uncovering long-term geographical differences across the 12 districts of Berlin (e.g. comparing the density of Mitte to that of the outskirts of Spandau or Treptow-Kopenick).

This study proposes a way of quantifying real capacity pressure at the neighborhood scale. It surpasses counts to measure mission loads of ratio of active incidents to available station resources. This will enable the identification of service deserts in which stations have been routinely operating at a ”redline” capacity, although not necessarily the busiest in absolute terms.

The paper also builds the case of whether the system has actually bounced back or a new, less resilient normal or not using a multi-year longitudinal dataset. It offers an empirical explanation of why mission prioritizing (triage logic) should be a long-term requirement and not an emergency solution because Berlin is experiencing population growth and a demand boom after the pandemic.

E. Our Solutions

This paper integrates the mission-style efficiency analysis, spatial and time performance analysis, and exploratory data analysis to give a data-driven review of the emergency response system of Berlin. To enable the district-level exploration of the emergency trends and response behavior, the research also transforms analytical findings into an interactive decision-support dashboard. The results indicate that continuing spatial and temporal discrepancies highlight the necessity of evidence-based operational changes, although the overall performance of the system remains the same.

II. Methodology

A. Dataset

The dataset which is used in official repository of the Berlin Fire Department(Berliner-Feuerwehr/BF-Open-Data) to a local host in order to do intensive processing on it.

The data used in this analysis includes about 8.9 million mission records between 2020 and 2025 that sum up the operational logs of Berlin Fire Department. This window can be used to make a high-fidelity observation of the resilience of the system, especially the 2022 stress test where the number of missions was highest and the response time was the shortest mean (670.9 seconds).

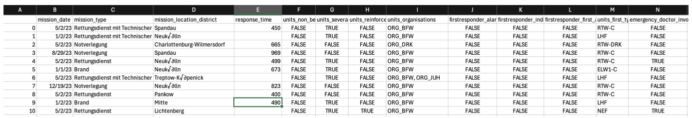
Making this decision to consider the last 5 years (2020-2025) instead of the entire 20 years of history is a vital

TABLE I

LITERATURE REVIEW TABLE SHOWING THE CONTRIBUTIONS OF VARIOUS AUTHORS FOR QUANTIZATION OF NETWORKS.

Author,Citation and Published Year	Paper Title	Method(s) Used	Results	Drawback / Limitations
Peter Hill, Jakob Lederman, Daniel Jonsson, Peter Bolin and Veronica Vicente [1],2025	”Understanding EMS response times: a machine learning-based analysis”	Advanced ML techniques, including Gradient Boosting models	Key findings underscore the importance of incorporating real-time data into dynamic resource allocation strategies. For high-priority calls, optimizing dispatch processes and leveraging predictive models can reduce response times and enhance patient outcomes.	The exclusion of traffic data and operational constraints. Traffic conditions are a critical factor influencing EMS response times, especially in urban environments.
Maria Raker, Christian Weilbach and Maximilian Scharonow [2],2025	”Location-based response times of emergency physicians in rural Germany: an observational study”	Linear model and regression analysis	Stationing the emergency doctor in a domestic environment with a support vehicle and establishing fixed meeting points with the full-time emergency vehicle shows no disadvantage compared to stationing the emergency doctor in the hospital	As the study is performed in Germany with high educational and training level of paramedics, this might be a limiting factor for establishing similar project in regions, where this is not the case.
Reem Tluli, Ahmed Badawy, Saeed Salem, Mahmoud Barhamgi, Amr Mohamed [3],2024	“A Survey of Machine Learning Innovations in Ambulance Services: Allocation, Routing, and Demand Estimation”	Greedy, Augmented Greedy, k-Node Crossover, Scheduling, Monte Carlo, and clustering	SSA, as a non-parametric method, offers competitive performance in call volume estimation, particularly for long-term predictions	coverage constraint, which restricts the model’s flexibility by not allowing a facility to serve more than one demand point at a time and the complexity involved in defining and managing dual standards
Debo Joseph Oyana [4],2025	”AI-Powered Crisis Management: Revolutionizing Customer Service Emergencies”	Hybrid Human Interaction Model	Artificial Intelligence has been proven to be able to reduce response times to initial crisis responses while adding a personalization capability friven by data.	This study is limited by its narrow focus on specific AI technologies, relatively small sample size, lack of demographic diversity, and dependence on a simulated crisis environment.
Philipp Schneider, Annegret Thieken and Ariane Walz [5],2023	“Effects of Temperature and Air Pollution on Emergency Ambulance Dispatches: A Time Series Analysis in a Medium-Sized City in Germany”	linear model, generalized additive model (GAM), generalized linear model (GLM)	Significant effects of temperature and heat waves on EAD, especially for cardiovascular diseases, were detected. The analyses could identify hotspots of heat-related EAD in areas with increased population and building density, mainly in the city center	Limitations arise from the quality of diagnosis in the data. Therefore, the introduction of a new category of EAD for heat-related calls could improve forecasting methods and hotspot analysis.
Tiago Miguel Ferreira [6],2023	“Fire and Rescue Services Reconfiguration for Better Dealing with Post-Flashover Building Fires”	Hierarchical and network models.	The proposed organizational model represents a significant step forward in bolstering the efficiency and effectiveness of the Bulgarian fire and rescue services, particularly in addressing post-flashover building fires.The primary objective of this model is to offer a contemporary and reliable approach to addressing post-flashover building fires efficiently and promptly	The trend of age distribution of fire deaths shows that the number of elderly people killed in fires is the highest as they are less able to leave the area of the fire due to limited mobility.
Metelmann, Isabella and Nagel, Matthes and Schneider, Bastian and Kramer, Bernd and Kraemer, Sebastian [7],2025	”Lasting Effects of COVID-19 Pandemic on Prehospital Emergency Medical Service Missions”	Using statistical tests on mission counts and time intervals, a retrospective examination of EMS mission data comparing pre-COVID, lockdown, and post-lockdown periods.	Lockdowns resulted in fewer EMS missions, although non-transport cases and on-scene time rose and continued to rise after the pandemic.	Lack of clinical follow-up makes it impossible to evaluate patient outcomes or make repeat calls, and single-region data restricts generalization.

