Journal of Systemics, Cybernetics and Informatics (2023) 21(3), 47-55
https://doi.org/10.54808/JSCI.21.03.47

Data-Driven Security Measurements to improve Safety in NYC and NJ MassTransit

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ABSTRACT

Public transit in America in recent years is potentially vulnerable to terrorist or mass casualty attacks. These vulnerabilities are in part due to the lack of strict screening and content policing, unlike security at airports, but also their attractiveness as a potentially high-value target. Although current public transit systems are designed to efficiently allow passengers to quickly travel, screening of individual riders for weapons remains limited due to current technology limitations and high peak throughput requirements. This paper aims to develop an understanding of the current state of security check systems as applicable to high-traffic subway stations. We also worked towards creating a proof-of-concept risk analysis model using crime and other types of publicly available data for the New York City and New Jersey transit regions.

Keywords: Active security, passive security, risk analysis model, public transit, antiterrorism, patron screening, public safety

1. INTRODUCTION

Public transit is an important method of transportation for millions of Americans, especially in densely populated areas. Public transit offers Americans an attractive travel option when using a car is not an option, or otherwise infeasible due to congestion or parking considerations. In places like New York City, public transit is often the most efficient way to travel. New York City alone has over 5.5 million weekday riders and over 178,000 passengers who travel through its Times Square station each day [1]. Since public transit is in high demand and used in many cities and densely populated areas of the country, the US government has designed public transit stations, whether it is trains, subways, or buses, with a focus on accessibility and handling large throughput. As airport-level security measures are not deployed due to infrastructure limitations and high throughput requirements, making public transit potentially vulnerable to mass casualty attacks. In particular there have been at least 29 successful terrorist attacks on rail transit, causing the loss of life of 1,418 people and 6,135 injuries between 2000 and 2017 [2].

How can we improve current public transit security measures without decreasing the throughput of passengers? A potential partial solution would be fully utilizing passive security measures; however, this has privacy and deployment challenges. Before diving into a proposed solution, it is necessary to understand the complex levels of security and surveillance checks utilized at both airports and public transit.

2. PROPOSED APPROACH

Our project reviewed existing technologies to understand the feasibility of deploying them in a mass transit setting, along with reviewing pilot deployments in the literature. We also identified existing publicly available datasets that may be useful in gathering information about past security incidents on public transit, and data that would be helpful to create a crime/terrorism risk map or model. We visualized these datasets for New York City and New Jersey to gain insights in order to recommend future work. All of this has the goal to prevent large-scale attacks on public transit in the New Jersey and New York City metro areas.

Our original approach only focused on the New York City subway stations. However, through the duration of the initial literature and technology reviews, it was evident it would be beneficial to work with more than subway station security and expand to New Jersey public transit and commuter rail transit as well. Supporting this approach is a 2017 Regional Plan Association study that

The Authors would like to thank Dr. Larry Pearlstein, Chelsea Popoola, and Thomas Henry for their help peer-editing this paper.

found that out of the 1.6 million people who commute to the city on a daily basis, 320,000 of them are from New Jersey [18]. Adding New Jersey to this project helps us get more insight into how the public transit system is being used and by whom.

The project's methodology involved five main steps. The first step was a literature review on the different types of surveillance and security measures around the world in airports and public transit. Next, the technology review allowed for the needed exposure and research for new and emerging technologies for screening individuals in public locations and the feasibility of their use in public transit stations. The dataset review included crime, census, transportation, and other datasets that are made publicly available in New York City and New Jersey. After this, data analysis and visualization were performed using modeling tools in FME, ArcGIS, Tableau, and Python APIs to discover trends and patterns in the data. The final step, recommended for future work, is the creation of the risk analysis model. The risk analysis model is a predictive model based on the given inputs, and crime data of New York City.

3. LITERATURE REVIEW

Security check systems consist of many layers of surveillance, scanning technology, and physical screening. In the traditional airport or venue screening, these layers can include a visual inspection by law enforcement, K9 units, ticketing, bag checks via x-ray and visual inspections, walk-through metal detectors, and handheld wands. In the United States and Europe, multilayer screening systems are utilized at metro stations, but typically without in-depth patron and bag screening procedures. Instead, safety is approached through a combination of show-of-force, ticketing, CCTV cameras, preemptive surveillance, and more. An example of successful American anti-terrorism surveillance can be found in the foiled 2009 NYC bombing attempt by Najibullah Zazi and Al-Qaeda [3].

