Analysis of TTC Subway Delays (2020–2024): Trends, Causes, and Predictive Insights

By

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Introduction

The Toronto Transit Commission (TTC) serves as the primary public transit agency for the City of Toronto, facilitating the daily movement of approximately 1.7 million commuters across Toronto and the Greater Toronto and Hamilton Area (GTHA). [1] As one of North America's busiest urban transit systems, the TTC plays a vital role in supporting the mobility of a densely populated and culturally diverse city of Toronto.

Given the high volume of daily ridership, disruptions to subway service—particularly delays—can significantly impact customer satisfaction and operational efficiency. A delay, in this context, refers to any instance where a subway train remains at a platform longer than its scheduled dwell time. These interruptions not only inconvenience passengers but also ripple through the broader transit network, compounding congestion and reducing reliability.

Recognizing the urgency of this issue, the TTC Chair introduced a motion on January 27, 2025, aimed at addressing persistent service delays, as reported by CBC News Toronto. [2] Given the significance of this issue, our group conducted a comprehensive analysis of TTC subway delays to investigate their underlying causes, uncover consistent patterns, and propose data-informed strategies for improving the rider experience.

Objectives

This report presents a comprehensive analysis of TTC subway delays from 2020 to 2024, drawing on delays incident data sourced from the City of Toronto Open Data Portal[3] and analyzed using Python, including exploratory data analysis, visualization, and machine learning techniques. The primary aim is to uncover insights into the frequency, causes, and patterns of delays across the system.

Specifically, the analysis seeks to answer the following key questions:

- What is the annual volume of subway delay incidents across the TTC network?
- Are delays trending upward or downward over the five-year period?
- What are the primary drivers of these delays—are they rooted in system-level challenges or influenced by external factors such as passenger behavior, or weather conditions?

- Are subway delays more frequent during specific times of the day, such as peak commuting hours or late evenings?
- Do certain TTC stations experience a higher volume of delays compared to others across the network? Which stations experience most delays?
- Can the most common causes of delays be identified and analyzed to reveal meaningful patterns or trends?
- Can we predict the cause category of a delay (Passenger-related, System, Fire/Weather) based on features like time of day, day of week, and delay length?

By exploring these questions, this report aims to illuminate the key causes and underlying patterns of subway delays across the TTC network, and to highlight evidence-based suggestions to improve system performance and customer experience.

Data Cleaning and Preparation

We began our analysis by loading the raw TTC subway delay incident data (2020–2024) from the City of Toronto Open Data Portal. We then narrowed the dataset to essential columns: Date, Time, Day, Station, Code, and Min Delay.

Next, the Date and Time columns were combined and converted into a standardized datetime format, from which we extracted relevant temporal features such as hour, day of the week, and month for further analysis.

To better understand delay causes, we introduced a code categories lookup table created as a separate Excel file. This lookup was based on the TTC delay codes and their meanings, supplemented by official documentation from the City of Toronto Open Data Portal. Merging this lookup with the dataset allowed us to assign descriptive cause categories to each delay code, such as Passenger-related, System, and Fire/Weather.

During this process, we identified and corrected typos and inconsistencies in delay codes (e.g., MUNCA corrected to MUNOA). Finally, records with missing or invalid category data were removed to ensure data quality for analysis. Please note that delays with 0 minute duration were included into the analysis, based on industry practices, as these delays are recorded by Transit Control as separate incidents.

For the station column, there were no established standards for entering records. A consequence of this was a significant number of spelling variations for the same subway station. This inconsistent spelling meant that any grouping by station was suspect. Particularly, there was an overrepresentation of stations that were easier to spell consistently, like "FINCH STATION," and an underrepresentation of stations with more spelling variations like "Bloor Station," "BLOOR STATION–YONGE," or "BLOOR YONGE," since the latter were broken apart across several groupings. To create a consistent classification of stations, we made a lookup table to map the numerous name variations to a set of standard station spellings for Lines 1, 2, and 4. This lookup table was then merged with the full dataset to create a cleaned station column.

When a station record could not be clearly mapped to a TTC subway station, such as instances that referred to an entire line like “BLOOR DANFORTH LINE” or there was no way to identify the station, such as “CHANGE OVERS / GENERAL,” then the stations were classified as “Other.” The classifications also had a significant number of variations that identified a set of stations affected by a single delay, such as “VMC TO ST GEORGE STATI.” While it would have been possible to determine the set of stations within these bands, it would have been too laborious and time-consuming for the scope of this project. The simplified approach chosen was to classify these records as “Multiple Stations.” It should be noted that this underestimated station-specific measures of system delays, which were more likely to involve multiple stations. However, given that most passenger disruptions were probably restricted to a single station, they were likely not affected

Analysis and Findings

Overview

Our analysis begins with a comprehensive examination of the annual volume of subway delay incidents across the TTC network from 2020 to 2024. We observed a significant increase in both the number of delay incidents and the total minutes delayed. The number of delays rose from approximately 14,700 in 2020 to over 26,400 in 2024, nearly doubling over the five-year period. Similarly, total minutes delayed increased from around 46,000 minutes in 2020 to almost 74,000 minutes by 2024, showing an escalation in overall delay impact. From 2023 to 2024, the total delay minutes increased by 8.94%, and the number of incidents increased by 15.32%.

