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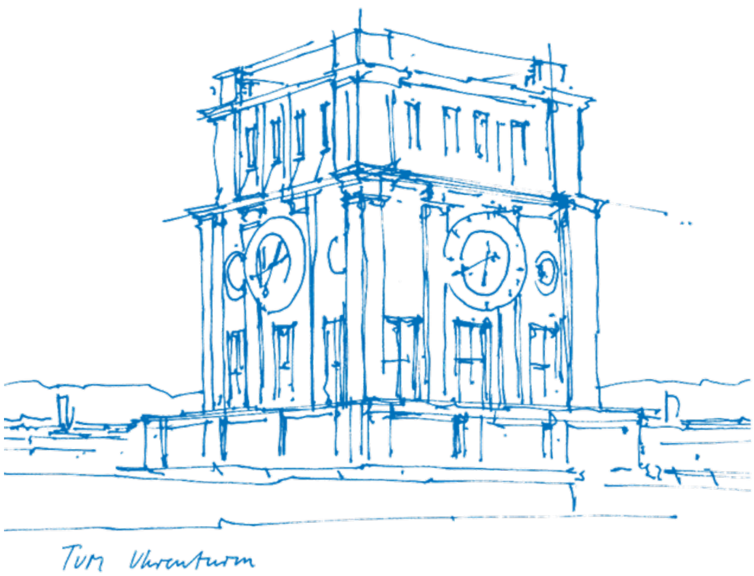

Revealing the Performance of a Rail-Transit System using Social-Media Data: The Case of the Munich S-Bahn

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Abstract

The Munich metropolitan area relies heavily on its rail network, the "S-Bahn", a Regional Rail Rapid Transit (RRRT) system, to provide fast rail access to many city districts and suburbs. Yet, the entire system has become unreliable, with many train cancellations and delays in recent years. So far, only aggregated performance statistics without much detail are available, e.g., on the average duration of certain disruptions, limiting the opportunity to make disruption announcements meaningful for individual travelers for re-planning their journey. However, for a couple of years, the "S-Bahn" operator has published real-time announcements of disruptions on social media that inform on the beginning and end of larger disruptions, allowing the creation of a rich database of individual disruption with meaningful attributes such as cause, effect, location, and duration. In this paper, we explore how these social media posts can be used to infer the performance impacts of disruptions to the "S-Bahn" system and how this data can be made useful for individual travelers to re-plan their journey. The social media data reveals that, on average, five disruptions are published daily, leading to around one out of four scheduled train trips being affected by delays or cancellations. Overall, we find that the disruption patterns published on social media seem to match the official figures, allowing the use of such data for building prediction models to help travelers re-plan their journeys in case of a disruption announcement.

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1 Introduction

Munich is a city with around 1.5 million people and a total of 6 million in the greater metropolitan area, Germany's third largest conurbation. This polycentric area sees a diverse commuting pattern: more than half a million commute within the city's boundaries, half a million commute from the surroundings into the city, and a quarter million commute from the city towards the surrounding area. These traveler flows require a high-capacity, multimodal transportation system with road and rail services. Munich has such a system: it is comprised of a multi-layer orbital road system, a well-connected grid-like subway network called "U-Bahn", running within the city's boundaries, and a radial rail system called "S-Bahn", which stretches outside of the city and into many regions of the metropolitan area. According to the typology of public transport systems presented by Vuchich (2007) the "S-Bahn" falls into the category of Regional Rail Rapid Transit (RRRT). Its main characteristic is long lines reaching far out to the suburbs, with their inbound services not ending at inner-city termini but transversing city centers in tunnels with multiple underground stations. Unlike regional rail or commuter rail, RRRT has an even and relatively short headway throughout the day and serves travel purposes beyond commuting. The "S-Bahn", "U-Bahn", some regional train lines as well as buses and trams of Munich have an integrated fare system, called "Verkehrsverbund" which allows travelers to use all services with a single ticket or travel pass (Pucher and Kurth, 1995; Buehler *et al.*, 2019).

Compared to other metropolises, Munich's rapid transit systems are fairly new, established around the 1972 Olympics. Nevertheless, both are facing substantial overcrowding, not only in peak hours but also outside the peak hours. The "S-Bahn" is transporting twice the number of passengers compared to its design capacity; nevertheless, its design, development, and operations are considered successful from a global perspective (Hale and Charles, 2010). Recent fare innovations (Loder *et al.*, 2024) and population growth are likely to further increase ridership in the future. While the "U-Bahn" operates reliably, the "S-Bahn" is disrupted frequently, delaying or disrupting the journeys of many travelers regularly. Annually, the operating agency publishes aggregated performance indicators (Bayerische Eisenbahngesellschaft, 2024), showing that on average, around 10% of service stops at train stations get canceled, and out of the remaining, only 90% happen on time - with more six minutes being the operator's own threshold for calling a service delayed. However, precise data on disruptions causes, and their corresponding effects, e.g., disruption duration and effects, are not public. Hence, the aggregated statistics are not useful for travelers, e.g., to plan or reschedule their journey in the event of disruptions (Cats *et al.*, 2011; Leng and Corman, 2020), or for researchers, e.g., to assess the accessibility losses on the entire region due to disruptions (Alitani *et al.*, 2023) or to elaborate on system improvements (Corman *et al.*, 2010). Only shortly before the start of the pandemic in 2020, the "S-Bahn" operator started to provide real-time information (RTI) to travelers for some disruptions over its official social media channels. Providing RTI to travelers aims at decreasing wait and travel times in case of being required to change the route, leading to an increase public transport ridership through an associated increased satisfaction with the service (Brakewood and Watkins, 2019). Here, a 2% increase in ridership attributed to the introduction of RTI is reported for bus routes in New York City (Brakewood *et al.*, 2015). The information published by the “S-Bahn” operator includes information on the start time, location, cause, and effect, and finally, the announcement of the end of the disruption. By publishing these, the operator creates a rich database for a disaggregate analysis of disruptions in the Munich “S-Bahn” system.

In this paper, we contribute with an empirical analysis of using this social media data as a data source for assessing the impact of disruptions in the Munich “S-Bahn” system, including an analysis of the validity of this data compared to the officially filed statistics. We use twelve months of social media data, containing around 2,000 published disruptions from November 2022 to October 2023, and General Transit Feed Specification (GTFS) data to approximate the aggregated performance indicators. We find that around one-quarter of all planned services face disruptions, where the variance in the social media data matches the reported aggregated performance indicators. We conclude that this data is informative for travelers and can be used to some extent for, e.g., making predictions for travelers on the impact of an announced disruption in space and time so that they can re-plan their journey.