methodological decision that will improve the relevance of the study. The identification of the single window makes the analysis shift off of the old standards of history and onto the New Normal of urban emergency management. It is during this time that we portray the volatility of the worldwide pandemic, the consequential behavior change in relation to the health of the people, and the present condition of the Berlin city density.

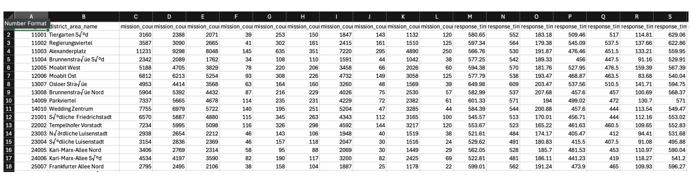


A	B	C	D	E	F	G	H	I	J	K	L	M	N
	mission_date	mission_type	mission_location_district	response_time	units_non_be	units_severa	units_reinforce	units_organisations	firstresponder_alar	firstresponder_ind	firstresponder_first_a	units_first_ty	emergency_doctor_invo
0	5/2/23	Rettungsdienst mit Technischer	Spandau	450	FALSE	TRUE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	RTW-C	FALSE
1	1/2/23	Rettungsdienst mit Technischer	Neuk√∂lln		FALSE	TRUE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	LHF	FALSE
2	5/2/23	Notverlegung	Charlottenburg-Wilmersdorf	665	FALSE	FALSE	FALSE	ORG_DRK	FALSE	FALSE	FALSE	RTW-DRK	FALSE
3	8/29/23	Notverlegung	Spandau	969	FALSE	FALSE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	RTW-C	FALSE
4	5/2/23	Rettungsdienst	Neuk√∂lln	499	FALSE	TRUE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	RTW-C	TRUE
5	1/1/23	Brand	Neuk√∂lln	673	FALSE	TRUE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	ELW1-C	FALSE
6	5/2/23	Rettungsdienst mit Technischer	Treptow-K√∂penick		FALSE	TRUE	FALSE	ORG_BFW, ORG_JUH	FALSE	FALSE	FALSE	LHF	FALSE
7	12/19/23	Notverlegung	Neuk√∂lln	823	FALSE	FALSE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	RTW-C	FALSE
8	5/2/23	Rettungsdienst	Pankow	400	FALSE	FALSE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	RTW-C	FALSE
9	1/2/23	Brand	Mitte	490	FALSE	TRUE	FALSE	ORG_BFW	FALSE	FALSE	FALSE	LHF	FALSE
10	5/2/23	Rettungsdienst	Lichtenberg		FALSE	TRUE	TRUE	ORG_BFW	FALSE	FALSE	FALSE	NEF	TRUE