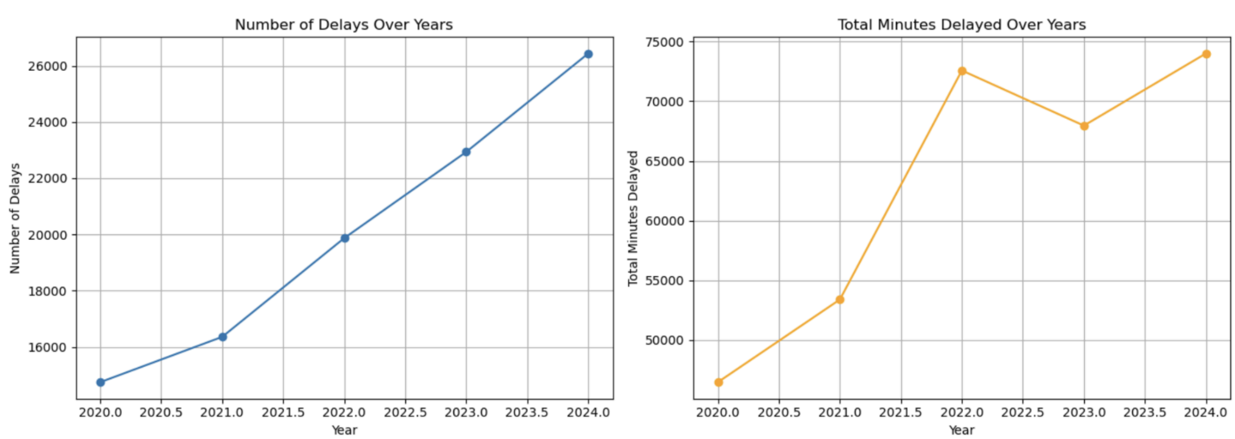

Figure 1. Number of delays (left) and total delay minutes (right) over the years, showing overall trends in frequency and duration.

We decided to split the incidents by type, so we created 3 categories (Passenger-related, System, and Fire/weather) and used bar graphs. The bar plots provide a clear comparison of the delay caused by both the number of incidents and the total minutes delayed. Passenger-related delays represent the largest portion of the total delay events, with over 54,000 occurrences, followed closely by system-related delays at just over 46,000. Fire and weather-related delays are comparatively rare, accounting for only about 200 incidents.

When examining the total minutes delayed, passenger-related delays again lead the impact with roughly 160,000 minutes, slightly exceeding the system-related delays, which contribute nearly 153,000 minutes of delay. Fire and weather delays, while minimal in number, account for just under 2,000 total delay minutes, indicating that although infrequent, these incidents can still cause noticeable service disruptions.

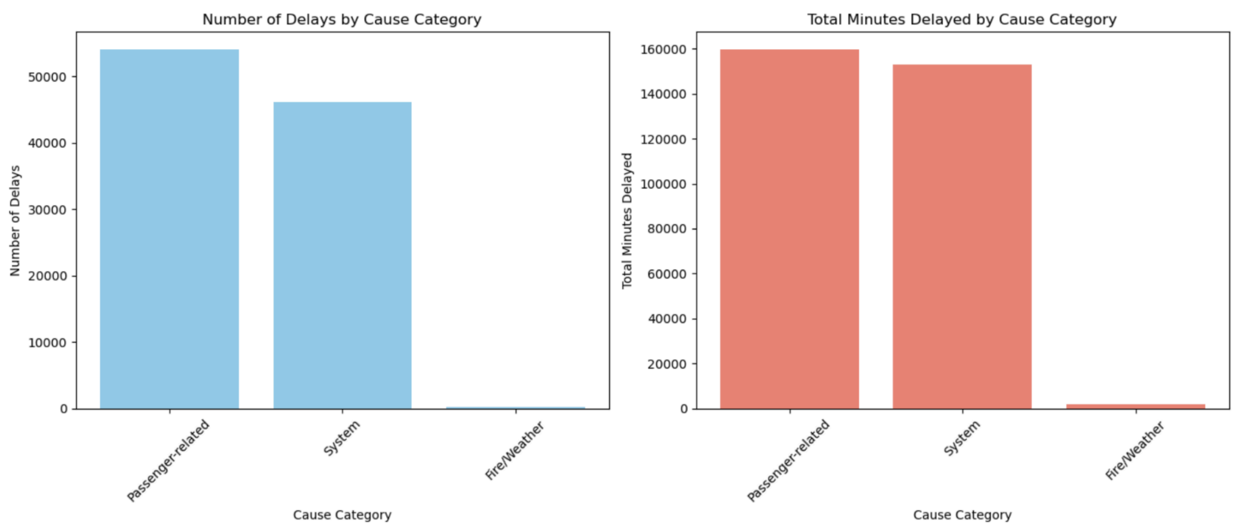

Figure 2. Number of delays (left) and total minutes delayed (right) by each Cause Category type: System, Passenger-related, and Fire/Weather.

We then tried to break down the delay data by cause category to reveal any trends between Fire/Weather, Passenger-related, and System delays over the five-year period. Passenger-related delays have seen a marked increase, with the number of incidents rising from around 6,200 in 2020 to over 15,400 in 2024. Correspondingly, total minutes delayed for this category surged from approximately 18,800 minutes to over 40,500 minutes, indicating both higher frequency and longer impact per delay.

System-related delays have remained relatively stable in terms of incident counts, fluctuating between roughly 8,200 and 11,000 per year, but showing some variability in total delay minutes, peaking around 36,000 minutes in 2022 before dropping slightly thereafter. This finding reflects the impact of COVID on the system and riders returning post-COVID to the system causing more passenger-related delays. Fire/Weather-related delays remain a minor component of overall delays, with consistently low numbers both in frequency and total minutes delayed, contributing a small fraction to the total delay impact.