2 Public transport disruptions and social media

Public transport disruptions can be planned, or unplanned (Zhu and Levinson, 2010). Planned disruptions are primarily concerned with maintenance of the infrastructure, while unplanned disruptions are concerned with all other unexpected events such as malfunctioning of tracks or rolling stock, unavailability of staff, power supply failures, other system-relevant failures, or weather impacts (Leng and Corman, 2020), where several phases exist: pre-disruption, warning, response, impact, and recovery (Papangelis *et al.*, 2016). Such unplanned disruptions usually impact safety, operation efficiency, and service quality (Chen *et al.*, 2022). In particular, the latter is relevant for travelers when the disruption leads to delays or even canceled services, requiring travelers to adapt their journey, in the worst case, even canceling the trip altogether (Adelé *et al.*, 2019). The operation control centers of transit agencies react to unplanned incidents by applying manifold dispositive measures. Such measures can add to the delays and service cancellations in order to return the entire system quickly to normal operation

(Bachmann *et al.*, 2022). Hence, providing RTI to travelers in case of service disruptions can be beneficial (Cats *et al.*, 2011). In such a disruption, communicating the disposition timetable to affected travelers allows them to adapt their journey in such a way that they can minimize their travel time considering the new situation (Brakewood and Watkins, 2019; Leng and Corman, 2020), a feature that has the ability to increase ridership as travelers feel better-informed (Brakewood *et al.*, 2015; Brakewood and Watkins, 2019). Here, a simulation study quantified that RTI can lead to travel utility improvements of 3% during peak hours, increasing up to 30% in situations with denied-boarding and substantial overcrowding (Drabicki *et al.*, 2021).

In recent years, social media has become a new communication channel for public transport companies and agencies. Accelerated by the COVID-19 pandemic (Diaz *et al.*, 2021; Zhang *et al.*, 2023), companies and agencies can communicate to customers (Das, 2024; Portland State University *et al.*, 2017; Liu *et al.*, 2016; Kocatepe *et al.*, 2015; Chan and Schofer, 2014; Pender *et al.*, 2014a; Alam and Sadri, 2022), quickly distribute surveys to customers on social media during disruptions (Perroy *et al.*, 2023), respond to service requests of customers (Cottrill *et al.*, 2017), but also can customer communicate their problems and sentiment to the public and hence companies and agencies (Osorio-Arjona *et al.*, 2021; Kuflik *et al.*, 2017). In all cases, the immediate nature of communication and monitoring on social media has been cited as highly appealing (Pender *et al.*, 2014b). Communication with customers also includes RTI in times of service disruptions (Georgiadis *et al.*, 2021), which can even be personalized (Gault *et al.*, 2019).

3 The Munich S-Bahn

The Munich “S-Bahn” system opened in April 1972. Formerly, the suburbs of Munich were connected to the city by many regional rail lines with uneven service patterns. They spread into the periphery from two termini, the Central Station and the Eastern Station located on opposite sides of the center. The eastern and western branches did not have a direct connection to one another. The “S-Bahn” introduced an inner-city tunnel (Trunk Line or “Stammstrecke”) that enabled the eastern and western branches of the regional rail to be merged into diametrical lines. At the same time, platforms were elevated and lengthened, modern, accessible electric multiple units (EMU) with superior acceleration and speed characteristics were deployed, and an identical headway was introduced to all lines. The basic headway at the branches was initially 40 minutes, which was shortened to 20 minutes during peak hours. The significant improvement in quality through the introduction of the “S-Bahn” led to a substantial increase in

Figure 1: Munich's "S-Bahn" network in 2020. source: Zeno Heilmaier on Wikimedia commons, license: CC BY-SA 4.0

travel demand. The initially estimated circa 220,000 passengers per year rose to over 470,000 passengers already in 1973 (Schricker, 2005).

As of 2024, the "S-Bahn" consists of eight lines, seven of them using the trunk line through the city center. Figure 1 shows the network map. Services on all seven of those lines run on a 20-minute basic headway, with single lines operating every 10 minutes during peak hours. The lines operate on a fixed schedule with published departure times at each station. The continuous increase in ridership and the resulting shortening of headway quickly revealed several bottlenecks in the system's initial design. The trunk line – meanwhile seeing thirty EMU per hour and direction during peak hours (S-Bahn München, 2024) - is the most vulnerable part of the network. Disruptions immediately affect all branches towards all suburbs. Importantly, several of the branches do not have dedicated infrastructure for the "S-Bahn". Services share the track with regional and sometimes with freight traffic. Disruptions in these network parts immediately affect all services in the corridor. Finally, several branches have single-track sections that limit capacity and cause delayed propagation (DB InfraGo, 2024). To solve the increasing capacity and reliability problems of the "S-Bahn", a second trunk line, called "2. Stammstrecke", is currently being built and is set to open in the 2030s alongside targeted enhancements in the branches (Wenner *et al.*, 2020).

4 Data and methods

For this analysis, we use the social media posts on X, formerly Twitter, from "@streckenagent_M", the official account of the Munich "S-Bahn" for communication with customers, which includes RTI, to determine disruption frequencies, their duration, as well as their causes, locations, and effects on passengers and the operational state of the system. The account has, as of early 2024, around 70,000 followers and more than 41,000 published posts. A total of 5,475 posts from the time span between November 1st, 2022, and October 31st, 2023, have been gathered for the analysis.

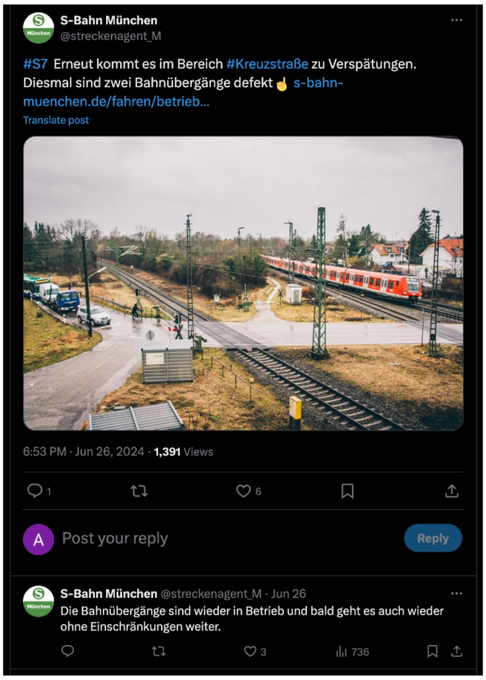
4.1 Data structure

All posts can generally be divided into two categories: Advance information and real-time information (RTI). While advance information posts are common when reminding customers of planned service disruptions, e.g., construction works or announced staff strikes, real-time information is used in unplanned disruption scenarios, e.g., spontaneous infrastructure failure or emergencies.