In heavily crowded public environments, there may be many complex layers of security measures. Figure 1 contains an illustrative example of some of the possible security measures for public transit. Some of the layers of security shown are deterrence, visual inspection, K-9 inspection, and reinforcements within the subway. The first level of deterrence is the act of discouraging an action or event by creating doubt or fear of the consequences [22] and is done immediately before patrons enter the subway. Having street-level policing outside of subways with surveillance cameras and constant updates on social media about many possible threats around the outside of subway perimeters makes it much more difficult for terrorist groups or individuals to fulfill a potential attack. A second layer is the turnstiles upon entering the subway — this is where the passengers' tickets and as well as bag screening can be done. A third layer occurs as patrons enter the subway platform where there should be active police and K9 presence, and random screening. The fourth layer would be once passengers are in the subway cars where there would be an expectation from passengers to reach out to law enforcement if they see anything suspicious. These many layers to enter a subway station makes it difficult for terrorists and individuals with malicious intent to smuggle dangerous items in or to carry out an attack. Upon entering the station there are active policing and K-9 units by all the entrances and exits. Adding all these complex areas of patrolling, screening, and surveillance makes the station less desirable to execute a mass casualty attack despite them being a high-value target. Overall the combination of constant surveillance, policing/law enforcement presence, and active attendance at the station platform and on the subways/trains could make public transit less of the desired place to attempt a mass-casualty attack.

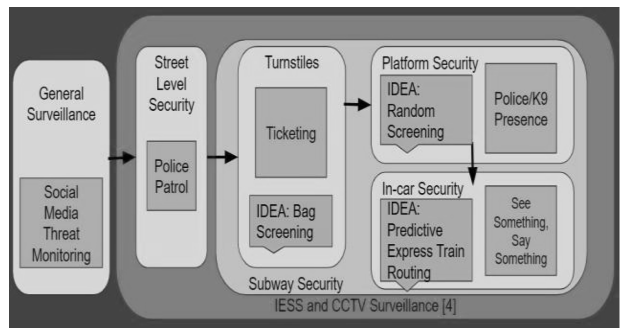

Figure 1: Flowchart illustrating the different layers of security measures that could be implemented on public transit, specifically for subway stations.

In other parts of the world, such as China, there are various types of well-executed security measures using comprehensive, two- stage security check systems. The two-stage security check system has been in place in Chinese cities since the 2008 Beijing Olympics. In Beijing, the first stage of a single-lane security system consists of an X-ray bag check machine like those found in US airports and a walk-through metal detector (WTMDs). If an individual alarms at either one of these screenings, they enter the next stage for a secondary inspection. This system has resulted in the confiscation of several million prohibited items through the first eight years of service [4]. While these systems may improve security in mass transit, one study found that they result in 14.2 seconds of wait time per passenger [4]. During event peaks, some transit-goers report screening wait times of over two hours [5]. When security checks are overwhelmed, the large number of people waiting in these queuing bottlenecks can become a target/security risk as well.

Keeping the tradeoff of safety and throughput in mind, the goal of this paper is to evaluate the viability of new data-focused screening methods and technologies and to establish a proof-of- concept for data that may eventually feed into a predictive analysis model to predict security risk areas on public transit locations within the New York City and New Jersey regions.

4. TECHNOLOGY REVIEW

Security check system improvements have historically followed technological advancements. In airport screening, Millimeter Wave Screening Technology, which identifies anomalous items outside of an individual's body using millimeter wave electromagnetic energy, was first patented in 1995 [6,7]. This Advanced Imaging Technology (AIT) was first implemented by the Transportation Security Administration in January 2008 and has been shown in studies to be advantageous over comparable walk-through metal detectors (WTMD). AIT is able to detect non-ferrous threats, such as improvised explosive devices and also ceramic knives, which WTMDs cannot detect [8]. As with many security technology advancements, while Millimeter Wave Screening is able to detect a wider range of potential threats, it falls behind WTMDs in other categories when thinking about deployment. A new Millimeter Wave AIT costs $430,000 in addition to the cost of maintenance and staffing [9]. A standard WTMD costs just $3,500 [11]. AIT systems also can have longer screening times required. This can be a reasonable tradeoff for airline travel, where there is less total traffic and a culture of ensuring a buffer period for security, but this increased wait time would create potentially immense commute travel delays for rail transit. The implementation of AIT and other TSA-style screening elements in a standard Connecticut Metro-North commuter station in New York City was shown to result in 66 out of 100 passengers missing their train due to the increased screening time, despite them arriving at the station an hour before the scheduled train departure [11]. If these screening methods were implemented at the commuter rail and subway stations, they would result in much longer commutes, less utilization of public transit, and reduced mobility of those without access to a personal automobile.

