# TransportAItion: AI and the Environment Final Report

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# Introduction

## Background and Context

Air pollution is a critical concern globally, as it has extremely large impacts on humanity's health and the environment. It is one of the most common and relevant types of pollution and is increasingly concentrated in urbanized areas. These urbanized regions have exponentially increasing populations where large industrial activities centralize, exacerbating the negative effects of pollutants. The World Health Organization (WHO) has identified air pollution to be the largest environmental risk factor to humans, attributing to over 4.2 million premature deaths per year due to the exposure to air pollution (WHO, 2020). Traffic-Related Air Pollution (TRAP) is a web of pollutants emitted by vehicles which include nitrogen oxides and carbon monoxide. According to recent studies, TRAP holds a substantial factor in the matter of urban air pollution and pose severe health risks to those residing near high-traffic areas (Gurjar, et al. 2016).

Some currently implemented strategies to address these issues include Artificial Intelligence Guided Autonomous Vehicles. Vehicles that have self-driving features utilize AI to find and go through the best route for traffic optimization and reduce greenhouse gas emissions (AI for Good, 2021). This paper aims to find a solution towards alleviating the root cause of air pollution in urbanized areas by decreasing amounts of traffic through implementation of public transportation planning to increase its usage by commuters. This will be done through an AI system that implements ACT-R at a very basic level in terms of decision making to incorporate an ethical and ubiquitous form of transportation catered towards benefiting all people in the midst of a racialized society with a vast difference in the sociocultural structures.

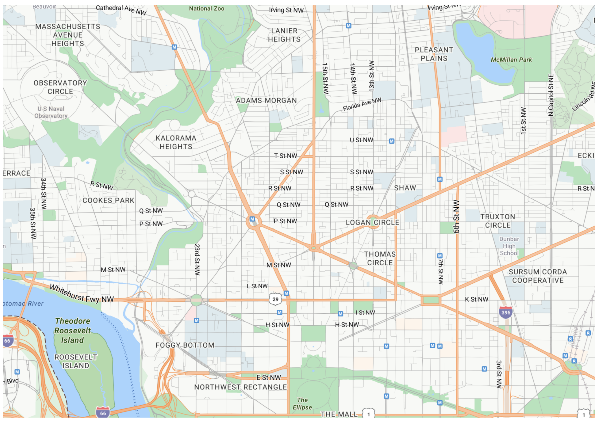
# Description of System

## System Architecture

The AI system we have designed encompasses a multi-staged process that derives actionable insights from map images. Our system architecture integrates various algorithms and techniques to transform raw map data into a comprehensive and informative format to place train stations in up and coming urbanized areas. Given a map of an urbanized location with population data, optimal locations for train stations are determined based on clusters that are found to be suitable. The system begins by taking in an image of a map of an urbanized area, preferably limited to an area of a city in the downtown area. For the sake of the example we will use within this paper, Washington D.C. will be the city utilized as the urban location.

Figure 1

*Example of input map to AI system of Washington D.C.*




Following this, K-means clustering will be run as an algorithm on the map that was inputted. This means that there will be two categories based on the characteristics of the terrain, distinguishing specific areas:

1. Areas such as bodies of water or other impassable and unnavigable spaces
2. Navigable spaces such as streets and pathways

The resulting grayscale mapping based on the categorization of the terrain simplifies the map so it is visually comprehensible, aiding the understanding and analysis. The following figure shows an example of a map being simplified to a grayscale map.

Figure 2

*Example of grayscale mapping on Washington D.C.*


Weighted values based on population density data obtained from Global Human Settlement Layers are placed onto the grayscale map, where higher density population areas receive proportionally higher weights. K-means clustering is then implemented, as it is a uniform weighted point placement algorithm and the places positions points across the map. This clustering approach algorithm was tested on the top 10 largest cities in America, and some outlier cities focused on downtown areas in smaller sections. An elbow method graph was produced from it, resulting in around 2-4 clusters from all the cities on average, hence we opted for 3 clusters to maintain a balanced representation across various urban topologies. The points are distributed based on the density of the weighted areas, accentuating high-density regions. This means that more points would be placed in higher weighted areas, to accommodate for the higher population density in those areas. A critical aspect of our system lies in the utilization of a weighted Voronoi diagram for point placement. The diagram, using the information from K-means clustering and population density data, enables strategic point allocation. This method yields a modified map representation of cities, offering insights into terrain features, population distribution, spatial density, and optimal areas to place train stations.