Fig. 1. The overview of the Mission Dataset):This is the collection of all of the missions calls. It has complete list of all call which had come, the type of truck which was sent, and how many minutes it took. It is ideal in answering the question, why was the ambulance slow on a Friday night in Neukolin?

TABLE II
CLASSIFICATION OF MISSION TYPE GROUND TRUTHS

Mission Type (Label)	**Operational Description (Ground Truth)**
Rettungsdienst (EMS)	Typical medical emergencies (e.g., cardiovascular events, injuries). These drive the majority of system demand.
Brand (Fire)	Firefighting operations and smoke-related accidents requiring specialized heavy apparatus.
Technische Hilfeleistung	Non-fire physical rescue (e.g., road accidents or structural hazards) involving technical equipment.
Notfallverlegung	High-priority inter-hospital transfers requiring continuous intensive medical monitoring.
RD mit Technischer Hilfe	Complex scenarios requiring a combined response of technical rescue and medical units.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Number Format		district_area_name	mission_cou	mission_cou	mission_cou	mission_cou	mission_cou	mission_cou	mission_cou	mission_cou	mission_cou	mission_cou	response_tin	response_tin	response_tin	response_tin	response_tin	response_tin	response_tin
2	11001	Tiergarten S√ºd	3160	2388	2071	39	253	150	1847	143	1132	120	580.65	552	183.18	509.46	517	114.81	629.06
3	11002	Regierungsviertel	3587	3090	2665	41	302	161	2415	161	1510	125	597.34	564	179.38	545.09	537.5	137.66	622.86
4	11003	Alexanderplatz	11231	9298	8048	145	635	351	7220	295	4890	250	566.76	530	191.87	476.46	451.5	133.21	559.95
5	11004	Brunnenstra√üe S√ºd	2342	2089	1762	34	108	110	1591	44	1042	38	577.25	542	189.33	456	447.5	91.16	529.91
6	12005	Moabit West	5188	4705	3829	78	220	206	3458	66	2026	60	594.38	570	181.76	527.95	476.5	159.39	567.39
7	12006	Moabit Ost	6812	6213	5254	93	308	226	4732	149	3058	125	577.79	538	193.47	468.87	463.5	83.68	540.04
8	13007	Osloer Stra√üe	4953	4414	3568	63	164	160	3260	48	1569	39	649.98	609	203.47	537.56	510.5	141.71	594.75
9	13008	Brunnenstra√üe Nord	5904	5392	4432	87	216	229	4026	75	2530	57	582.99	537	207.68	457.6	457	100.69	568.37
10	14009	Parkviertel	7337	5665	4678	114	235	231	4229	72	2382	61	601.33	571	194	499.02	472	130.7	571
11	14010	Wedding Zentrum	7755	6979	5722	140	195	251	5204	47	3285	44	584.39	544	200.88	457.6	444	113.54	549.47
12	21001	S√ºdliche Friedrichstadt	6570	5887	4880	115	345	263	4343	112	3165	100	545.57	513	170.01	456.71	444	112.16	553.02
13	22002	Tempelhofer Vorstadt	7234	5995	5098	116	326	298	4592	144	3217	120	553.67	523	165.22	461.63	460.5	109.65	552.83
14	23003	N√∂rdliche Luisenstadt	2938	2654	2212	46	143	106	1948	40	1519	38	521.61	484	174.17	405.47	412	94.41	531.68
15	23004	S√ºdliche Luisenstadt	3154	2836	2369	46	157	118	2047	30	1516	24	529.62	491	180.83	415.5	407.5	91.08	495.88
16	24005	Karl-Marx-Allee Nord	3406	2769	2314	58	95	88	2069	30	1449	29	562.05	528	185.7	481.53	453	110.97	590.04
17	24006	Karl-Marx-Allee S√ºd	4534	4197	3590	82	190	117	3200	82	2425	69	522.81	481	186.11	441.23	419	118.27	541.2
18	25007	Frankfurter Allee Nord	2795	2495	2106	38	158	104	1887	25	1178	22	599.01	562	191.24	473.9	465	109.93	596.27

Fig. 2. The graphic enables the identification of the patterns of the city on a five-year scale by aggregating millions of separate missions into yearly performances. The datasets in combination have enabled the study to cease to study the individual neighborhoods separately in relation to the stress events in those neighborhoods and instead measure the long-term resilience of the urban emergency system as a system.