Considering the screening speeds required for deployment of AIT and WTMDs, as studied in Beijing and Connecticut, a technological advancement of note is the incorporation of artificial intelligence into the walk-through screening. Such technologies aim to use past data and machine learning techniques to reduce false positives and increase screening throughput in a familiar form factor. At least one manufacturer has technology that claims to have faster screening thanks to the combination of AI and electromagnetic sensors. The technology claims to screen up to 3,600 patrons per hour, which is 10 times the maximum capacity of a WTMD and does not require the removal of common items from pockets or the separate screening of bags [12]. While this technology is promising, claiming to have already screened over 200 million individuals, its feasibility for deployment in subway and rail station environments would still be challenging. The system can only sustain two lanes directly next to each other. In subway stations, where there are often six or more turnstiles operating simultaneously, space limitations could lower throughput to unacceptable levels. The technology has also not been shown to be effective in high- vibration environments, such as near train tracks. For any sensor system to be effective in a metro environment, it must be highly robust to vibrations.

5. DATA ANALYSIS AND VISUALIZATIONS

New York City

New York City is an ideal location to pilot a public transit mass- casualty risk model. The city, being the most populous and thus having one of the largest tax bases in America, has the resources to develop the subway system with the world's most stations, in addition to the ability to create and publish enormous amounts of public data [13]. New York City also features the highest public transit ridership in the United States [14]. The alignment of high public transit ridership, thorough public data collection, and a high-value target for terrorist threats in New York makes it a strong market for the evaluation of the viability of a public transit mass-casualty route risk model.

The risk models we studied heavily relied upon geospatial data to develop their models. The risk assessments used many different levels of quality of data. Risk Terrain Modeling (RTM) utilizes many layers of GIS data, requiring the addresses or coordinates of incident locations and risky places to determine spatial risk [15]. Other risk assessment models use similar geospatial data regarding risk incidents but do not share the many layers of place data used by RTM [15, 16]. Subway and rail routes have highly localized entrance and exit points. High-risk events or locations only must be associated with one or more nearby stations, potentially reducing the precision required. This was shown in the TCRP Tools and Strategies for Eliminating Assaults Against Transit Operators user guide, where the focus was on constructing risk for a route and its constituent stations rather than for arbitrary locations in the city [17].

Focusing on publicly available datasets with these precise and imprecise standards for location data allows us to use a wide variety of data. As seen in Figure 3, Historic and up-to-date data on entries into the New York Police Department (NYPD) 911 system, their improved computer-aided dispatch system (ICAD), are available with over 29 million instances of coordinate-bound events like reported gun crimes, narcotic sales, suspicious packages, and Train Order Maintenance

Sweeps (TOMS) during which police officers investigate a train and its platform for terrorist activity.

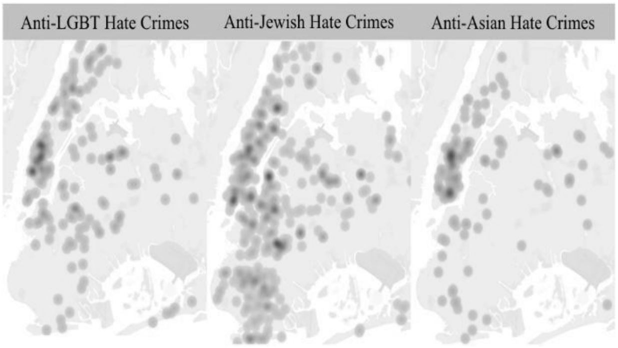

Figure 2: Density map of Anti-LGBT, Anti-Jewish, and Anti- Asian hate crimes illustrating the neighborhoods where they were most common in the New York City region.

Historical complaint data for 7.8 million valid felony, misdemeanor, and violation crimes, as well as a subset of those complaints considered hate crimes, were available dating back to 2006. The density and location of select hate crimes are shown in Figure 2. Combined with subway route and station geospatial data, Census data, and hate crime data, these datasets alone could prove a useful component of a pilot risk model. New York City and other organizations provide many other potentially useful public datasets as well, such as those on the bicycle movement, demographics, and land use data.

Figure 3: A comparison of the density of Train Order Maintenance Sweeps (TOMS) and transit-bound suspicious packages by location shown for the New York City region.