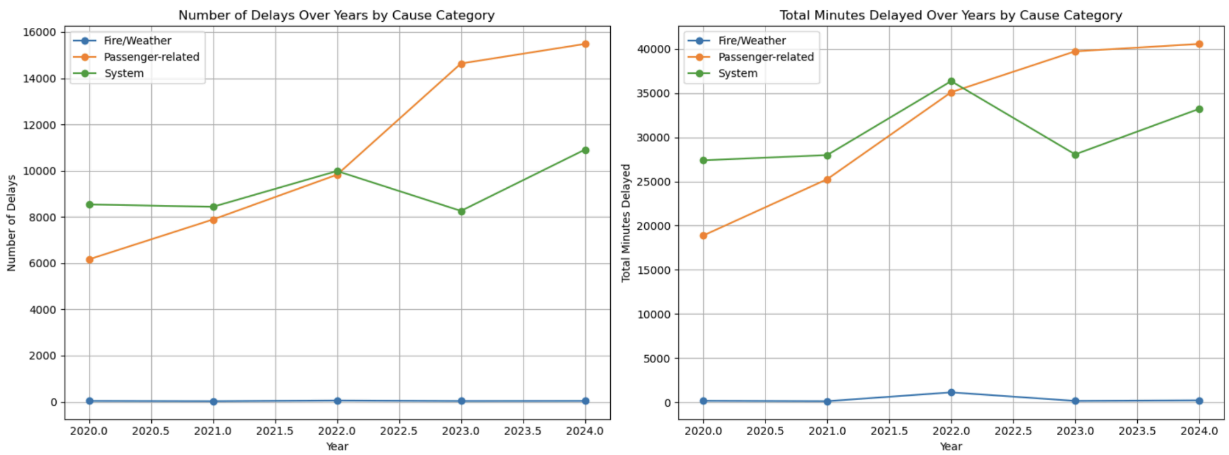

Figure 3. Number of delays (left) and total minutes delayed (right) for the three Cause Categories over the years, shown as line plots.

In a further exploration of the TTC subway delay data from 2020 to 2024, we shifted our focus to a more granular analysis, examining the patterns of delays across hours of the day. This temporal analysis helps to pinpoint when the most significant disruptions occur, providing insights that can inform operational adjustments and resource allocation. We broke down the data into three key metrics: average delay duration per hour, the number of delays per hour, and total minutes delayed per hour.

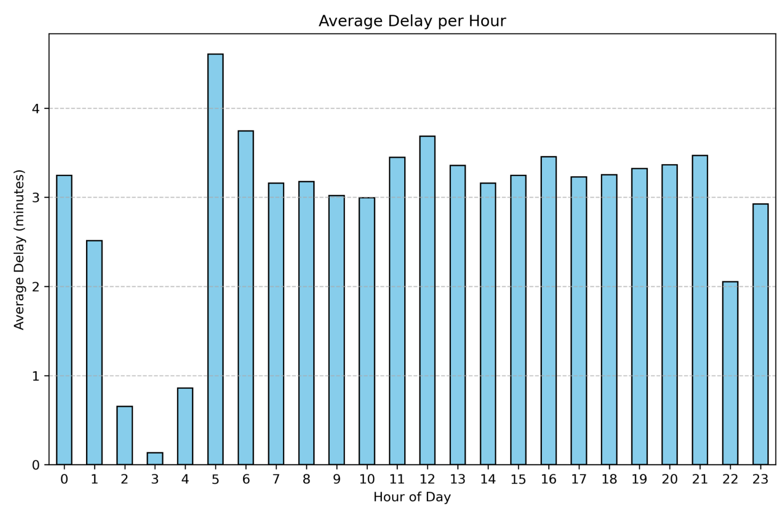

Figure 4. The average delay per hour bar chart plot which shows the average delay in minutes for each hour of the day, from 0 (midnight) to 23 (11 PM).

Our analysis of the average delay per hour revealed that while delays are generally consistent throughout the day, a notable spike occurs in the early morning hours, particularly around 5:00 AM. The delay spikes remain low between the after midnight and before very early morning (2:00 AM to 4:00 AM). This early-morning peak, exceeding 4 minutes on average, suggests that initial service start-up or morning preparation activities may be a source of recurring, albeit short, delays. For the remainder of the day, average delays typically stabilize between 3 and 4 minutes.

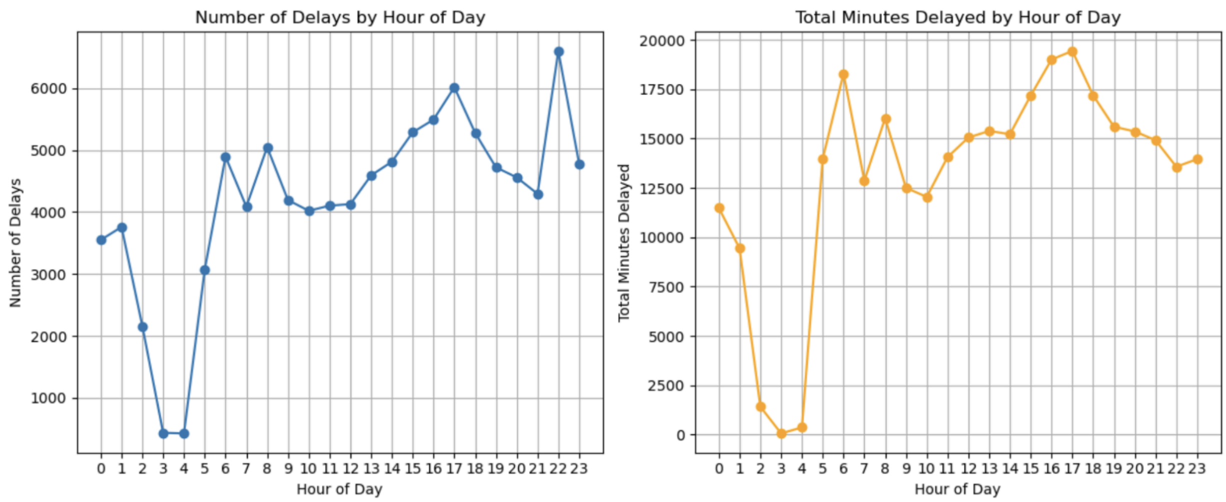

Figure 5. (Graph in left) Plot of number of delays by hour of day illustrates the total count of delayed flights per hour, from 0 to 23. (Graph in right) Plot of total time delay time in minutes for each hour of the day, from 0 to 23.