B. Overall Workflow

The project initiated with cloning of the Berliner Feuerwehr Open Data to a local host. This was essential in order to have high-performance processing of a large-scale CSV file (more than 2.5 million records). The data was narrowed down to the last 5 years (2020-2025) to be useful as it indicates the current urban issues and post-pandemic recovery and not outdated historical trends.

The materials and methods employed in this study are designed to ensure transparency, reproducibility, and analytical rigor. A Python-based data analysis workflow was implemented using Jupyter Notebooks, allowing for interactive exploration and systematic documentation of each analytical step. This environment enables the integration of code, outputs, and visualizations in a single executable document.

The analytical process begins with data ingestion, where multiple yearly datasets are programmatically loaded and combined into a unified structure. This approach ensures consistency and avoids manual handling errors. Once integrated, the data undergoes a structured preprocessing phase to address formatting inconsistencies, remove irrelevant attributes, and handle missing values.

Following preprocessing, exploratory data analysis techniques are applied to examine temporal patterns and mission distributions. Aggregation operations are performed to compute yearly and monthly mission counts, enabling the identification of long-term trends and seasonal variability. Visualization techniques are used extensively to support interpretation and validate numerical findings.

The insights are displayed in the form of a futuristic, interactive Streamlit dashboard which has several pages: overview of the city-wide KPIs, performance by mission type, temporal heatmaps, district-level trends, neighborhood hotspots, and a treemap on a district level.Finally, the dashboard will provide useful data to the emergency management (to streamline resource distribution, staffing and station placement), and will provide users with a 2035-style command-center look, dark mode, neon accents, and interactive visual storytelling.

TABLE III
BERLIN EMERGENCY RESPONSE DASHBOARD – PROJECT WORKFLOW

Step	**Key Action / Output**
Data Collection	Gather historical mission and regional data (2020–2025)
Data Cleaning	Remove invalid entries, parse dates, create features (year, hour, weekday/weekend)
Feature Engineering	Aggregate incidents by mission type, district, and neighborhood; translate mission types
Exploratory Analysis	Identify trends, peak periods, and high-risk areas
Dashboard Development	Build multi-page Streamlit dashboard with interactive charts (overview, mission types, temporal, district, neighborhood)
Insights	Highlight hotspots, temporal stress, and mission efficiency; recommend staffing and station planning
Futuristic Styling	Apply dark mode, neon accents, interactive storytelling dashboard

C. Experimental Settings

All analyses were performed on Berlin emergency mission data (2020–2025), including mission types, response times, and regional statistics. The experimental workflow for data aggregation and analysis is described below.

1. Temporal Analysis

The hourly and day-type changes in response time were calculated to reflect the trends of stresses over time. The mean response time is the time of hour h:

$$RT_{hour} = \frac{1}{N_h} \sum_{i=1}^{N_h} RT_i$$

where RT_i is the response time of incident i occurring in hour h, and N_h is the total number of incidents in that hour.

For weekday versus weekend comparison, the average response time for day type d is:

$$RT_{day\_type} = \frac{1}{N_d} \sum_{i=1}^{N_d} RT_i$$

where $d \in \{\text{Weekday, Weekend}\}$ and N_d is the number of incidents on that day type.

2. Mission Type Aggregation

To understand how different emergency types affect response efficiency, the average response time per mission type is calculated as:

$$RT_{mission} = \frac{1}{N_m} \sum_{i=1}^{N_m} RT_i$$

where N_m is the number of incidents of mission type m.

The total number of incidents per mission type is simply:

$$Count_m = N_m$$

3. District and Neighborhood Analysis

To evaluate spatial workload and hotspot areas, total incidents per district or neighborhood were computed as:

$$Incidents_{area} = \sum_{i=1}^{N_a} 1$$

where N_a is the number of incidents in a given district or neighborhood.