New Jersey

New Jersey is the fourth smallest state in America, but it is a heavily populated state. It has a population density of 462.36 persons per square kilometer [19]. The New Jersey government has created a mass transit system; individuals can travel to large neighboring cities out of the state, New York City and Philadelphia. New Jersey Transit (NJ Transit) is the state's public facility, and it manages three separate lightweight rail systems, eleven commuter rail lines, and a bus system [20]. Other transportation routes in NJ include the Port Authority Trans- Hudson (PATH), which connects Manhattan and northeastern New Jersey, the PATCO Speedline, which connects the downtown Philadelphia urban center to various cities in New Jersey, Amtrak operates intercity rail on the Northeast passageway between the main population centers of the Northeastern United States [20]. New Jersey is also home to Newark Liberty International landing field, the country's fifth busiest international entrance. New Jersey also houses the Port Newark-Elizabeth Marine Terminal, a large ship facility within the New York metropolitan space [20].

New Jersey was also an ideal state to create a risk analysis model, as there are many vulnerabilities to all forms of public transportation. However, the real challenges for this project start when realizing that even the densely populated parts of New Jersey are still vastly less populous than nearby New York City, and this greatly affected the number of publicly available datasets that we were able to find. With fewer people, the available datasets on New Jersey transportation, census, and crime are also smaller, which makes our analysis more difficult.

Datasets from transportation information (i.e., NJ Transit stops, stations, and routes), crimes and terrorist attacks; terrain and geographical data, and detailed census data were all utilized to some degree and used to create visualizations to better understand New Jersey. One promising dataset was the hate crime dataset. This dataset had 20,000 incidents from the years 1991 to 2020; this helped further indicate certain trends in crimes before and during the COVID-19 pandemic [21]. Using this hate crime dataset and merging it with other datasets, domestic violence, terrorist attacks, and gun violence have proven to be very useful for data visualizations and clustering and may prove beneficial for future geographical risk analysis modeling.

Figures 4, 5, and 6 are some of the visualizations created from reported hate crimes in New Jersey from the years 2015 to 2020. These show maps of hate crimes and were created using the software FME (Feature Manipulation Engine), which allows users to efficiently convert spatial data between digital and geometric formats.

These three visualizations are shown below to display that since 2017, there has been a significant increase in hate crimes. Since the start of the COVID-19 pandemic, this trend has unfortunately continued. COVID-19 is believed to have emerged in Wuhan, China, in late December 2019 and began rapidly spreading around the globe throughout the spring months of 2020 [23]. As COVID-19 proliferated across the United States, Asian Americans reported a surge in racially motivated hate crimes involving physical violence and harassment [23]. This explains the spike in hate crimes around the country and in New Jersey. However, one interesting trend from Figure 6 illustrates that in 2020 the number of reported hate crimes occurring on public transit actually decreased. This may be simply because transit ridership during the lockdown and in the early pandemic greatly decreased.

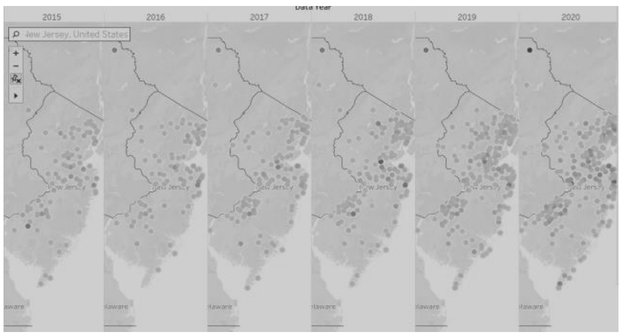

Figure 4: All reported hate crimes in New Jersey from 2015 to 2020.

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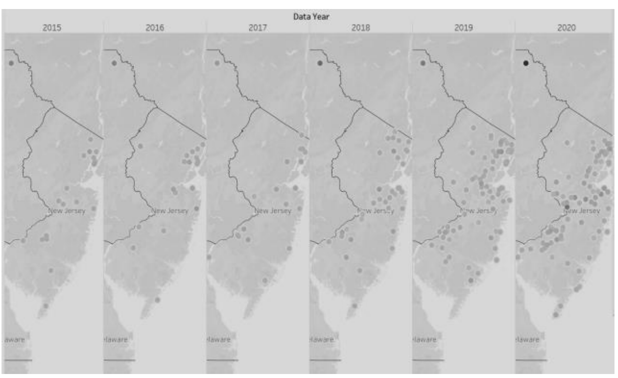

Figure 5: All reported hate crimes in New Jersey from 2015 to 2020, showing just those near public locations: public transportation, airports, buses, trains, government buildings, public buildings, highways, alleys, roads, and sidewalks.