In this analysis, we utilize both kinds of posts. In case of communicating unplanned disruptions within the Munich "S-Bahn" system as RTI, the account releases messages, an example is shown in Figure 2. The initial message usually lists the line number and the affected station, sometimes the direction, and the cause of the disruptions. In the case of Figure 2, the disruption results from an issue with a level crossing. Once the issue is resolved, the social media account usually publishes a post declaring the end of the disruption. Arguably, the time difference between the first and last post serves as an estimate of the disruption duration for a specific incident. Sometimes there are more than two posts per disruption to provide updates, e.g., on rail replacement services. Contrarily, disruptions communicated as advance information, i.e. planned disruptions, are usually published within just one post before the disruption event.

Formatting, structuring, and phrasing of the posts are neither automated nor standardized and depend on the social media agent currently on duty. Inconsistencies, ambiguities, and misspellings are possible and have occasionally been observed. Communication about disruptions can not generally be connected to a specific threshold regarding the resulting operational state of the system. Whether a specific disruption is significant enough to be mentioned on social media seems to be, to a certain degree, an arbitrary decision made by the social media agent

Figure 2: Screenshot of a social media post.



on duty. As this is not the original data of disruptions, but a secondary data source, it bears limitations:

- not all disruptions might be posted, e.g.
  - bias in the selection of disruptions mentioned
  - minor operational disruptions irrelevant to customers such as delays
- negligence in communicating the end of disruptions cannot be ruled out, i.e., the end post might be delayed or forgotten
- inconsistent phrasing and structuring within posts

4.2 From posts to disruptions

The aim of this analysis is to gain insight into the number of disruptions that occurred within the aforementioned time span, their causes, locations, duration, and effects on customers. As a single disruption is frequently referred to in multiple posts across the disruption phases defined by (Papangelis *et al.*, 2016) (see initial message, updates and end posts), analyzing individual posts alone would fail to capture the full scope of the disruption. We must, therefore, identify all individual posts related to a single disruption and then group them together to one disruption event. This process is to be referred to as regrouping. Given the inconsistent structure and phrasing of the posts, the regrouping process is streamlined by initially organizing the relevant data contained within them. The body texts of all posts are searched in a semi-automated process based on keywords for information regarding the following disruption parameters: (i) affected Line; (ii) disruption cause; (iii) effect of disruption.

For each disruption parameter, relevant categories are defined by manually scanning the data set along with a set of keywords corresponding to each category. In a second step, posts containing one or more keywords from the set get automatically cataloged under the corresponding category. Keywords to organize posts by affected line include line names as well as station names. In case a station served by multiple lines is disrupted, all passing lines are considered to be affected. This is also the case of the Trunk Line that is serviced by seven of the total eight “S-Bahn” lines. Due to its significant traffic load, short headway and high vulnerability to disruptions, this segment is treated as a separate line for the purpose of this analysis.

The list of keywords used to organize posts by cause of disruption is shown in Table 1. A total of 20 different possible causes (categories), along with their respective keywords were defined. This number is later increased to 27 during the regrouping process. Causes of disruptions range from infrastructure-related faults, emergency situations, operational disruptions, and other unforeseen events to faults related to weather, rolling stock, and construction sites, as shown in Table 2. Organization by disruption effect follows a similar approach with categories and associated keywords listed in Table 3.

The regrouping process is subsequently carried out manually by identifying commonalities between individual posts, taking into account both the previously revealed three disruption parameters as well as additional parameters: (iv) location of disruption; (v) timestamp of post (disruption). Posts containing similar data are grouped into the same disruption event. Each disruption event gets assigned all aforementioned disruption parameters from all associated posts: (i) affected Line, (ii) disruption cause; (iii) effect of disruption; (iv) location of disruption; (v) duration of disruption. In this analysis, we use the duration between the first-posted entry and the last-posted entry as an estimate for the disruption duration, assuming that the information propagation time is identical for the onset and end of the disruption from the place of ocurance to the social media agent. Disruption events containing only one associated post consequently have no disruption duration. In this analysis, we consider all of these disruptions planned, while all disruptions with a non-zero duration are considered unplanned.

Table 1: Categories and keywords for organization by disruption cause (ii)

Disruption	Keywords
Police deployment (Polizeieinsatz)	Police deployment (Polizeieinsatz), Official measure (behördlich(e Maßnahme)), Police (polizeilich)
Emergency medical response (Notarzteinsatz)	Emergency medical response (Notarzteinsatz), medical treatment (ärztlich(e Versorgung))
Firefighting operation (Feuerwehreinsatz)	Firefighting operation (Feuerwehreinsatz), Fire alarm (Feueralarm)
Disruption in signal tower (Stellwerksstörung)	Signal tower disruption (Stellwerksstörung), Signal tower (Stellwerk)
Disruption at track switch (Weichenstörung)	Disruption at track switch (Weichenstörung), Track switch (Weiche)
Disruption at signal (Signalstörung)	Disruption at signal (Signalstörung), Signal (Signal)
Train repairs (Zugreparatur)	Train repair (Zugreparatur), Repairs on a train (Reparatur am Zug), Repairs of a train (Reparatur eines Zuges), Repairs on several trains (Reparatur an einigen Zügen), Door disruption (Türstörung), Disruption with a train (Störung an einem Zug)
Construction site (Baustelle)	Construction site (Baustelle), Construction works (Bauarbeiten)
People on tracks (Personen im Gleisbereich)	People on tracks (Personen (im Gleis)), Children (Kinder)
Bridge repairs (Brückenreparatur)	Bridge repairs (Brückenreparatur), Bridge (Brücke)
Staff strike (Streik)	Strike (Streik)
Repairs to track infrastructure (Reparatur an der Strecke)	Repairs to track infrastructure (Reparatur an der Strecke), Track repairs (Streckenreparatur), Repairs at the tracks (Reparatur an der Strecke), Repairs on the tracks (Reparatur auf der Strecke), Disruption at the track (Störung an der Strecke), Rep. at the tracks (Rep. an der Strecke)
Catenary repairs (Reparatur an der Oberleitung)	Catenaries (Oberleitung)
Spontaneous staff shortage (Personalausfall)	Spontaneous staff shortage (Personalausfall), Spontaneous staff shortages (Personalausfälle)
High passenger volume (Erhöhtes Fahrgastaufkommen)	Passenger volume (Fahrgastaufkommen)
High line capacity utilization (Streckenauslastung)	(Line) Capacity utilization ((Strecken-)Auslastung), Backlog (Rückstau)
Weather (Witterung)	Weather (Witterung), Thunderstorm (Unwetter), Snow (Schnee), Weather (Wetter)
Objects on tracks (Gegenstände im Gleisbereich)	Objects (Gegenstände)
Disruption to level crossing (Störung am Bahnübergang)	Level crossing (Bahnübergang)
Animals on tracks (Tiere im Gleisbereich)	Animals (on tracks) (Tiere (im Gleis))
Other	