When we looked at the number of delays by the hour, a clear trend emerged. The number of incidents is at its lowest in the very early morning, between 3:00 AM and 4:00 AM, which aligns with the lowest passenger volumes. As the day progresses, the number of delays steadily increases, peaking dramatically in the late evening, around 10:00 PM, with over 6,000 incidents recorded. This suggests that while individual delays may not be the longest, the sheer frequency of delays is highest during the late-night service period.

Finally, our examination of the total minutes delayed by the hour provides a comprehensive view of the overall impact. This metric combines both the frequency and duration of delays. The data shows a sharp increase in total minutes delayed as the day goes on, with significant peaks occurring in the late afternoon/early evening (4:00 PM to 6:00 PM) and again at 8:00 PM. These peaks, which reach nearly 20,000 total minutes of delay, are likely associated with the evening commute and peak travel times, when a combination of higher passenger volume and more frequent incidents leads to the greatest cumulative disruption for the TTC network.

Station Analysis

As of 2024, Bloor-Yonge had the greatest number of delay minutes by a significant margin, followed by St. George and Kipling. This is after significant growth in delays across almost all stations, with a notable exception of Vaughan Station which saw a massive decline in delay minutes. Both total and growth in delay are heavily skewed to the left meaning that a disproportionate amount of delay minutes are clustered among a few key stations. The top two stations are notable given that they house 2 lines, the Yonge-University and the Bloor-Danforth.

These station’s high share of delay minutes may be due to 3 factors 1 that there is a greater number of delays because more riders are transferring between both the Yonge-University and the Bloor-Danforth lines; 2 that the existence of 2 lines means that disruptions on one line propagate to the other, compounding delay minutes at the shared platforms; or 3 more trains scheduled through these stations, increases exposure to delay events and total delay minutes.

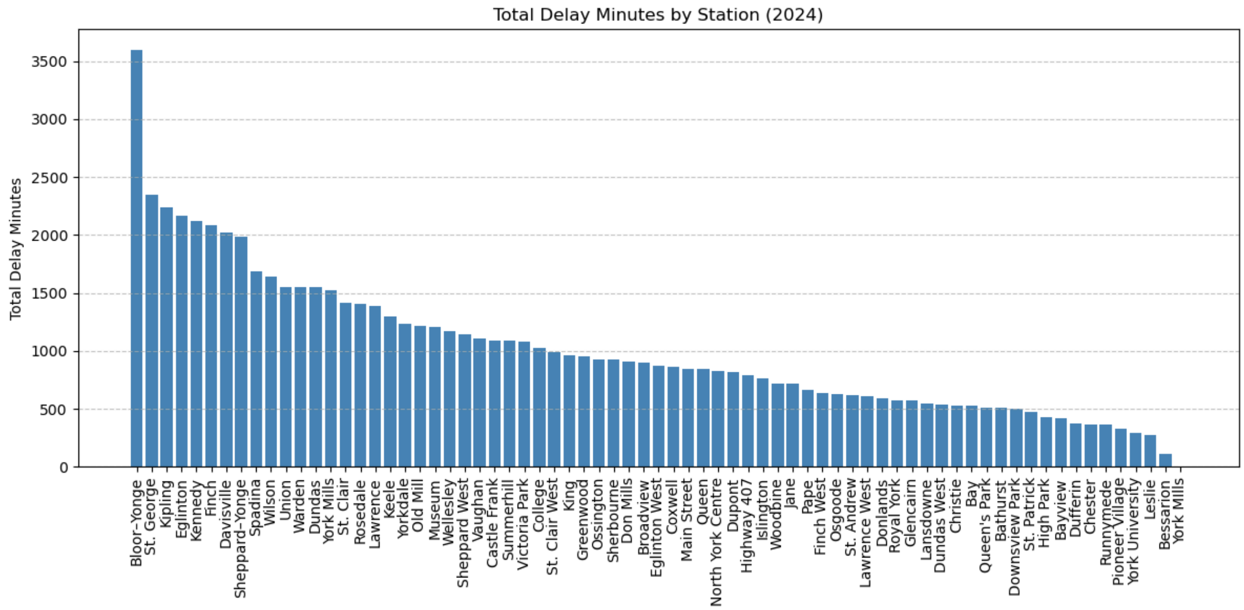

Figure 6. Total delay minutes by station in 2024, displayed as a bar plot.