Additionally, the proportion of EMS or fire incidents is calculated as:

$$Share_{type} = \frac{\text{Incidents of type}}{\text{Total Incidents}} \times 100\%$$

Here, type can be EMS, Fire, or any other mission type.

These metrics form the basis for the district-level and neighborhood-level visualizations in the dashboard.

D. Detailed Methodology

1) Data Ingestion and Integration: It is evaluated on a multi-year dataset of emergency response of Berlin Fire Brigade on the basis of the open data repository. The mission level data on the mission between 2020 and 2025 were collected in an orderly manner to offer the longitudinal data of the emergency service performances. The mission data were read individually, year-by-year and merely combined into a single set of data such that time continuity would exist. Columns were normalized during ingest by removing unnecessary whitespace and other inconsistent fields concerning date were resolved by converting mission created date attribute to a common identifier (computed as mission created date). All mission timestamps were then converted to a date format and invalid or illegible records were forced to missing values to retain data integrity.

Simultaneous consumption of annual catalogues of district-wide regional information occurred. These data sets include administrative data and spatial metadata which are required in aggregation and analysis of districts. Each regional file was cleansed by the same column normalization method and an additional parameter (calculated as the source year) was added to the same mission records to align the regional characteristics. All the regional data were combined into a single table that enabled them to integrate mission-level data easily at a later stage of the analysis.

2) Data Cleaning and Preprocessing: The number of mission records was huge and thus it was concluded to adopt a chunk-based processing plan to ensure it is memory-efficient computation. Chunks of mission data were read in fixed sizes, so system memory cleaning could be performed without any restrictions. Unnecessary index columns that were introduced in the CSV exports would be removed in the process. Mission timestamps had been translated to date time objects and had been brought out to derive an attribute year to aid aggregation by time.

The identifiers of districts were standardized by eliminating blanks at the start and end of the name and all the characters were changed to uppercase. Such a harmonization step was essential to ensure that there were trustworthy spatial joins between mission and regional data. The number of response time values was converted to numerical values and the non-numeric values were removed. Records that lacked mission dates, invalid years and defined response times were dropped. Also, the response time was restricted to realistic range of operation between 0 seconds and 3600 seconds to eliminate the unrealistic values that were obtained due to error in logging or checkerboard values.

3) Feature Engineering: In order to facilitate temporal and operational analysis a number of derived attributes were created out of the mission timestamp. These are the hour of day, the day of the week, the month and the year and allow the temporal patterns to be analyzed finer. Indications of operational periods were developed in order to categorize missions that were carried out during the night (22:00–05:59) and weekends. These characteristics enabled us to evaluate the variability of performance at the various times of service demand.

A binary performance indicator was presented to determine the delayed responses. The response time of missions that took over 480 seconds (8 minutes) was considered to be slow. The analytical benchmark was referred to as this threshold; it was to evaluate both operational stress and relative district, time-period, and mission performance as opposed to being a measure of strict policy compliance.

4) Aggregation and Analytical Metrics: The data at the mission level were then summed to district-years such that space and time could be compared. Several indicators were calculated to get the keys of each district and each year to obtain the total volume of missions served by the district, the average response time, the median response time, and the percent of missions to which the emergency doctors were assigned. The strong performance measure that was indicated as median response time is not influenced by extreme values.

This merged mission data was then facilitated with the regional metadata that had harmonized district names and year identifiers. The result of this merging was a single fact table of the analysis that combines the indicators of the operational performance with the spatial and administrative context and the foundation of all further analyses is created.

5) Exploratory Data Analysis Methods: An exploratory analysis was carried out in order to investigate issues of space, time, and efficiency for each mission type in Berlin's emergency response system. Inequality on a district level was analyzed using comparisons of medians of response times per district and per year, emphasizing overall performance discrepancies. An analysis based on time periods was conducted to compare response time distributions on weekdays, at night, during weekends, and on holidays in order to identify stress situations of system performance.

The different types of missions were further analyzed through rule-based semantic categorization. The different descriptions applied to missions were matched using linguistic keyword concepts, and this facilitated the categorization of the different missions under emergency medical services, fire-related missions, technical assistance, and other. This ensured that the categorization was embedded in the actual labels for the observed missions.