Table 2: Grouping of disruptions cause categories

Category	Disruption
Infrastructure	“Level crossing (Bahnübergang)”, “Bridge (Brücke)”, “Catenaries (Oberleitung)”, “Signal (Signal)”, “Signal tower (Stellwerk)”, “Track switch (Weiche)”, “Tracks (Strecke)”, “Reduced speed (verminderte Geschwindigkeit)”, “Signal box, Bridge (Stellwerk, Brücke)”,
Emergencies	“Firefighting operation (Feuerwehreinsatz)”, “Emergency medical response (Notarzteinsatz)”, “Police deployment (Polizeieinsatz)”
Unforeseen events	“Objects (Gegenstände)”, “Emergency brake (Notbremse)”, “People (Personen)”, “Strike (Streik)”, “Animals (Tiere)”, “Vandalism (Vandalismus)”, “Soiling (Verunreinigung)”
Weather	“Weather (Witterung)”
Rolling stock	“Train repairs (Zugreparatur)”
Construction site	“Construction site (Baustelle)”, “Construction site, Level crossing (Baustelle, Bahnübergang)”, “Construction site, Bridge (Baustelle, Brücke)”, “Construction site, Catenaries (Baustelle, Oberleitung)”, “Construction site, Tracks (Baustelle, Strecke)”, “Signal tower, Construction site (Stellwerk, Baustelle)”, “Signal tower, Construction site, Bridge (Stellwerk, Baustelle, Brücke)”, “Track switch, Construction site (Weiche, Baustelle)”
Operational	“Passenger volume (Fahrgastaufkommen)”, “Embarking/Debarking (Fahrgastwechsel)”, “Spontaneous staff shortage (Personalausfall)”, “Line capacity uitilization (Streckenauslastung)”, “Train sequence delays (Zugfolgeverzögerungen)”, “Previous train (vorausfahrender Zug)”
Other	“Construction site, Passenger volume (Baustelle, Fahrgastaufkommen)”, “Catenaries, Objects (Oberleitung, Gegenstände)”, “Police deployment, Construction site (Polizeieinsatz, Baustelle)”, “Police deployment, Tracks (Polizeieinsatz, Strecke)”, “Train repairs, People (Zugreparatur, Personen)”

4.3 Final disruption data

The resulting data lists a total of 1,944 disruption events from November 1st, 2022, to October, 31st, 2023. Approximately 51 % of these events are fully described by two individual posts, a start post and an end post respectively, while 16 % contain only one associated post. After conducting sample-based testing, these are found to be mostly disruption events comprised of advance information posts concerning construction works, i.e., they are as assumed planned disruptions. 33 % of disruption events consist of three or more posts, thus including real-time updates. Table 4 summarizes the five derived disruption parameters with their identification rate, i.e., for how many disruptions this parameter has been identified, and a summary of how the parameter was derived.

Table 3: Categories and keywords for organization by disruption effect (iii)

Disruption effects	Keywords
Line closure (Streckensperrung)	Closure (Sperrung), closed (gesperrt)
Train cancellations ((Teil-) Zugausfälle)	Cancellation (Ausfall), Cancellations (Ausfälle), Cancellation (Entfall), no train journeys (keine Zugfahrten)
Delays (Verspätung)	Delays (Verspätung), Delays (Verzögerung)
Premature train turns (Vorzeitige Zugwendungen)	Train turns (Zugwenden), Train turns (Zugwendungen), Trains turn prematurely (Züge wenden vorzeitig), turn in (wenden in), turn there (wenden dort), terminate in (enden in)
Stop omission (Haltausfall)	Stop omission (Haltausfall), without stop (ohne Halt), do not stop (halten nicht)
Line rerouting (Abweichende Linienführung)	Differently (Abweichend), Bypass (Umleitung), rerouted (umgeleitet)

Table 4: Selected disruption parameters, their allocation rate, and derivation.

Disruption parameter	Identified (%)	Derivation
Affected Line	99.4	explicit mentions of line names and/or station names
Cause of disruption	97.7	keywords corresponding to 27 different disruption causes
Effect of disruption	91.8	keywords corresponding to 6 different disruption effects
Location of disruption	89.3	explicit mentions of station names and/or track sections
Duration of disruption	84.1	disruptions with duration > 0

4.4 Approximation of affected train trips

The indicator of canceled service stops used in the official statistics of the transit agency has - in the opinion of the authors -little value to passengers who plan journeys as an itinerary with a concrete route rather than singular events of boarding and alighting. Furthermore, it does not help to understand the propagation of the delay in the network. The indicator of affected train trips on distinct lines seems more suitable for the purpose of this study.

In order to approximate the share of train trips affected by disruptions, we compare the final disruption data with GTFS data of the agency (gtfs.de, 2024) using a MATLAB script and taking into account start dates and end dates of disruptions as well as departure and arrival times of scheduled train trips. A train trip is defined as a journey made by one train from its respective departure station to its destination during a specific time period. Any train trip partly or wholly taking place within the time frame of a disruption on its respective line is marked as affected. For the purpose of this analysis, disruptions that occurred on the Trunk Line are considered for every line traversing this network segment. In order for a trip to be considered affected, at least one of the following three criteria has to be true:

1. Disruption occurs during trip

   $$t_{t,s} \leq t_{d,s} < t_{t,e}$$

2. Disruption ends during trip

   $$t_{t,s} < t_{d,e} \leq t_{t,e}$$

3. Entire trip takes place during disruption

   $$t_{t,s} \geq t_{d,s} \wedge t_{t,e} \leq t_{d,e}$$

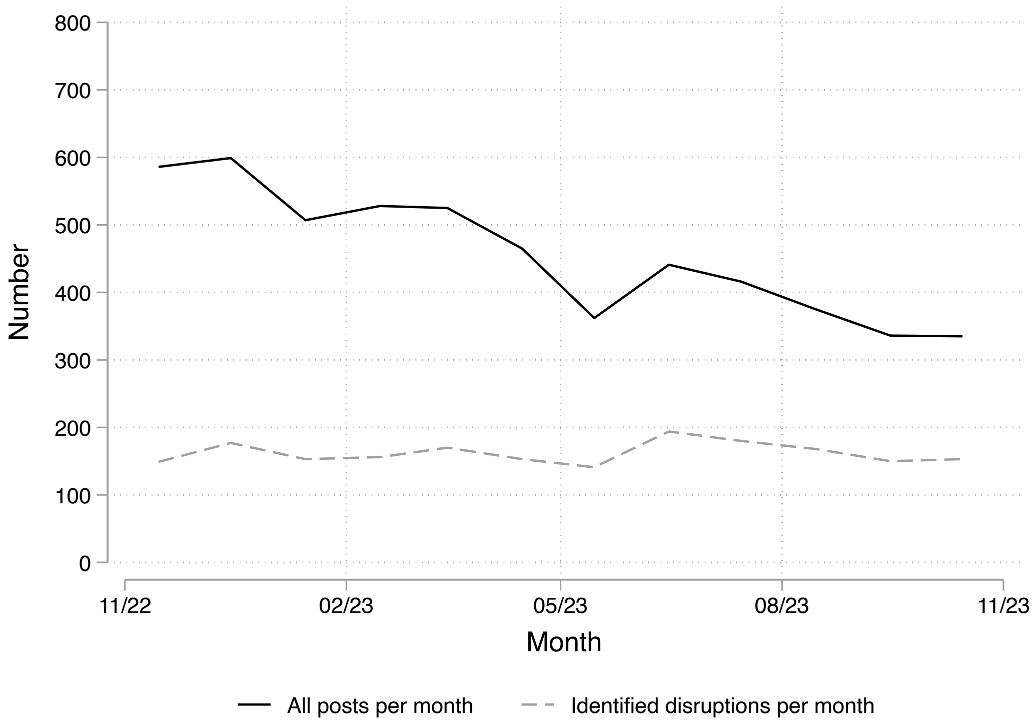
As the duration of disruptions is used to map the two data sets, disruption with only one associated post does not cause any trips to be affected.

5 Results

The time series of the number of disruptions per month and in comparison, the number of social media posts made per month are shown in Figure 3. Here, two observations can be made. First, the number of posts per month is declining throughout the observation period, while second, the number of disruptions revealed from these posts seems to remain constant for the entire time. Hence, it can be concluded that the number of posts published per disruption is declining, i.e., presumably resulting from a change in the underlying data generation process within the "S-Bahn" Munich communications department. Further, Figure 3 suggests that the overall level of disruptions in the system is neither improving nor worsening during the observation period.

The disruptions affect all parts of the Munich "S-Bahn" system as seen in Figure 4. The Trunk

Figure 3: Time series of monthly social media posts and disruptions of the Munich “S-Bahn” system during the observation period.



Line, the “Stammstrecke” is located in the city center and is used by all lines except the “S20” (c.f. Figure 1). Hence, a disruption in Figure 4 listed under Trunk Line affects all lines except “S20”. A disruption listed for every other line in Figure 4 consequently implies that the disruption occurred not on the Trunk Line, but on the respective branch of the line as seen in Figure 1. Figure 4 shows the frequency distribution of disruptions by line for all planned and unplanned disruptions, i.e., without and with an end post (left), all unplanned disruptions, i.e., with an end post (middle), and the latter weighted by the disruption duration (right). Here, it can be seen by comparing the left and middle graphs that the Trunk Line, “S2” and “S8” have the most planned disruptions, compared to the other lines. Further, it can be seen that the Trunk Line has the most unplanned disruptions too, followed by the “S2”, while the other lines experience around half or fewer disruptions than the Trunk Line. Note, however, that all Trunk Line disruptions affect all lines except the tangential “S20”. As the “S20” only has limited services, it is not surprising that it experiences the lowest number of disruptions. Weighting the disruptions by their duration reveals that the ones on the Trunk Line seem to be resolved rather quickly compared to the other lines, e.g., “S2” or “S7”, which is intuitive considering the importance of this line section.

Figure 4: Frequency distribution of disruptions by line: planned and unplanned disruptions (left), unplanned disruptions (middle), and unplanned disruptions weighted by the disruption duration (right).

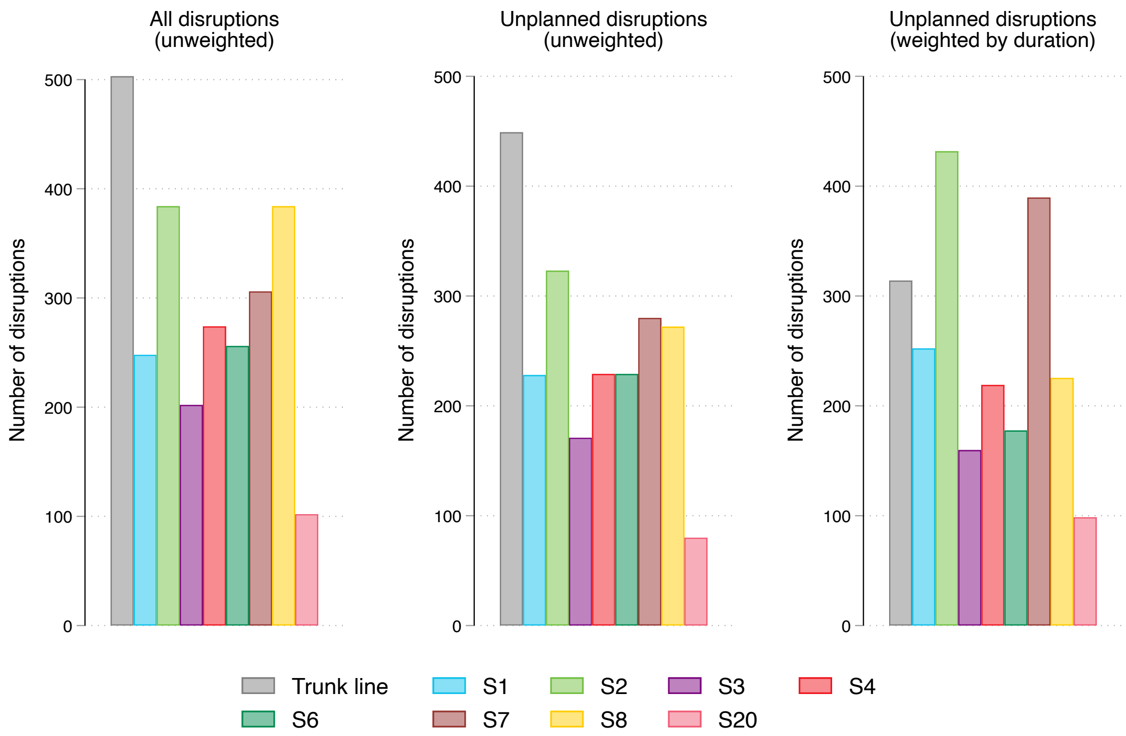
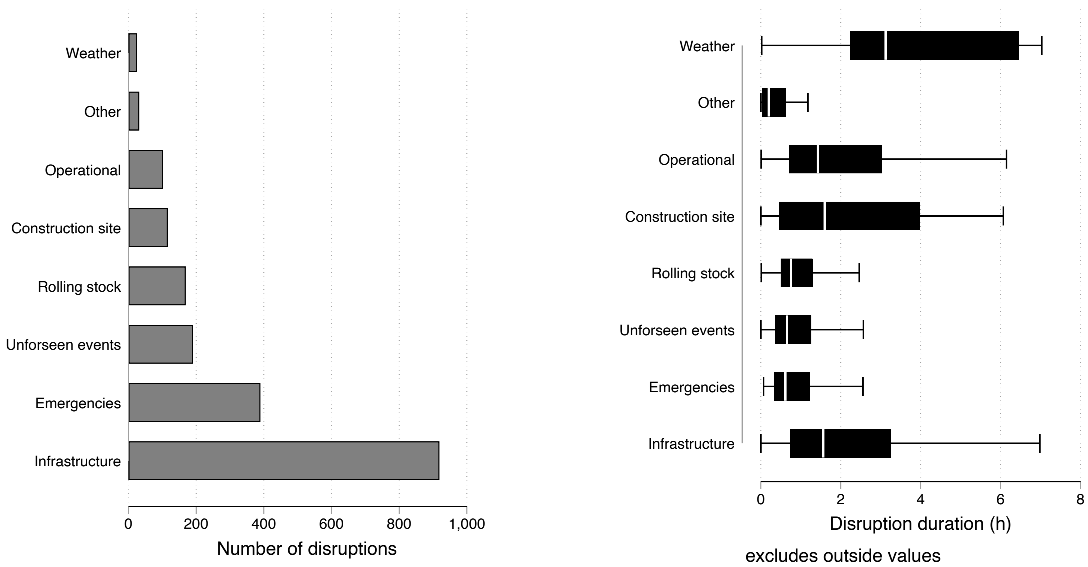