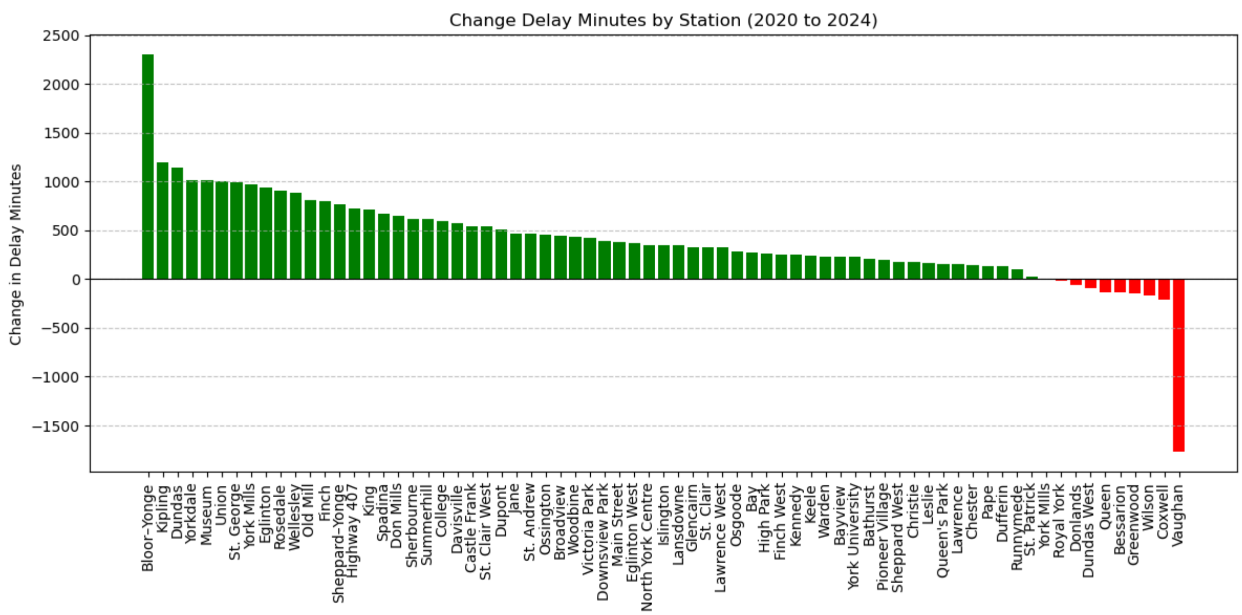

Figure 7. Change in delay minutes by station from 2020 to 2024.

Diving Deeper - Passenger Related Delays

To better understand the nature of passenger-related delays, we categorized them into four subgroups based on the delay codes: Disruptive, Criminal, Medical, and Other. The analysis reveals that Disruptive delays overwhelmingly dominate passenger-related incidents, both in frequency and total delay minutes.

A breakdown of the passenger-related delay categories shows:

- Disruptive delays account for the highest number of incidents, with over 30,000 occurrences, representing the majority of delays in this category. These also contribute nearly 98,500 total delay minutes.
- Medical incidents are the second most common, with about 19,500 delays and approximately 45,000 delay minutes.
- Criminal incidents, while fewer in number (around 4,400), still contribute a significant total delay time (over 15,600 minutes).

The bar plots below illustrate these counts and their relative percentages, highlighting the dominance of disruptive delays within the passenger-related category.

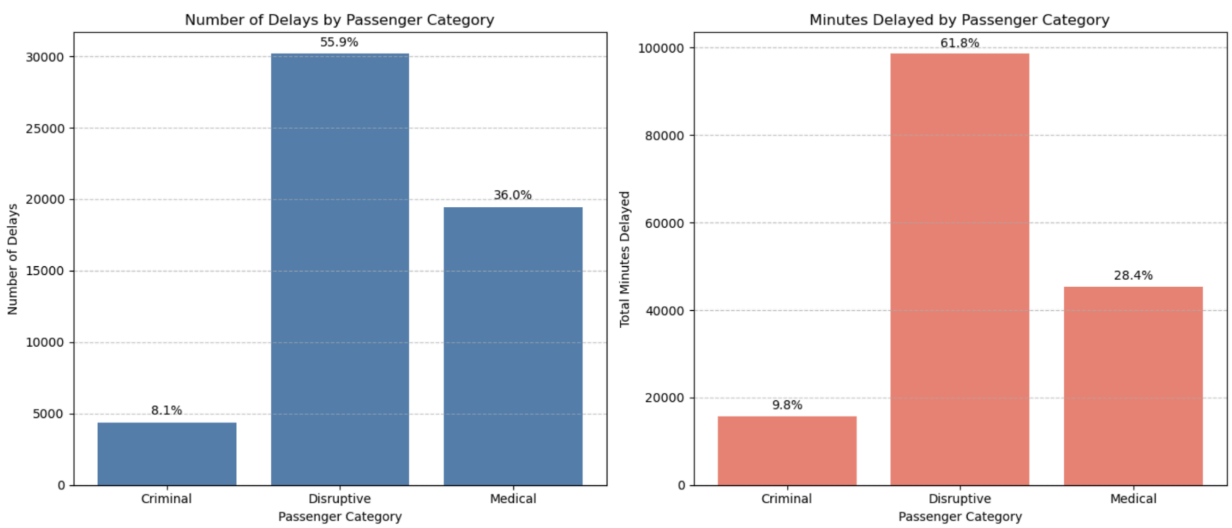

Figure 8. Number of delays (left) and total minutes delayed (right) for each passenger-related delay category (criminal, disruptive, and medical).

Examining trends over the years 2020 through 2024, a clear pattern emerges in the line charts displaying the number of delays and total minutes by year and category. Disruptive delays consistently increase each year, peaking in 2024 with nearly 9,000 incidents and over 26,000 total delay minutes. Medical delays also show a steady rise over the period, though at a slower rate. Criminal delays fluctuate but generally remain the least frequent category.

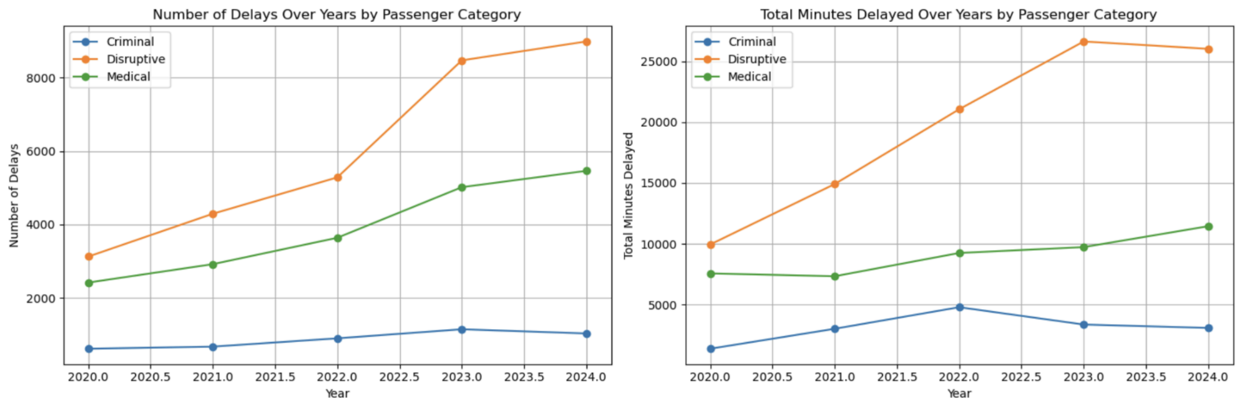

Figure 9. Total delays (left) and total minutes delayed (right) for the three passenger-related delay subcategories (criminal, disruptive, and medical) over the years.