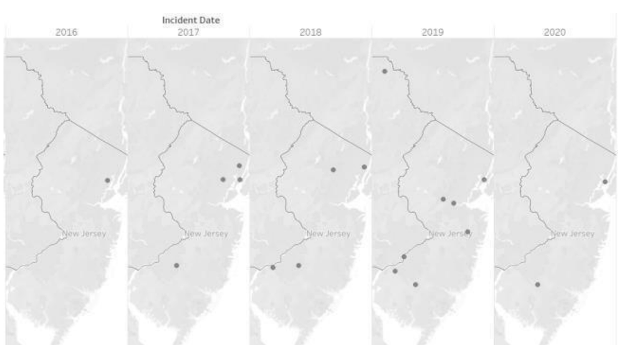

Figure 6: All reported hate crimes in New Jersey from 2016 to 2020, showing just those nearby public transportation locations: airports, buses, and trains.

Figures 7, 8, and 9 are the other visualizations created from various datasets on census [26], traffic [27], and domestic violence [28]. These figures were also created using the software FME and Tableau. They offer more insight into understanding New Jersey to better improve the security needed to be implemented in certain areas.

Using different datasets allowed for the exploration and better understanding of where people live in New Jersey, and how this affects public transportation, specifically the NJ Transit routes. Figure 7 shows a heat map of different racial groups and where they are concentrated throughout New Jersey. Most citizens live in the northern part of the state, however, there is also a significant population living in the southwest part of New Jersey.

The dataset used in Figure 7 can be utilized to understand the different types of housing, income, and different types of crimes that are more likely to happen. From Figures 4 and 9, security and surveillance are critical in highly populated areas, as they are more prone to crimes, so potentially vulnerable to becoming a target for attacks on public transit.

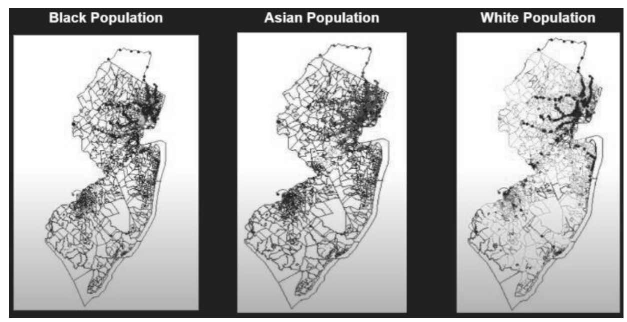

Figure 7: Using government census data from 2010-2012 to filter out the racial populations in New Jersey, we layered the population density over the dark outline of NJ Transit Rail Stations and their railway paths throughout New Jersey.

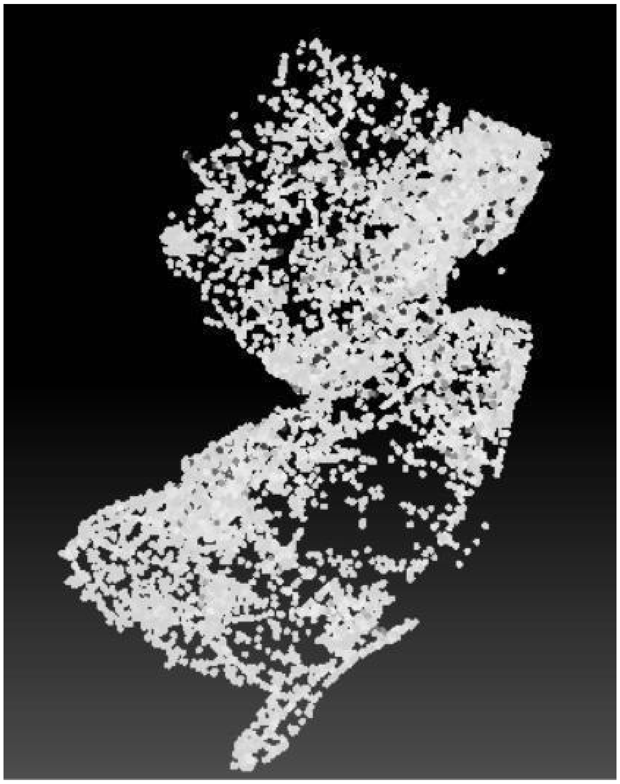

Figure 8: Density map for road traffic in New Jersey using the specific latitude and longitude coordinates of traffic density within each county.

