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Promoting Equitable AI Applications in Transportation

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The goal of this project is to advance understanding of AI's potential in transportation and provide practical knowledge that can promote equitable applications of AI technologies in transportation. The project has three main tasks: 1) Provide a synthesis of the fundamental concepts in AI and sources of AI bias; 2) Conduct a literature and practice review of the existing AI applications in transportation; 3) Survey transportation professionals to understand their perceptions of AI and their AI knowledge level. Specifically, we performed a literature and practice review of AI applications in transportation. We also surveyed transportation entities in both public and private sections to learn about their perception of AI systems, AI's potential impacts, the major barriers to widespread AI adoption, and their current knowledge level of and training in AI. The report also addresses the topic of equity and ethical considerations for AI applications in transportation. This research generates novel insights regarding the state of practice of AI adoption in transportation and identifies workforce development and future research needs.

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ABSTRACT

Artificial intelligence (AI) is revolutionizing human society and the transportation sector. The USDOT Intelligent Transportation System (ITS) Joint Program Office has identified 60 AI-enabled applications in transportation. While AI has the potential to improve safety, efficiency, and reliability in transportation, there are challenges to its widespread adoption. The perception and acceptance of AI among transportation professionals, as well as equity and ethical concerns regarding AI bias, need to be addressed. However, our knowledge about these topics is quite limited at present. Little research has been conducted so far to connect the recent advances in AI technologies with key considerations of transportation applications.

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Keywords (up to 5): Artificial Intelligence, Transportation Equity, AI ethics, AI perception, Transportation Workforce

EXECUTIVE SUMMARY

Artificial intelligence (AI) is revolutionizing human society and the transportation sector. The USDOT Intelligent Transportation System (ITS) Joint Program Office has identified 60 AI-enabled applications in transportation. While AI has the potential to improve safety, efficiency, and reliability in transportation, there are challenges to its widespread adoption. The perception and acceptance of AI among transportation professionals, as well as equity and ethical concerns regarding AI bias, need to be addressed. However, our knowledge about these topics is quite limited at present. Little research has been conducted so far to connect the recent advances in AI technologies with key considerations of transportation applications.

The goal of this project is to advance understanding of AI's potential in transportation and provide practical knowledge that can promote equitable applications of AI technologies in transportation. The project has three main tasks:

- Provide a synthesis of the fundamental concepts in AI and sources of AI bias.
- Conduct a literature and practice review of the existing AI applications in transportation.
- Survey transportation professionals to understand their perceptions of AI and their AI knowledge level.

Findings from each task are presented in Sections 2, 3, and 4, respectively. In particular, **Section 2** starts by explaining the concept of artificial intelligence and the typical technical steps involved in developing AI algorithms. Then we delve into AI bias, discussing its increased prevalence and potential negative impacts. We also identify sources of bias in algorithms, such as biases in data collection and exploration, system design choices, and biases introduced in each phase of AI model development. Examples of bias types include measurement bias, institutional bias, design bias, and exclusion bias. Moreover, we discuss the concept of AI fairness, the various methods for measuring fairness (e.g., fairness through awareness, counterfactual fairness, and demographic parity), and the approaches for achieving fairness in AI algorithms as well as their pros and cons. Finally, we provide a brief description of three tools developed by tech firms to improve algorithm fairness: IBM'S AI Fairness 360, Microsoft's Fairlearn, and LinkedIn's Fairness Toolkit (LiFt).

Section 3 discusses the growing use of AI in the transportation industry, covering a variety of topics such as the benefits of AI, barriers to AI applications, AI ethics and equity concerns, and existing AI applications in several transportation domains. The potential benefits of AI applications in transportation are outlined, such as increased efficiency, reduced costs, enhanced accessibility, and positive environmental outcomes. For example, AI has been used to optimize traffic flow and the operation of transit systems. However, there are also major barriers to AI applications in transportation, including technical barriers such as the need for large amounts of data and infrastructure investments, the lack of skilled personnel, and the need to address public perceptions and concerns about AI.