These trends suggest that disruptive passenger behavior has become an increasingly significant factor impacting TTC operations over recent years, underlining the need for targeted strategies to mitigate such delays.

Let's Dive Even Deeper! - Disruptive Passenger-related Delays

Within the broader passenger-related delay category, disruptive incidents represent a significant and complex subset affecting TTC operations. To gain a clearer understanding, we analyzed the specific causes contributing to these disruptive delays, their frequency, total delay time, and their relationships over time. The bar plots below summarizes the number of delay incidents and total minutes delayed by each specific cause within the disruptive passenger-related category.

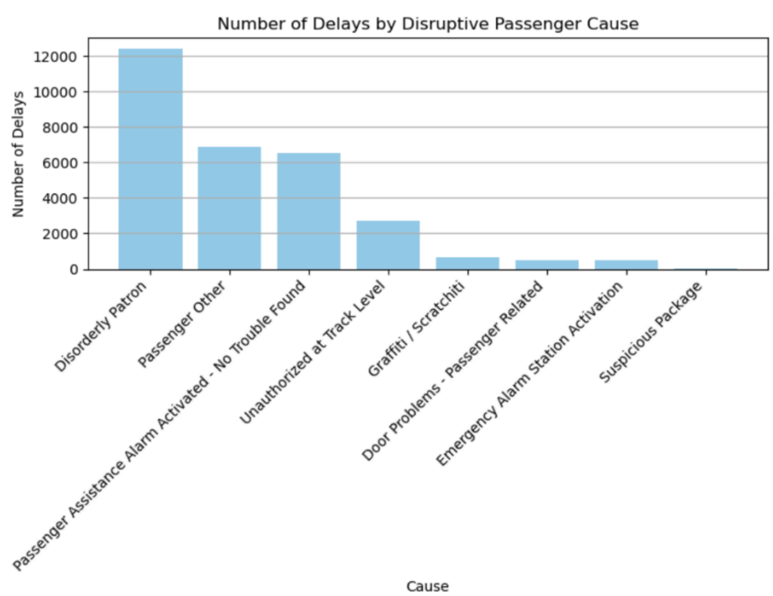

Figure 10. Number of delays by each disruptive passenger-related cause.

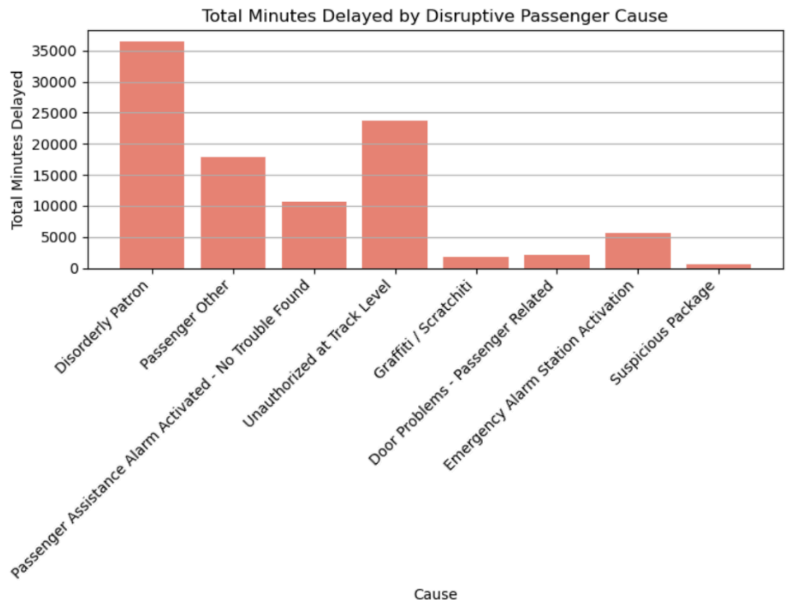

Figure 11. Total minutes delayed by each disruptive passenger-related cause.

The most prevalent cause is Disorderly Patron incidents, accounting for over 12,000 delays and approximately 36,400 total delay minutes. This category alone contributes the largest share of disruptive delays and associated service disruptions. Following Disorderly Patron incidents are: Passenger Other, a broad category covering miscellaneous passenger-related disruptions, with nearly 6,900 delays and 17,800 minutes of delay. Then, Passenger Assistance Alarm Activated – No Trouble Found, which involves alarm activations without actual incidents, with over 6,500 occurrences and more than 10,500 delay minutes. Unauthorized at Track Level incidents were fewer in number (around 2,700), but highly impactful in terms of delay minutes (over 23,700). Smaller contributors include Graffiti / Scratchiti, Door Problems – Passenger Related, Emergency Alarm Station Activation, and Suspicious Package, with varying but less frequent impact.

This breakdown highlights how certain disruptive behaviors, especially disorderly conduct and unauthorized track presence, disproportionately affect service delays.