Figure 5: Frequency distribution of disruption causes (left) and distribution of the disruption duration by disruption cause (right).

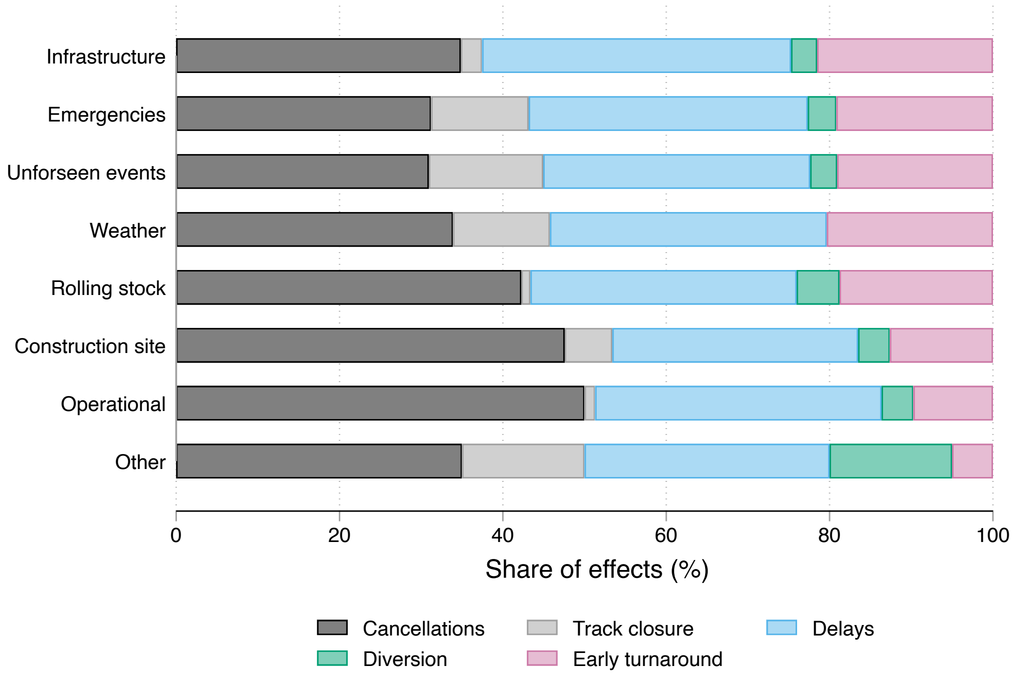


The left side of Figure 5 shows the frequency distribution of unplanned disruptions by cause as grouped in Table 2. It can be seen that the majority of unplanned disruptions are related to the infrastructure, e.g., a malfunction of a signal or a switch, or an emergency situation, e.g., calling the police or an emergency physician. Perhaps surprisingly, the number of weather-related, operational, or unforeseen events is considerably smaller. On the contrary, the right side of Figure 5 shows the corresponding revealed disruption duration from the social media data. It shows that, in particular, unplanned infrastructure malfunctions, construction sites and operational disruptions have a duration greater than one hour. Weather-related disruptions last substantially longer than that. Combining the large number of infrastructure-related unplanned disruptions with their long average duration, indicates where the substantial decline in performance and customer satisfaction of the “S-Bahn” originates. Intuitively, emergency situations are usually resolved for most disruptions within less than one hour.

5.1 Effects of disruption

Figure 6 shows the distribution of unplanned disruption effects by disruption causes. Importantly, as emphasized, one disruption can have multiple effects, which might overlap, i.e., they might not be mutually exclusive. For example, track closures can lead to train trip cancellations, but this may not be explicitly stated. Overall, it can be seen that all disruption effects can lead to all disruption causes, but with different overall outcomes. For example, rolling stock- and infrastructure-related disruptions rarely lead to track closures. The perhaps most interesting findings from Figure 6 are that emergencies and unforeseen events, according to Table 2, lead to a substantially lower share of trip/stop cancellations, while the share of delays and in particular short turns is increased. In contrast, construction sites, and operational reasons lead to more trip/stop cancellations. Considering the ambiguity in the data generation process for the effects and the fact that the social-media data does not inform precisely on which trips/stops are canceled or how the delays develop, the conclusion from Figure 6 becomes that the social media data used may not be adequate enough to make inference regarding disruption effects.