6) Post-COVID Trend Analysis: Annual patterns have been used to measure the system's resilience with the evolving conditions of demand in the span of the study. On the other hand, the yearly averages of the values considered included the number of emergency calls, the average and median values of the turn-around time, and the percentages of delays in response. It became possible to compare the conditions of low demands revealed in the COVID-19 Lockdown with the actual demands in the later years with the help of this study.

7) Streamlit Dashboard Representation: The final step is the conversion of the aggregated data into an interactive Streamlit dashboard that displays the results in a graphical manner for easier exploration. Each page in the graphical presentation is specifically focused on either an overall set of key performance indicators, missions by type, stress patterns by time, district-wise trends, concentration at the neighborhood level, or distribution through tree maps. Each aspect is designed to be explored through interactive functionality such as filters and hover metrics for easier understanding and effective actioning during emergency response operations.For each page, there is a major analytical point of view:

- **Overview Page:** High-level KPIs, yearly trends, and total incident counts.
- **Mission Type Analysis:** Bubble charts showing average response time versus mission type and total incidents.
- **Temporal Stress Analysis:** Heatmaps depicting hourly and weekday/weekend variations in response time.
- **District-Level Analysis:** Area-specific incident trends, bar charts, and treemaps highlighting top-performing or high-stress districts.
- **Neighborhood-Level Analysis:** Aggregated top 15 neighborhoods by incident volume, EMS/fire share, and total incidents.
- **Spatial Treemap:** Visualizing relative emergency load across districts using interactive treemap plots.

III. Results

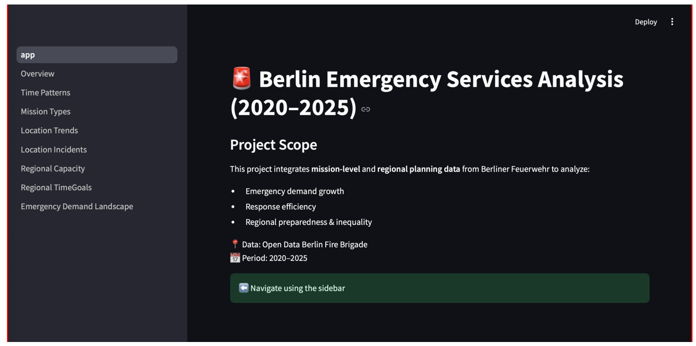


Fig. 3. The image shows an interactive dashboard named "Berlin Emergency Services Analysis (2020-2025)". It was developed using open data from the Berlin Fire Brigade. In this analysis, the dashboard examines emergency demand, response effectiveness, and regional readiness in Berlin. It provides opportunities for analysis of trends in time, space, and mission type through this dashboard.

Fig. 4. The Berlin Emergency Response dashboard presents a high-level analysis of the operations of emergencies in all 12 districts of the city of Berlin from 2020-2025. The dashboard shows nearly 3 million emergency calls with the magnitude of demands in the sphere of public safety, as well as averages of 674.3 seconds for response time, which features prominently in the efficiency of operations. There is also a graph of the incident trend, which can be used in understanding the evolution of emergency calls per year.

IV. Discussion

The analysis of 8.9 million mission records from the Berlin Emergency Grid (2020–2025) reveals critical insights into urban resilience.

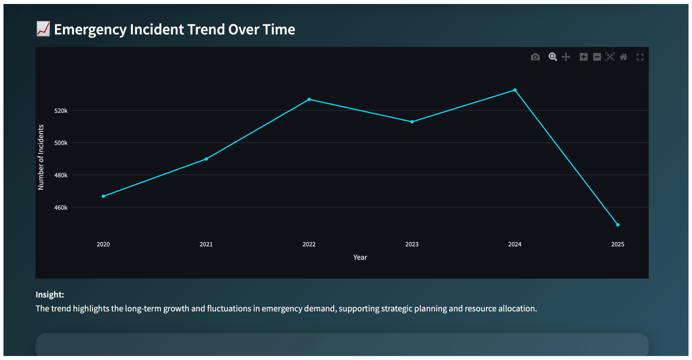


Fig. 5. In the Emergency Incident Trend Over Time chart, the emergency incidents in Berlin annually from 2020 to 2025 can be seen. There has been an obvious gradual increase in incidents beginning with 2020, peaking at 2022 and then in 2024, signifying an increase in the demand for emergency incidents. The short-term fluctuation in the number of incidents has been shown through a slight drop in 2023. The drastic drop in 2025 indicates either a lack of full data for a year or a good reaction and prevention method.