To understand how these top disruptive causes interact over time, we conducted a correlation analysis on monthly aggregated delay minutes for the five most frequent causes:

- Disorderly Patron
- Passenger Other
- Unauthorized at Track Level
- Passenger Assistance Alarm Activated – No Trouble Found
- Emergency Alarm Station Activation

We anticipated a positive correlation in delay minutes among these codes, since many disruptive incidents likely arise from related passenger behaviors or occur under similar conditions that exacerbate delays. For example, increased passenger unrest might trigger both disorderly conduct and multiple alarm activations, causing overlapping disruptions.

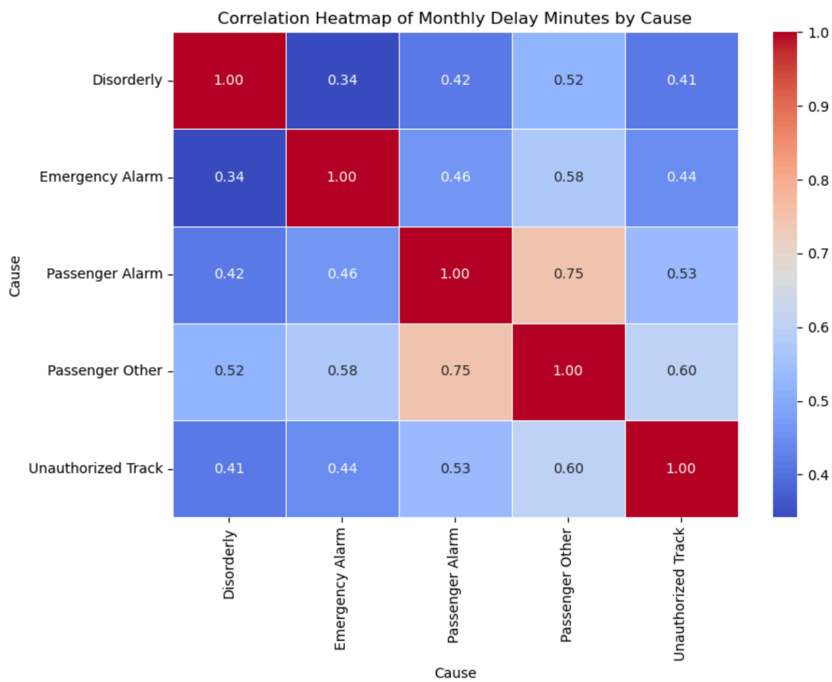

Figure 12. Correlation heatmap of monthly delay minutes for the top five disruptive passenger-related causes.

The correlation matrix showed positive relationships among the five main disruptive passenger-related delay causes, indicating these types of incidents tend to increase and decrease together over time.

The strongest correlation is between Passenger Alarm activations and Passenger Other delays, with a coefficient of approximately 0.75. This suggests that months with more false alarms often coincide with a higher number of miscellaneous passenger-related incidents.

Passenger Other also shows strong correlations with Unauthorized Track Access (around 0.60) and Emergency Alarm activations (about 0.58), indicating these disruptive incidents frequently occur alongside each other.

Disorderly patron incidents have moderate positive correlations with other causes: approximately 0.52 with Passenger Other, 0.41 with Passenger Alarm, 0.41 with Unauthorized Track Access, and 0.34 with Emergency Alarm. This pattern suggests that disorderly behavior tends to rise alongside various other passenger disruptions, though less strongly than some other pairs.

Unauthorized Track Access shows moderate correlations ranging from about 0.41 to 0.60 with the other categories, highlighting its tendency to co-occur with other disruptive behaviors like alarms and miscellaneous incidents.

Finally, Emergency Alarm activations correlate moderately (roughly 0.34 to 0.58) with all other causes, emphasizing its role as a frequent companion to other passenger disruptions.

The scatter plot matrix further illustrates the relationships between the top disruptive delay causes by visualizing their monthly delay minutes against each other. These plots reveal consistent positive trends, supporting the correlation findings. For example, upward slopes in the scatter plots show that months with high delay minutes for one cause tend to coincide with higher delay minutes for others. Clusters of points along these trends suggest that increases in disruptive behaviors often happen simultaneously rather than independently. This visual evidence reinforces the idea that these disruptive incidents share common drivers and frequently compound one another, intensifying the overall impact on service delays.