Figure 6: Distribution of unplanned disruption effects by disruption cause

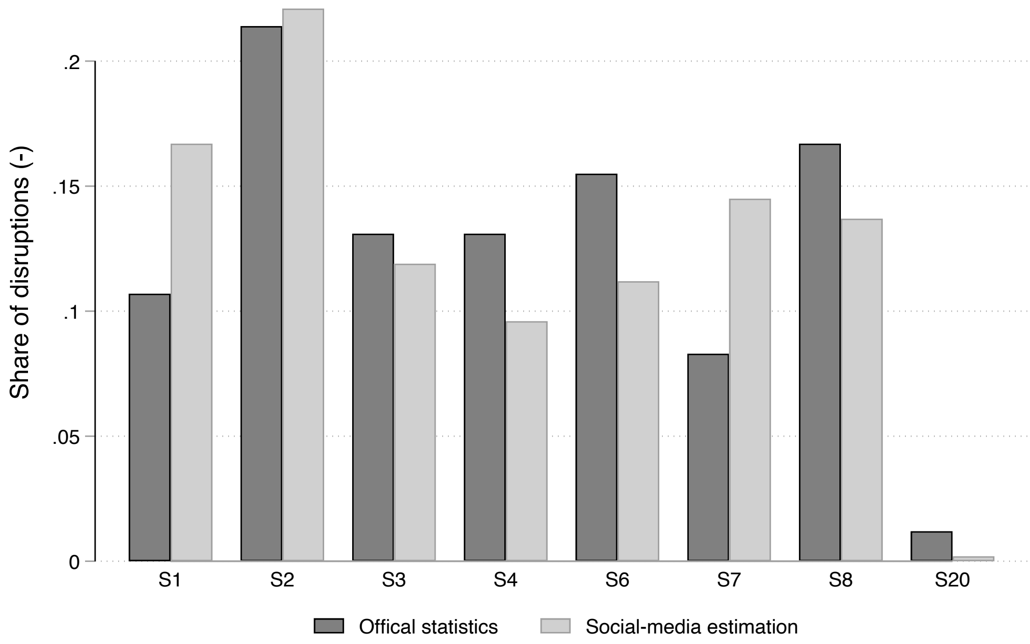


5.2 Comparison to official statistics

In the following, the validity of the disruption data from social media is assessed using the official aggregate disruption statistics (Bayerische Eisenbahngesellschaft, 2024). These are published by the "Bayerische Eisenbahngesellschaft" (short "BEG"; German for Bavarian Railways Company), the public agency overseeing the regional railway services in the State of Bavaria. Here, Figure 7 shows the share of affected train trips per line and Figure 8 their time series for the entire network from the social-media data and the official statistics.

Figure 7 uses the social media data of the introduced method to estimate the affected train trips, while from the official statistics, only the number of canceled service stops is available. In other words, our estimate might be larger in many instances as we may label a trip as affected on the respective line network, although due to some (operational) reasons, the operator was able to run the service, presumably with delays. Nevertheless, Figure 7 only compares the distribution of disruptions within the data. It can be seen that the overall share pattern seems to match reasonably, with some differences observed for the "S1", "S4", "S6", and "S7". Again, the fact that our estimate considers only timetable services and not operational flexibility might be an explanation for the differences next to, of course, a bias in the social media data and the labeling of affected train trips.

Figure 7: Distribution of affected trips across lines based on the social-media analysis and official statistics.

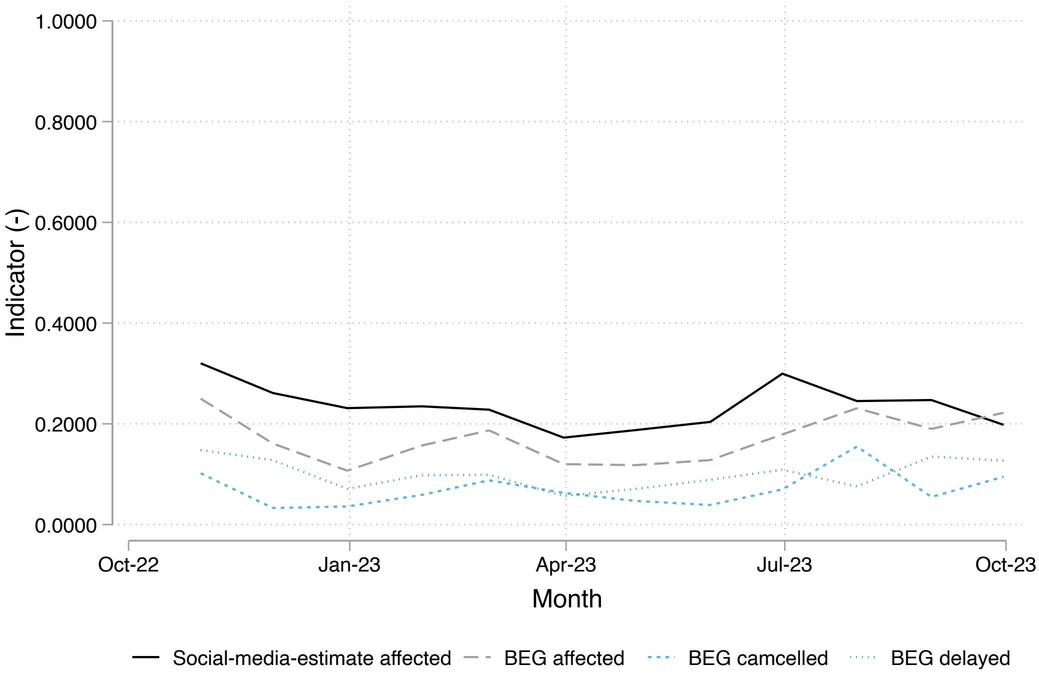


In Figure 8 we compare the monthly time series of our overall estimated number of affected train trips to the official statistics. From the latter, we use the number of canceled service stops and delayed train trips as well as their sum as an approximation of affected train trips. Using these estimates, we see in Figure 8 that the overall magnitude of affected trips and the pattern between the two data sources show a convincing match. Considering that our estimate presumably overestimates the impact, while the official statistics do not report delays shorter than six minutes, the gap might be smaller than observed. The pattern in the months of July and August 2023 can be explained by the fact that the German rail operator usually uses the summer months with less commuting demand for track maintenance, leading to usually fewer planned trips in the first place. This is factored into the official estimate, but not in ours, as we use an average reference timetable.