Regarding AI ethics and equity considerations, there have been ongoing discussions and debates about establishing ethical frameworks for AI. For example, the European Union (EU) has established guidelines for AI development, and the focus areas include ethics, liability, data governance, and societal well-being. Trustworthy AI principles encompass respect for human autonomy, prevention of harm, fairness, and explicability. Corporate guidelines align with the FAST principles (Fairness, Accountability, Sustainability, Transparency) and prioritize transparency, justice, non-maleficence, responsibility, and privacy. However, there are still many unknowns about AI, and existing work guidelines often lack specificity for specific application areas. Moreover, the challenges of regulating general-purpose AI models such as ChatGPT highlight the difficulty in balancing regulation and technological development.

While there have not been extensive discussions on AI ethical frameworks in the transportation sector, the ongoing conversations about transportation equity and justice can inform how the transportation community should view AI applications. Historically, transportation investments in the U.S. have prioritized driving over alternative travel modes, and the goal of enhancing mobility (e.g., congestion mitigation) is often prioritized over enhancing access to destinations. Moreover, the transportation benefits and transportation-caused harms (e.g., air pollution) are not equitably distributed, with marginalized communities and population groups bearing disproportionate harms while enjoying fewer benefits. We believe that it is crucial to bring these perspectives into the development and design of AI applications in transportation.

The transportation industry has been increasingly incorporating AI applications in various areas. We have reviewed AI applications in four domains: traveler decision support tools, transportation systems management and operations, transit operations and management, and asset management. For example, AI is used to provide information and assistance to travelers in planning their trips, providing real-time traffic prediction and estimated times of arrival (ETA) estimates. AI is also used to optimize the performance, efficiency, and reliability of transportation infrastructure. Some traffic management centers have implemented AI technology to improve incident detection and response times. In transit operations and management, AI is used to enhance the performance of transit systems by enabling bus arrival time predictions, transit routing optimization, and transit signal priority system design. Finally, regarding asset management, AI is being used for rail track maintenance and inspection, rolling stock inspection, pavement condition detection, signage inspection, and curve safety detection.

The case study on the use of AI by the Delaware Department of Transportation (DelDOT) generates rich insights regarding the state-of-practice in AI applications by state transportation agencies. DelDOT has implemented AI into its Integrated Transportation Management System (ITMS) to improve the performance and efficiency of Delaware's transportation network. The AI technologies have been applied to control, monitoring, and information areas within the ITMS. An example is the use of AI systems, enabled by real-time traffic data, to predict traffic volumes up to an hour in advance. The challenges DelDOT faced with AI use mainly lie in workforce requirements, compatibility issues between AI systems and existing tools and infrastructure, and cost burdens introduced by additional infrastructure investments (e.g., smart sensors and serve clusters). DelDOT also noted the importance of ongoing education and outreach efforts to enhance media and public perception of AI technology. Finally, DelDOT has prioritized equity in AI implementation, aiming for inclusive data collection methods and fairness testing across various traffic scenarios.

In **Section 4**, we present results from a survey that collects information on how transportation professionals perceive Artificial Intelligence (AI), its potential impacts, and the major barriers to widespread AI adoption. The survey also asks respondents about their knowledge of and training in AI as well as some questions about equity and ethical considerations for AI applications in transportation.

The survey results indicate that most respondents believe that AI will be widely adopted in transportation planning and engineering practices within the next 5-20 years. There is particular optimism regarding the potential for AI applications in advanced driver assistance systems, automated driving systems, and transportation systems management and operations. Respondents also perceive more potential for AI in urban and developed areas compared to rural and underserved areas.

The major benefits of adopting AI in transportation, as perceived by respondents, include improved operational efficiency, reduced human error, and enhanced safety. Respondents largely agree that AI can lead to more efficient transportation services, cost-savings, and data-driven decision-making. They also believe that AI has the potential to automate routine tasks and improve labor productivity. However, there is some skepticism regarding AI's ability to remove bias in government decision-making processes and address social inequalities.

The main barriers to widespread AI adoption in transportation, as perceived by respondents, include the lack of trust in AI, insufficient strategic vision for AI across agencies, and a shortage of skilled staff trained in AI. Interestingly, resource and technical barriers such as computing resources and cybersecurity were not seen as the primary challenges.