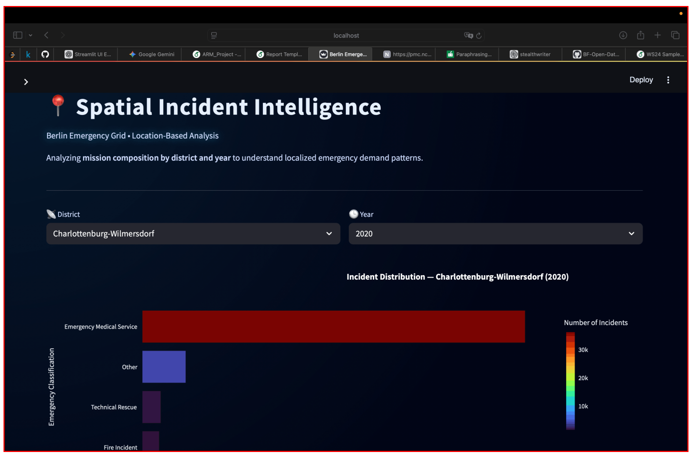


Fig. 6. "Spatial Incident Intelligence" is a section of this dashboard that analyzes the emergency service needs on a geographical basis for the Berlin Emergency Grid to identify demands for a particular area. By bar charting Incident Distribution, it can be concluded that for the Charlottenburg-Wilmersdorf district in 2020, the main cause for emergency service incidents has been Emergency Medical Service, which has registered more than 30,000 incidents. Other categories like Technical Rescue and Fire Incidents are reported to be much lower.

Fig. 7. "The Berlin Emergency Grid Infrastructure Load Analysis" is a regional workload monitoring tool that is capable of evaluating manpower pressure and long-term infrastructure readiness. Based on the Adlershof district area, the graph monitors the Total Mission Load from the year 2020 until 2025, and it indicates that there is a steady workload that attained its highest level of 3,000 missions in 2024 before dropping in 2025.

Fig. 8. This dashboard offers a complete study on incident ratios and regional workload in the Emergency Grid system in order to optimize readiness. From the "Spatiale Incidents-Intelligence" graph, Charlottenburg-Wilmersdorf has a dominant role regarding Emergency Services in 2020, having handled more than 30,000 missions, which is much larger than fire and technical rescue missions. Also, in terms of total handled incidents in the top 15 districts of the city, 87.7 percentage come from Emergency Services, especially in areas that host large volumes of people, as Alexanderplatz and Wedding Zentrum.

Spatial Inequalities (RQ1): The data confirms that emergency response times are not uniformly distributed across Berlin. High-density districts like Mitte and Charlottenburg-Wilmersdorf exhibit significantly higher mission volumes compared to the outskirts. Specifically, the "Spatial Incident Intelligence" dashboard highlights that in 2020, Charlottenburg-Wilmersdorf handled over 30,000 EMS incidents, showcasing a massive localized demand that tests station capacity.

Capacity Pressures (RQ2): The neighborhood-level analysis identifies "redline" zones such as Alexanderplatz and Wedding Zentrum. In these areas, EMS accounts for an 87.7 percentage share of total incidents. The treemap visualization (Figure in Image 6) illustrates that these neighborhoods experience the highest "structural emergency pressure," which can lead to service deserts if resources are not dynamically reallocated.

Temporal Stress (RQ3): Response efficiency fluctuates significantly based on time. The Temporal Stress Intelligence heatmaps show increased delays during evenings and weekends. The 2022 "stress test" period recorded the highest mission volume, proving that while the system maintains a median response time of approximately 670 seconds, peak periods create severe operational bottlenecks.