5.3 Predicting disruption duration for RTI

The findings from the previous analysis of the social media disruption data and its comparison to the official statistics suggest that this secondary data source can be carefully used for

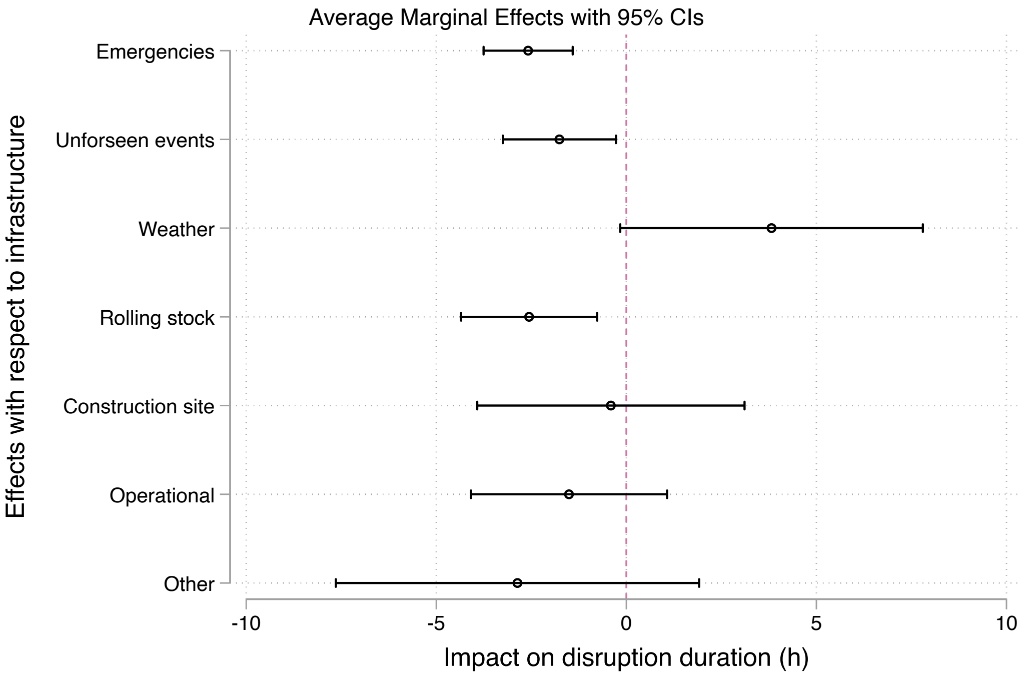
Figure 8: Monthly comparison of the affected trip share from the social-media analysis to the official statistics of the BEG (Bayerische Eisenbahngesellschaft, 2024), approximated from canceled and delayed trips.



investigating disruptions in the Munich “S-Bahn” system. One possible outcome of such an investigation could be an application that informs travelers in real-time with an estimated end time of the disruption so that they can adapt their journey, eventually building it into automated bot systems (Gault *et al.*, 2019).

We use the data of 1,635 unplanned disruptions where we were able to estimate a disruption duration to build a model to predict the expected duration given the cause of the disruption. To achieve this, we regress the duration of disruptions on the variables of disruption cause as well as affected line and the weekday as further control variables. We then predict the marginal effects from the disruption cause, which are shown in Figure 9. The effects of the disruption cause are referenced to infrastructure. In other words, the estimates show whether longer or shorter disruptions can be expected for a given disruption cause. Here, the pattern from Figure 5 can be refined and operationalized.

Figure 9: Average marginal effects from the disruption cause. The effects of the disruption cause are referenced to infrastructure. In other words, the estimates show whether longer or shorter disruptions can be expected for a given disruption cause.



6 Discussions and conclusions

In this paper, we investigated how real-time information data provided on social media by the Munich “S-Bahn” operator can be used to reveal the disaggregate performance of the “S-Bahn” system, i.e., how different disruptions affect services in the network. Disruptions have become more frequent and services have become less reliable in recent years. Considering that the “S-Bahn” is a key mode of transportation in Munich, this development is not only decreasing travelers’ satisfaction but is having a real economic impact. For the analysis, we collected social media posts published by the “S-Bahn” operator from November 1st, 2022 to October 31st, 2023, and identified more than 1,944 disruption events in those posts, where 1,635 were unplanned disruptions. We found that one out of four train trips seems to be affected on average by disruptions, either through delays or cancellations, a number that matches, to some extent, the official statistics. Considering that the data seems to exhibit some validity, we further found the data can be used to predict the expected duration of a disruption based on the disruption caused and affected line, parameters readily available in the first social media post. Hence, we concluded that the social-media-based disruption data could be used in an application to inform travelers accordingly so that they can re-plan their journeys, e.g., like the TravelBot (Gault *et al.*, 2019).

This analysis bears limitations. First, as no official disaggregate disruption data is publicly available, a validation of our findings is not possible. Although the overall pattern and magnitude of patterns match the official statistics, given that not much is known about the data generation process on social media, i.e., when the operator selects to publish a disruption, the results are just an indication. Hence, a conclusion about whether the results present a lower or upper envelope cannot be made distinctively. Second, to assess the share of affected trips, we could not access the actual GTFS timetable during planned disruptions, e.g., maintenance. Hence, we cannot control for planned disruptions, which is likely to increase the estimate of the share of affected trips. This fact presumably explains the peak in our estimate in summer 2023 as seen in Figure 8, which is not present in the official estimate as their estimate relies on the specific timetable of those months. Third, considering that the “S-Bahn” Munich system is not a static system but evolves over time, our findings have, of course, limited validity for forecasting impacts. Improvements in the maintenance of infrastructure and rolling stock may reduce the number of disruptions in the future, leading to fewer disruptions. However, considering that the entire data collection process can be highly automated, any application for travelers can be updated regularly to account for the changes. Directions of future research include completing the disruption data with all posts since the beginning as well as making it operate in real-time, improving the validation of the data using other external data sources, and building prediction models for informing travelers using advanced statistical learning methods for networks based on the improved disruption data.

In closing, it is obvious that the presented data collection and analysis is not meaningful for the “S-Bahn” operator as they have access to the primary and unbiased disruption data, but for travelers and researchers who can use this data source to build applications that can improve the journeys of travelers as well as help to develop approaches that may improve the situation of the Munich “S-Bahn”. This investigation may not improve the performance situation of the “S-Bahn” directly, however, it may increase awareness for the matter as it is one of the first analyses showing at a disaggregate level in which performance situation single lines are and what different effects can be expected by a given disruption cause.

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8 Author contributions

The authors confirm their contribution to the paper as follows: Conceptualization AL, YE; Methodology AL, YE; Formal analysis and Investigation: YE; Writing - Original Draft: AL, AT, YE, KB; Supervision: AL, AT, KB.

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