The transportation professionals that responded to the survey have varying levels of knowledge in different AI-related domains. While respondents generally have limited knowledge of computer programming and AI concepts, they possess a higher level of familiarity with mathematics and statistics. Furthermore, their knowledge of data and computer infrastructure falls mostly in the medium range. Respondents expressed strong interest in learning more about AI use cases in transportation, AI ethics and equity concerns, and AI governance and performance evaluation.

There is widespread agreement among respondents that community engagement is crucial in the development of AI transportation systems and that biased datasets used for AI development can contribute to social inequalities. Most respondents also express concerns for AI algorithms to potentially exacerbate inequalities in transportation and reduce transparency in government decision-making processes. Furthermore, they believe that there is currently a limited understanding of AI ethics in the transportation community.

1.0 INTRODUCTION

Artificial intelligence (AI) is becoming an integral part of our daily lives, revolutionizing a variety of industries such as healthcare, advertisement, and transportation. In a July 2020 report, the USDOT Intelligent Transportation System (ITS) Joint Program Office identified 60 AI-enabled applications in ITS across 11 categories, covering various aspects of transportation that affect lives of almost all travelers. AI technologies can address ITS operational changes and transportation needs in a range of real-life scenarios such as multimodal corridors and underserved communities.

While AI holds a great potential to make transport safer, cleaner, more reliable, and more efficient, deploying AI to transform current transportation practices faces many challenges. Widespread adoption and deployment of AI in transportation requires the transportation community to accept and support it. However, as an emerging technology, AI is relatively new to many transportation professionals. Critical knowledge is lacking regarding how transportation professionals perceive AI's potential to transform transportation planning and engineering practices, AI's main application areas, the potential benefits to be delivered by AI systems, and the main barriers to AI adoption in transportation.

In addition, a major concern of AI is the issue of equity and ethics, considering that some existing AI applications such as facial recognition and résumés screening have shown high levels of bias. Accordingly, much research is underway in the scientific community to understand the causes of AI bias and to find solutions that address these biases. So far, while extensive research efforts are devoted to incorporating ethical and equity considerations into the design and development of AI systems, limited research has focused on the equity implications of deploying AI technologies across sectors. In the field of transportation, AI-enabled applications may lead to inequitable outcomes despite good intentions. For instance, a data-driven, AI-informed roadway maintenance decision-making procedure can cause the road infrastructure in disadvantaged neighborhoods to receive fewer investments; this happens when a lack of data results in a lower ranking of transportation facilities that are less well maintained, which are more commonly found in marginalized communities. Also, AI-based decision-support systems can lead to policies and decisions that leave out the needs of certain population groups if they are underrepresented in the data used to support decision-making.

1.1 Objectives

The goal of this project is to advance understanding of AI's potential in transportation and provide practical knowledge that can promote equitable applications of AI technologies in transportation. Given that AI technologies are transforming various transportation subfields, each of which has their own unique characteristics, to keep the project within a reasonable scope we have focused on AI's application in transportation planning and engineering. For example, while AI has widespread applications in vehicle automation, these are not included in the current study.

1.2 Scope

The project has three main tasks:

- Provide a synthesis of the fundamental concepts in AI and sources of AI bias.
- Conduct a literature and practice review of the existing AI applications in transportation.
- Survey transportation professionals to understand their perceptions of AI and their AI knowledge level.

The study approach involves conducting a systematic literature and practice review to synthesize the state-of-art practice in AI technologies, approaches in identifying and tackling AI biases, and case studies of AI applications in transportation. Moreover, through surveying and interviewing transportation agencies and professionals, we aim to gain a better understanding of the state of practice in AI development and deployment in the transportation sector, barriers to AI applications, how professionals have incorporated equity and ethical considerations in AI applications, and the level of transportation workforce readiness for widespread AI applications. In particular, this project addresses the following topics:

- Fundamentals of AI concepts
- Sources of AI biases, examples, and approaches to address AI bias
- Ethical principles of trustworthy AI
- AI applications in transportation
- Ethics and equity implications of AI applications in transportation
- Case studies of AI applications in transportation (e.g., asset management, transit operations, transportation systems manegement and operations, and traveler information)
- Implications of AI applications for transportation workforce development
- Future research needs regarding AI applications in transportation