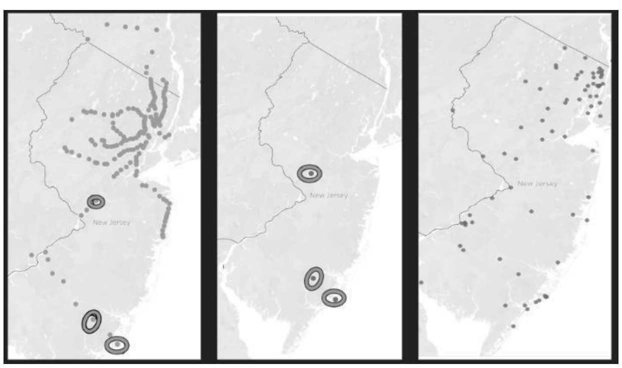

Figure 9: Map of NJ Transit Rail Stations (Left). Domestic violence incidents that took place at rail stations (Center). All the domestic violence that was reported in 2019 in New Jersey (Right).

Through our research, we have analyzed publicly available data to begin to identify datasets and data attributes that may be useful in a proof-of-concept model which would identify public transit stations or locations that may be a target or have heightened risk of a mass-casualty attack. In order to achieve this goal, we began doing early clustering analysis of our data utilizing the K-Means algorithm on the New Jersey data. The K-Means algorithm is an iterative algorithm that tries to partition the dataset into pre- defined distinct non-overlapping subgroups (clusters) where each data point belongs to only one group [24]. Using this algorithm allows for locational clustering of all the collected crime datasets based on latitude and longitude coordinates to identify what parts of New Jersey are more likely to face crimes, and this would help to continue to find trends, including where they are more at risk of happening.

Figure 10 was created using K-Means clustering analysis and was applied to a dataset of individual mass shootings that occurred between 2020 and 2023, sourced from the Gun Violence Archive database [29]. The clustering was performed based on latitude and longitude coordinates, shedding light on regions in New Jersey with heightened incidents of mass shootings. Over this four-year period, there were a total of 37 documented mass shooting instances in the state. The clustering algorithm was able to identify the number of mass shootings in certain cities in New Jersey, and this is depicted by the size of the data point representing the cities where the mass shootings happened. Figures 11 and 12 depict tables presenting clusters that correspond to different cities in New Jersey where mass shootings took place. Each cluster represents a group of cities sharing similar characteristics in terms of mass shooting incidents, offering valuable insights into the spatial distribution of these events across the state.

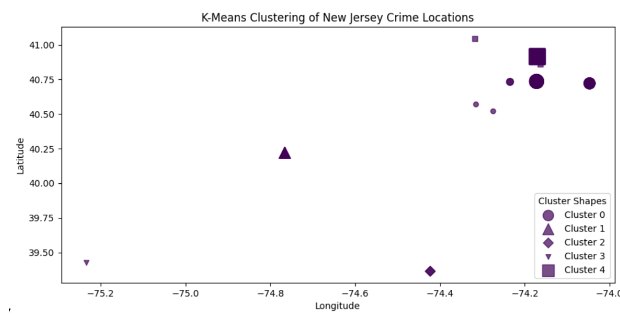

Figure 10: Clustering of mass shootings in New Jersey (2020-2023) by location, with data point sizes indicating the high number of crimes in a city.

Cluster	Atlantic City	Bridgeton	Clifton	Irvington	Iselin
0	0	0	0	0	0
1	0	0	1	0	0
2	2	0	0	0	0
3	0	1	0	0	0
4	0	0	0	2	1

Figure 11: Table displaying clusters representing cities with mass shootings in New Jersey.

Cluster	Jersey City	Newark	Passaic	Paterson	Perth Amb	Trenton
0	0	0	0	0	0	5
1	0	0	1	10	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	5	8	0	0	1	0

Figure 12: The continuation of the table displaying clusters representing cities with mass shootings in New Jersey.

6. CONTINUATION AND FUTURE WORK

The current state of surveillance and security measures in public transit, such as high-traffic subway and train stations, are vulnerable to mass casualty and terrorist attacks. In recent years, since the start of the pandemic, violent crime rates (i.e., shootings) have grown, and this has greatly affected public transportation. Exploring the new and emerging screening technologies and publicly available datasets around the New York City region and New Jersey, crime, transportation, and census data can be utilized to create a predictive model that can assess what stations are more at risk. This would involve using a risk analysis model to make these predictions. The end goal of this project, and potential future work, is to use the predictions and understanding of different types of active and passive security measures to improve public transit stations with no adverse effect on passenger throughput.