The resulting image outputted from the AI system is shown below in Figure 3, where the blue dots represent the train stations. The boxes surrounding the blue dots through the black lines (the intersecting points of those lines are indicated through orange points) represent the areas in which people should go to said train station. This is determined through the population density data, and the population density map shows that for the regions in which areas of higher density have smaller regions to go to said train station (the blue dot)

Figure 3

*Output image from the AI system compared with a population density map*

**Connection to Introduction Module**

In Herbert Simon's *Architecture of Complexity*, Simon emphasizes the modularity of complex systems, where smaller, interconnected modules perform specific functions. In our AI system, there are several small and distinct modules which handle separate functions such as image processing, clustering, weighting, and point placement. Each module focuses on a particular aspect of map analysis, which ultimately contributes to the overall functionality of the system. In a similar thought, Simon highlights the role of feedback mechanisms in complex systems- the AI system utilizes the clustering algorithm based on the feedback from diverse urban landscapes and adjusts the points based on the distance from other points.

**Connection to Cognitive Science Module**

In *Intelligent Behavior in Humans and Machines* by Pat Langley, fundamental concepts rooted in cognitive science such as decision making and problem solving are discussed. Ultimately, there are many ways models mimic decision making similarly to those that humans do. One of such ways that the AI system described in this paper does is through a decisive set of steps, from determining plausible locations points can be placed through K-means grayscale mapping followed with optimal clustering and placing points based on population densities and the distance from previous points that had already been placed. Furthermore, like explained in

Simon's emphasis on the importance of modules, ACT-R has a similar approach to cognition which our AI system implements.

## Connection to AI & Human Module

Based on Steven Cave's *The Whiteness of AI,* train station locations based on the inputted map and population density data sets could pose concern for biases in artificially intelligent systems. In his paper, Cave argues that AI is predominantly portrayed as white, which reflects already existing societa l biases. When choosing suitable train station locations, the biases inherent in AI algorithms could invertedly arise in the train station suggestions. By using historical data, patterns for urban development could alter calculations and reflect existing biases. Current transportation infrastructures often reflect this bias, and can sometimes prioritize efficiency and revenue over addressing implicit biases. Our project takes a more ethical approach to selecting train stations, by avoiding socioeconomic and racial biases. This aligns with Cave's critical evaluation of the societal impact of intelligent systems, and mitigates potential biases within the AI decision-making process (Cave & Dihal, 2020).

## Connection to AI in Context Module

Bender et al. highlights certain limitations of Large Language Models (LLMs), calling them "stochastic parrots." This term describes existing model's tendencies to produce content without actually understanding the underlying context. According to Bender, many models produce text that lacks true reasoning and simply generates responses. This raises ethical concerns for using such systems when presented with important decision-making situations (Bender, et al. 2021).

Although Bender's critique focuses on LLMs, the underlying message can apply to a more broader AI community. Our group avoids these concerns by using a more structured model. Namely, the AI system employs k-means clustering, which clusters the maps because of their characteristics. By using a structured decision-making process, our solution becomes more transparent than existing solutions and avoids the black-box nature that Bender describes in LLMs.

## Cognitive Systems and the Common Model of Cognition

The common model of cognition presents an approach to human cognition that models the way a brain works by taking a modular approach. Specifically, our system uses ACT-R, which is a way to use different modules that specialize in specific cognitive functions. Within ACT-R, our system uses the Where System, which serves as a component to handle visual-location buffers that locate specific relevant features in the visicon (Bothell). The way we use the ACT-R framework shares the idea of using cognitive processes that contain specialized modules with Laird's "Standard Model of the Mind." The Where function is a specific module within the broader cognitive architecture (Laird, 2017).

When selecting suitable terrain, the Where System facilitates different locations and makes selections based on certain constraints. For example, a train station should not be placed in the middle of an ocean. The visicon contains information about terrain that has been clustered, and locates those which are suitable for train stations. When one of these locations is identified, the object gets stored in the visual-location buffer. This highlights the modular nature of the ACT-R framework by picking a specific module that processes information for a certain state of the train location decision pipeline.