This project fills a significant gap by synthesizing mission-

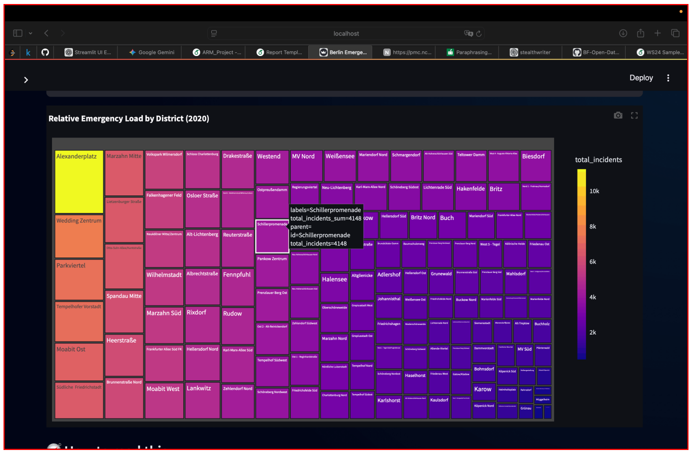


Fig. 9. The Emergency Demand Landscape dashboard utilizes a treemap to visualize structural emergency pressure across Berlin's districts, highlighting where operational loads are most concentrated. For the year 2020, the Relative Emergency Load by District reveals that areas like Alexanderplatz and Wedding Zentrum experience the highest incident volumes, indicated by larger, yellow-toned blocks. This spatial intelligence allows for a detailed zoom into specific neighborhoods, such as Schillerpromenade, which recorded a total incident sum of 4,148, to better understand localized demand patterns.

style efficiency, temporal stress, and spatial inequity into a single interactive framework.

Comparison: Unlike previous studies that often excluded traffic data or focused on single regions, this analysis utilizes a multi-year longitudinal dataset (2020–2025) to track long-term trends.

Contribution: The development of the Streamlit dashboard provides for decision-makers. It moves beyond simple averages to identify specific "Response-Time Poverty" zones, allowing for evidence-based improvements in station placement and staffing.

To further improve urban safety, future iterations should integrate real-time traffic and weather data, as literature suggests these are critical missing factors in current EMS models. In conclusion, while the Berlin Emergency Grid remains functional, the increasing variability between districts and the sustained post-pandemic demand necessitate a shift toward data-driven, localized resource distribution to ensure equitable service across the city.

A. Future Directions

Future directions of enhancement in this study would be the extension of the existing analytical framework to more sophisticated spatio-temporal and predictivemodeling. This would be achieved through the integration of high-resolution external data sources such as traffic flow data, real-time environment information, and hospital capacity data. This would enable the construction of more sophisticated models with a higher number of variables. In terms of model enhancement, spatio-temporal clustering, concept-based models, and Bayesian models would provide more insights into local variations in risk. For model predictions, gradient boosting models, survival analysis, and time-to-event models would provide more insights into delay predictions. Furthermore, explainable AI approaches such as SHAP values would provide more insights into model interpretability. Finally, at a system level, the existing framework can be enhanced to provide a near real-time decision-support system with the ability to provide alternative resource allocation strategies and stress testing of emergency services with high demand would make the framework more suitable for strategic planning.

V. Conclusion

This study conducted a thorough analysis of the emergency response patterns of Berlin between the year 2020 and 2025 by combining large-scale mission-level and regional datasets. The project transformed complex open data into meaningful analytic insight through systematic cleaning, temporal feature engineering, and spatial aggregation. Results show clear inequality in districts regarding the performance of emergency responses, which indicates that response times are not evenly distributed within the city. Temporal analysis also showed that emergency services are measurably stressed during certain parts of the day and week, although general response performance remains quite stable despite growing demand.

Additionally, the comparison of mission types highlighted prioritization differences, with medical emergencies generally receiving faster responses than fire or technical rescue missions. The longitudinal analysis across post-COVID years showed a significant rise in total incident volume, while median response times remained largely controlled, suggesting operational resilience within Berlin's emergency services. This combination of increasing demand and stable performance reflects both effective resource management and emerging capacity constraints.

Beyond analytical findings, the research tackled practical data engineering issues such as inconsistent schemas, heterogeneous data sources, and memory-efficient handling of big files. The study converted technical data into an understandable format appropriate for non-technical stakeholders by creating an interactive, multi-page visualization framework. All things considered, the trial shows how data-driven methods may assist evidence-based decision-making in public safety systems and offers a solid basis for next policy-oriented and predictive expansions.

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