Although the current results from this research are approaching the creation of the risk analysis model, there are many steps that are necessary to complete before model creation.

The main iterations can be divided into the following:

1) Census Data Integration
- Finding the census blocks from coordinate points and adding them to each instance

2) Station-Based Clustering
- Association of factors from the census, hate crime, and other datasets, with each station's risk, weighted by distance

3) Route Risk Assessment (Risk Analysis Model)
- Calculating the risk of each route based on its stations

7. CONCLUSION

The goal of our work was to use existing methods and models to create a plan for risk analysis modeling, which would increase security knowledge and help identify measures as needed for public transit in the New York City and New Jersey regions. This proof-of-concept model would offer local governments and transit leaders a way to improve and enhance their public transit safely.

In the evaluation of contemporary security check systems and technologies, we have found that improving security in subway systems with high throughput that are high-value targets, like the New York subway system, is difficult with a traditional security check system. The slowing of passenger throughput would bring a city in which a large proportion of its citizens rely on public transit for mobility to a grinding halt. Until faster active screening technologies which can operate effectively in the high vibration, metro environment are developed, passive screening technologies may need to be used instead. While computer vision and AI-assisted facial recognition face technological and societal acceptance hurdles, we believe that a data-driven mass-casualty transit risk model has the potential to be implemented more immediately upon development to improve passive policing and improve transit safety.

8. ACKNOWLEDGMENT

The Authors would like to thank HDR TRIPODS award CCF- 1934924 for funding this project as well as the DIMACS REU program, and the Rutgers Externship Exchange program.

9. REFERENCES

[1] T. P. DiNapoli. "Financial Outlook for the Metropolitan Transport Authority," **Metropolitan Transport Authority**, New York, New York, United States of America. Report 10-2022, September 2021. Available: https://www.osc.state.ny.us/files/reports/osdc/pdf/report-10-2022.pdf

[2] "List of Terrorist Incidents involving Railway Systems," (2022, April 2). In **Wikipedia**. Available: https://en.wikipedia.org/w/index.php?title=List_of_terrorist_inc idents_involving_railway_systems&oldid=1080832691

[3] Colin Moynihan, "He Was Trained by Al Qaeda to Bomb the Subway. Then He Switched Sides.," **The New York Times**, Section A, Page 22. May, 2019.

[4] Zhang X, Wei Z, Wang W, Liu S, Qiu S. Paced Inspection Process Design of Security Check System in Beijing Subway. **Transportation Research Record**. 2017;2604(1):95-103. doi:10.3141/2604-12

[5] Charles Liu, "Extra Security Causes Massive Queues on Beijing Metro as Plenum Approaches," **The Beijinger**. October 16, 2017. Available: https://www.thebeijinger.com/blog/2017/10/16/beijing-metroflooded-massive-crowds-plenum-approaches

[6] "Millimeter Wave Technology at a Glance." Pacific Northwest National Laboratory, U.S. Department of Energy. February, 2022. Available: **Proceedings of the 14th International Multi-Conference on Complexity, Informatics and Cybernetics (IMCIC 2023)** 77 https://www.pnnl.gov/nationalsecurity/millimeterwave/learn_more.stm

[7] Patricia F.S. Cogswell, "Use of Advanced Imaging Technology at Checkpoints," **Transportation Security**

Administration, U.S. Department of Homeland Security. May 10, 2019. Available: https://www.dhs.gov/sites/default/files/publications/tsa_-_use_of_advanced_imaging_technology_at_checkpoints.pdf

[8] S. S. Ahmed, "Microwave Imaging in Security — Two Decades of Innovation," in **IEEE Journal of Microwaves**, vol. 1, no. 1, pp. 191-201, Jan. 2021, DOI: 10.1109/JMW.2020.3035790.