## The Man Genre of the Human in AI

Sylvia Wynter's concept of "Man" has certain implications for understanding human identity. Her essay, "Unsettling the Coloniality of Being/Power/Truth/Freedom," describes Man1 and Man2. These ideas challenge the exclusionary nature of the concept of "Man," with Man1 representing a Eurocentric, colonialist, and patriarchal conception of humanity and Man2 representing the potential for an alternative. When designing an AI system, the goal is to achieve "a more inclusive form of being" that breaks free from the colonialist mentality (Wynter, 2003).

When designing a system for train station locations, the Man1 perspective would have data that reflect historical patterns of development. It might suggest train station locations in mostly affluent areas. The result of this would be a concentration of resources in already well-developed areas that only further marginalize communities. Currently, some infrastructures are closer to the Man1 perspective, which contributes to social injustice in modern public transportation.

Designing a train station with the Man2 perspective in mind would mean that the dataset would include the entire scope of community needs. If done correctly, the AI would be able to address commuter needs of a wider spectrum of people. This is achieved in our project by utilizing a dataset that lends itself to a wider population. Once the data is selected, mathematical decisions are made that limit the distance from train stations to those who are most marginalized by ending up on the outskirts of a station's respective region.

## Conclusion

### Summary of Key Findings

In summary, our AI system addresses the issues of air pollution in urbanized areas by placing train stations determined through a variety of processes. Using K-means clustering, weighted Voronoi diagrams, and ACT-R, the system is able to pick train station locations based on population density. Inspired by Herbert Simon's Architecture of Complexity, our system uses a modular approach. Our AI system mitigates bias, enhances transparency, and promotes more ethical decision-making for AI systems. For these reasons, the project closely aligns with Steven Cave and Sylvia Wynter's call to recognize more diverse perspectives.

### Future Work

While our AI system addresses air pollution by promoting ethical transportation planning, there is still more room for future enhancements. Currently, our solution doesn't address the need for routing between stops because it was out of scope for our project based on our timeline expectations. A more advanced solution would be to also assess train station placement based on how easy it is to route them together, overall decreasing air pollution by making rides take less time. Another approach would be to make the first point placed a central hub and then use an algorithm that builds outward from a desired starting point. Generally, more data about commuter preferences and geographical anomalies would help to create a system with a better accuracy for suggesting suitable spots.

### Concluding Thoughts

In conclusion, our AI system combats air pollution in urbanized areas. The system not only shows promise for reducing traffic-related air pollution, but also emphasizes the importance of making ethical considerations that make public transportation more accessible and allows a wider spectrum of people to utilize this kind of transportation. As a proof of concept, our system shows that connecting transit systems can be done in a transparent way, and as a result, we have paved the way for future work to be done on such algorithms. Ultimately, our project navigates the complex challenges present between AI and the environment, and keeps ethical considerations in mind to gain a broader understanding of humanity while designing efficient systems.

# References


aiforgoodstg2. (2021, September 2). *8 ways ai can help save the planet*. AI for Good. https://aiforgood.itu.int/8-ways-ai-can-help-save-the-planet/

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots. Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency. https://doi.org/10.1145/3442188.3445922

Bothell, D. (n.d.). ACT-R 7.26+  Reference Manual. ACT-R. http://act-r.psy.cmu.edu/actr7.x/reference-manual.pdf

Cave, S., & Dihal, K. (2020). The whiteness of ai. Philosophy & Technology, 33(4), 685–703. https://doi.org/10.1007/s13347-020-00415-6

Gurjar, B. R., et al. (2016). Air pollution trends over Indian megacities and their local-to-global implications. Atmospheric Environment, 142, 475–495.

Laird, J. E., Lebiere, C., & Rosenbloom, P. S. (2017). A standard model of the mind: Toward a common computational framework across artificial intelligence, Cognitive Science, Neuroscience, and Robotics. AI Magazine, 38(4), 13–26. https://doi.org/10.1609/aimag.v38i4.2744

World Health Organization (WHO). (2020). Ambient air pollution: A global assessment of exposure and burden of disease. WHO Press.

Wynter, S. (2003). Unsettling the coloniality of being/power/truth/freedom: Towards the human, after man, its overrepresentation--an argument. CR: The New Centennial Review, 3(3), 257–337. https://doi.org/10.1353/ncr.2004.0015