2.0 FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE

2.1 What is Artificial Intelligence?

Artificial intelligence has had a long history starting from the 1950s with Alan Turing, a famous computer scientist, who created the Turing Test. It was a simple test that was meant to determine whether a computer could exhibit human behavior. At the time, artificial intelligence was unknown and there was simply not enough computing power for a computer to instantly compute data or processes large datasets. Artificial intelligence (AI) is now broadly considered as the ability for a computer program to perform processes that are associated with human intellect. In the 21st century, artificial intelligence rose to prominence due to the significant increase in computing power available and has become a more prevalent topic in scientific research and in our everyday lives. Researchers and people around the world believe that AI can bring the world considerable benefits from production and efficiency to a significant increase in the quality of life. AI has been used and is currently being used in a multitude of different industries such as the medical industry where researchers are trying to use convolutional neural networks to identify malignant patterns in different types of cancer, or in the financial industry where companies develop trading algorithms for stocks and utilize fraud detection for clients.

2.1.1 The Development Process of Artificial Intelligence

For the development process of AI algorithms, there are five phases that most researchers go through. The first phase is the **Study Design & Hypotheses Formulation** phase, which includes the overall study design and methods of sampling for the research project along with the researchers' hypotheses about the study. The next phase is the **Data Collection, Pre-processing, and Exploration** phase. In this phase, the researchers collect the data from their samples, pre-process the data, and then attempt to explain their data in the form of preliminary graphs and tables. The **Model Development** phase is the next phase where researchers attempt to convert their data from graphs and tables into a highly accurate machine learning model. The following phase, **Model Interpretation & Communication**, is about interpreting the results from the AI algorithm and being able to explain the results to someone else without skewing the results into your favor. The last phase is the **Model Validation, Testing, and Monitoring** which is about checking and ensuring the results for the machine learning model are accurate and representative to the population of which the datasets were taken from.

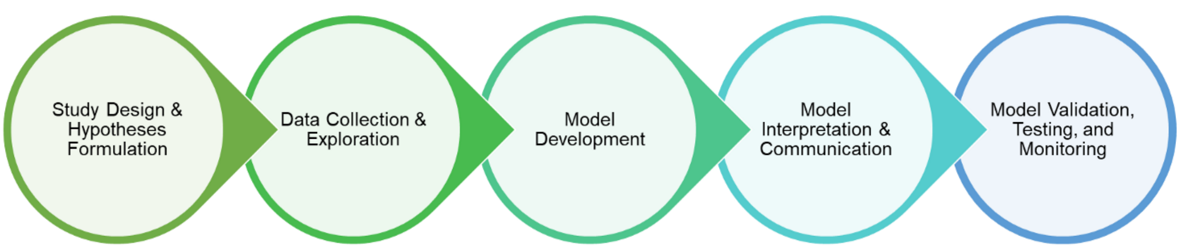


FIGURE 1: DEVELOPMENT PROCESS FOR AI ALGORITHMS
(Source: Srivastava, 2021)

2.2 AI bias

Bias is an older concept in society because it has been seen in many different types of fields such as in psychology, medicine, law, etc. Over the past few years, bias in artificial intelligence has become more prevalent today due to its potential to unfairly discriminate and negatively affect certain types of people. The general definition of AI bias is "the inclination or prejudice of a decision made by an AI system which is for or against one person or group, especially in a way considered to be unfair" (Ntoutsi et al., 2020). However, it is important to discuss how unintentional bias in AI algorithms can negatively impact a company's reputation. For example, in the medical field, there are multiple instances of data that was collected from patients that were skewed toward certain underprivileged populations involving medications (Wesson et al., 2022). With lives and social issues at risk, it is imperative to create a set of practices and guidelines to help guide developers of AI algorithms to avoid negatively affecting lives and creating social issues.