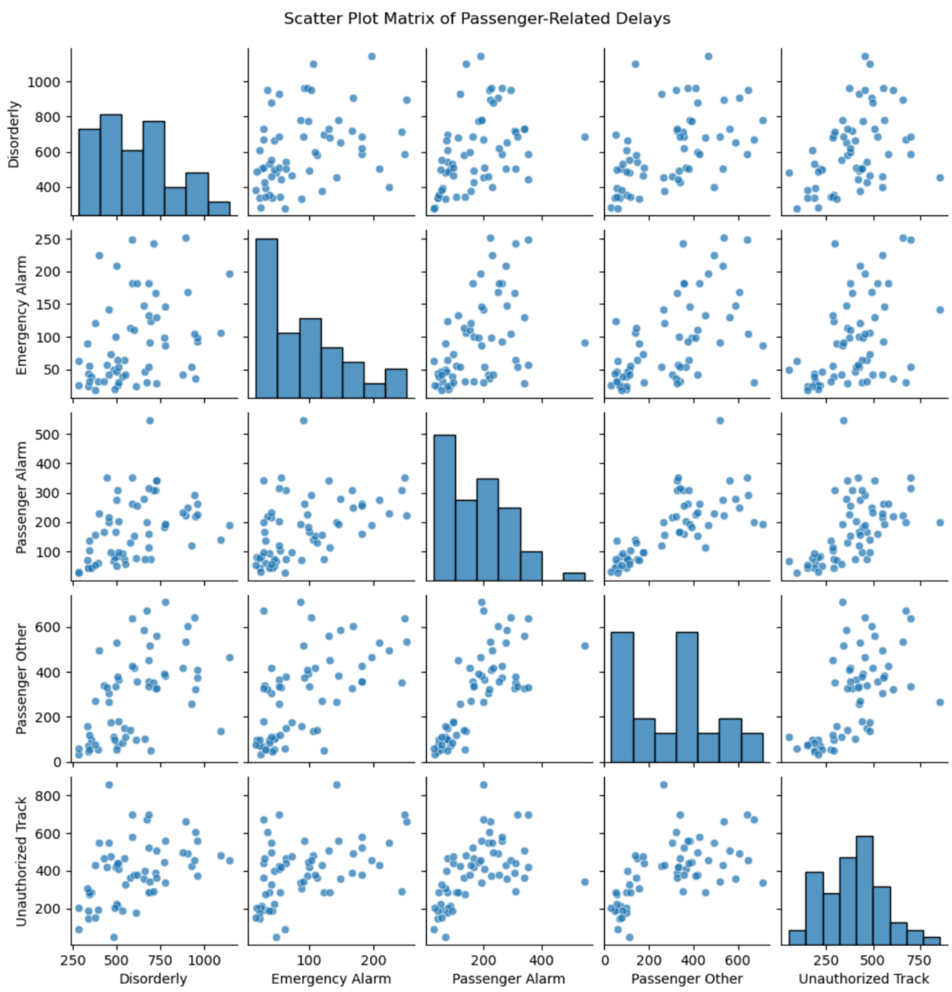

Figure 13. Scatter plot matrix of monthly delay minutes for the top five disruptive passenger-related causes.

Overall, these analyses highlight that passenger-related delays (especially disruptive behaviors) are the primary drivers of TTC service disruptions, with multiple interrelated causes that often occur simultaneously, underscoring the need for targeted strategies to effectively mitigate their impact.

Predictive Model for Delay Cause Classification

Our goal was to develop a predictive model to classify the cause of transportation delays into the three cause categories: Passenger-related, System, and Fire/Weather based on available features extracted from the delay data.

The predictive model used the features Min Delay (delay duration in minutes), Hour (hour of the day), DayOfWeek (day of the week), and Month (month of the year), with the target variable being the Category of the delay cause. We split the dataset into training and testing sets in a way that maintains the original distribution of the target classes in both subsets. We chose a Random Forest Classifier because it is robust and can capture interactions between features without needing extensive preprocessing. Key model parameters included 100 trees (n_estimators=100), balanced class weights to mitigate class imbalance, and a fixed random state for reproducibility

The classification report indicates that the predictive model performs moderately well overall, achieving an accuracy of approximately 61% on the test data. The model predicts passenger-related delays most effectively, with a precision and recall around 65%, resulting in an F1-score of 0.65. System-related delays are identified with slightly lower performance, showing an F1-score of 0.58. However, the model struggles significantly with Fire/Weather-related delays, reflected by very low precision (0.01) and recall (0.10), largely due to the small number of such cases in the dataset. The macro average F1-score of 0.41 highlights the imbalance in predictive performance across the categories, while the weighted average F1-score of 0.61 indicates that the overall results are heavily influenced by the majority classes.

The confusion matrix visualization in our notebook confirms that most misclassifications occur with the Fire/Weather class and between System and Passenger-related delays, reflecting overlapping feature patterns or insufficient distinguishing information for minority classes.
The model's feature importance scores indicate the relative influence of each predictor on classification.

Temporal features (Hour, Month, and Day Of Week) together contribute significantly more than the delay duration itself, suggesting that the timing of delays plays a critical role in determining the cause. The Hour of the day was the most important feature, possibly capturing peak times or patterns specific to certain delay causes.

Conclusion

Our comprehensive analysis of TTC subway delay data from 2020 to 2024 reveals a significant and concerning increase in service disruptions. Both the number of delay incidents and the total minutes of delay have risen substantially over the five-year period.

The analysis clearly identifies passenger-related delays as the primary driver of these disruptions, both in frequency and overall impact. These delays have seen a marked increase, with the number of incidents rising to 2.5 times within five years. System-related delays, while still a major factor, have remained relatively stable in comparison. Our analysis categorized passenger-related delays into three groups: disruptive behavior, medical incidents, and criminal causes, with disruptive behavior emerging as the most significant contributor to delays.

We also looked at when these delays happen from early morning to late midnight with an average delay time of 3 to 4 minutes. This time dependence analysis shows a clear trend of delay peaks in the late evening while station-level analysis identified Bloor-Yonge and St. George as the most affected stations, likely due to their function as major transfer hubs.

Correlation analysis provided important insights regarding disruptive passenger behaviour correlating with unauthorized at track level delays and activation of emergency alarm.

Our predictive model was moderately effective at classifying delays for the major categories (Passenger-related and System). The model's feature importance scores confirmed that temporal factors (hour of day, day of week, month) are more influential in predicting delay causes than the delay duration itself.

Based on these findings, we recommend the TTC take three key actions: boost staffing and security at high-delay stations like Bloor-Yonge and St. George during peak and late-night hours, launch public awareness campaigns to curb disruptive behaviors such as door-holding, and use predictive analytics to flag potential delays for faster response and better resource allocation, ultimately addressing root causes, improving reliability, and enhancing the rider experience.

References

[1] City of Toronto, “Toronto Transit Commission.” [Online]. Available:https://www.toronto.ca/city-government/accountability-operations-customer-service/city-administration/city-managers-office/agencies-corporations/agencies/toronto-transit-commission/. [Accessed: Aug. 2, 2025].

[2] C. Pasieka, “TTC chair puts forward motion to address service delays,” CBC News, Jan. 2025. [Video]. Available: https://www.cbc.ca/player/play/video/9.6624308. [Accessed: Aug. 2, 2025].

[3] City of Toronto, “TTC subway delays,” Open Data Portal. [Online]. Available: https://open.toronto.ca. [Accessed: Aug. 2, 2025]