[9] Stewart, Mark G and Mueller, John. "Cost-Benefit Analysis of Advanced Imaging Technology Full Body Scanners for Airline Passenger Security Screening" **Journal of Homeland Security and Emergency Management**, vol. 8, no. 1, 2011, pp. 000010220215477355 1837. https://doi.org/10.2202/1547-7355.1837

[10]"Walk-Through Metal Detector for Concerts/Events," **Blue Grass Wholesale**, Amazon.com. July 27, 2022. Available: https://www.amazon.com/Walk-Through-Metal-DetectorConcerts-Events/dp/B07GC5C457

[11] L. Fiondella, S. S. Gokhale, N. Lownes and M. Accorsi, "Security and performance analysis of a passenger screening checkpoint for mass-transit systems," **2012 IEEE Conference on Technologies for Homeland Security (HST)**, 2012, pp. 312-318, doi: 10.1109/THS.2012.6459867.

[12] "Evolv Express," **Evolv Technologies**. July 26, 2022.Available: https://www.evolvtechnology.com/products/evolvexpress

[13] "List of Metro Systems," (2022, July 28). In **Wikipedia**. Available: https://en.wikipedia.org/w/index.php?title=List_of_metro_systems&oldid=1100909754

[14] "List of U.S. cities with high transit ridership," (2022, March 20). In **Wikipedia**. Available: https://en.wikipedia.org/w/index.php?title=List_of_U.S._cities_with_high_transit_ridership&oldid=1078215571

[15] Kennedy, L.W., Caplan, J.M. & Piza, E. Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies. **J Quant Criminol** 27, 339–362 (2011). https://doi.org/10.1007/s10940-010-9126-2

[16] George Mohler, "Marked point process hotspot maps for homicide and gun crime prediction in Chicago," **International Journal of Forecasting**, Volume 30, Issue 3, 2014, Pages 491-497, ISSN 0169-2070, Available: https://doi.org/10.1016/j.ijforecast.2014.01.004.

[17] National Academies of Sciences, Engineering, and Medicine 2018. Tools and Strategies for Eliminating Assaults Against Transit Operators, Volume 2: User Guide. Washington, DC: **The National Academies Press**. Available: https://doi.org/10.17226/25114.

[18] "The Fourth Regional Plan." **RPA**, https://rpa.org/work/reports/the-fourth-regional-plan.

[19] "New Jersey Population Density, 1990-2021." **Knoema**, https://knoema.com/atlas/United-States-of-America/New-Jersey/Population-density.

[20] "Transportation in New Jersey." Wikipedia, **Wikimedia Foundation**, 5 Mar. 2022, https://en.wikipedia.org/wiki/Transportation_in_New_Jersey.

[21] "National Incident-Based Reporting System (NIBRS) Tables." **Crime, Federal Bureau of Investigation Crime Data Explorer**, https://crime-dataexplorer.fr.cloud.gov/pages/downloads.

[22] "Oxford Languages and Google." **Oxford Languages**, https://languages.oup.com/google-dictionary-en/.

[23] Gover, Angela R, et al. "Anti-Asian Hate Crime during the COVID-19 Pandemic: Exploring the Reproduction of Inequality." **American Journal of Criminal Justice : AJCJ**, Springer US, 2020, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7364747/.

[24] Dabbura, Imad. "K-Means Clustering: Algorithm, Applications, Evaluation Methods, and Drawbacks." Medium, **Towards Data Science**, 10 Aug. 2020, https://towardsdatascience.com/k-means-clustering-algorithmapplications-evaluation-methods-and-drawbacksaa03e644b48a.

[25] Best Practices in Anti-Terrorism Security for Sporting and ... **CCICADA A Department of Homeland Security University Center of Excellence**, 2013, https://safetyact.gov/externalRes/refdoc/CCICADA%20BPATS.pdf.

[26] U.S. Department of Commerce, U.S. Census Bureau. "Census Tracts (2010) in New Jersey, Edition 20140523 (govt_census_tract_2010)." The Official Web Site for The State of New Jersey, **U.S. Department of Commerce, U.S. Census Bureau**, Geography Division, Geographic Products Branch, 1

Jan. 1970, https://nj.gov/dep/gis/digidownload/metadata/statewide/Govt_census_tract_2010.html.

[27] “Annual Average Daily Traffic by Location and Route: NJOIT Open Data Center.” Data.nj.gov, **NJOIT Open Data Center**, https://data.nj.gov/Transportation/Annual-AverageDaily-Traffic-by-Location-and-Route/dfun-zupj.

[28] “Domestic Violence Reports.” NJ.gov, **New Jersey State Police**, https://www.nj.gov/njsp/ucr/domestic-violence-reports.shtml

[29] “MASS SHOOTINGS.” gunviolencearchive.org, **Gun Violence Archive**, https://www.gunviolencearchive.org/mass-shooting