2.2.1 Sources of AI Bias in Algorithms

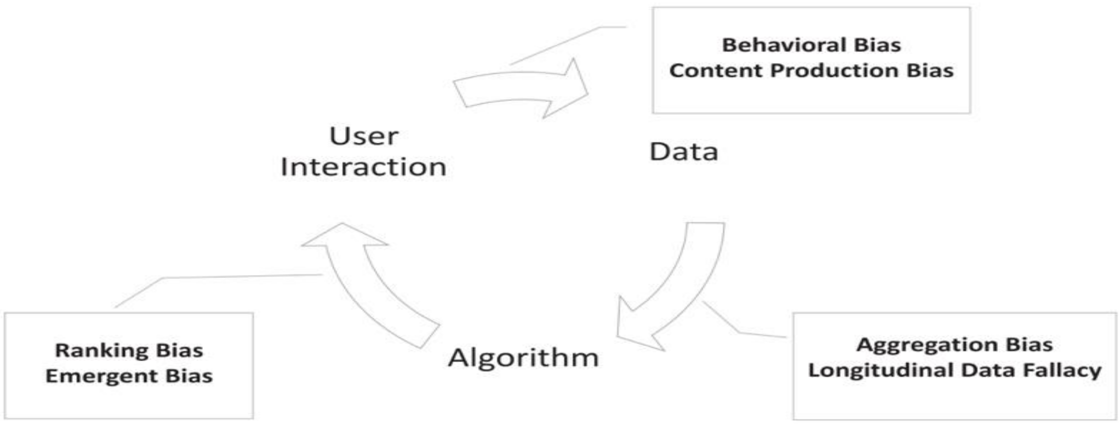


FIGURE 2: SIMPLE DIAGRAM OF BIAS INSIDE OF AI ALGORITHM.
(Source: Mehrabi et al., 2021)

AI bias can originate in multiple phases. Below we summarize the five phases of AI model development that can introduce bias:

Study Design & Hypotheses Formulation: There is the potential for there to be sampling or voluntary bias in this phase. Sampling bias occurs when a certain population of individuals or select type of individuals have a higher likelihood of getting sampled than other populations whereas voluntary bias is where individuals choose to be in the sample, essentially meaning that individuals who find the subject matter interesting will participate in the sample. An example of sampling bias would be a facial-recognition AI algorithm being trained with datasets that include more photos of light-skinned people than dark-skinned people, resulting in an algorithm that has poor results with recognizing dark-skinned people (Wilson, 2022). With bias originating this early in a project and in a phase that is commonly overlooked, it is often difficult and challenging for researchers to understand why an AI algorithm has failed to produce the results it was intended to when it is not.

Data Collection, Pre-processing, and Exploration: In order for an AI algorithm to be created, there needs to be training data that the algorithm can use to learn the patterns inside of the training data. The issues arise when the training data has underlying biases that are not initially visible to the professionals working with them. The algorithms will learn the biases associated with the data and make predictions with them. These issues typically form in the **Data Collection, Pre-Processing, and Exploration phase** (Wilson, 2022). Additionally, algorithms have the chance to amplify existing biases which can result in a bias reinforcement loop, with the algorithms gaining biased data back from users and using that data to make even more biased outcomes for users.

Certain system design choices can affect AI algorithm outcomes by introducing biases. One common type of bias that can originate in this phase is measurement bias. This occurs when the datasets used for training AI suffer from poor measurements. For instance, image and video datasets can reflect the techniques utilized by the photographer, such as a photographer shooting photos and videos from one particular point of view and certain angles. Additionally, the type of equipment used to capture photos or videos is a potential source of measurement bias. This is because the instrument used to capture the photos or videos could be defective or have low performance, resulting in lower quality images and poor AI algorithm decisions.

Another form of bias that can occur in this stage is institutional bias, where certain institutions tend to operate and conduct data collection on some ethnic groups rather than others. Design bias is a common type of bias that we see in AI system development due to the possibility of a sample being misrepresentative of a population. Also, exclusion bias is a type of bias that can occur during some AI system development. While investigating potential variables for the development of an AI system, it is possible for a researcher to undervalue the importance of a variable and consider the variable as irrelevant, which can lead to an inaccurate AI system.

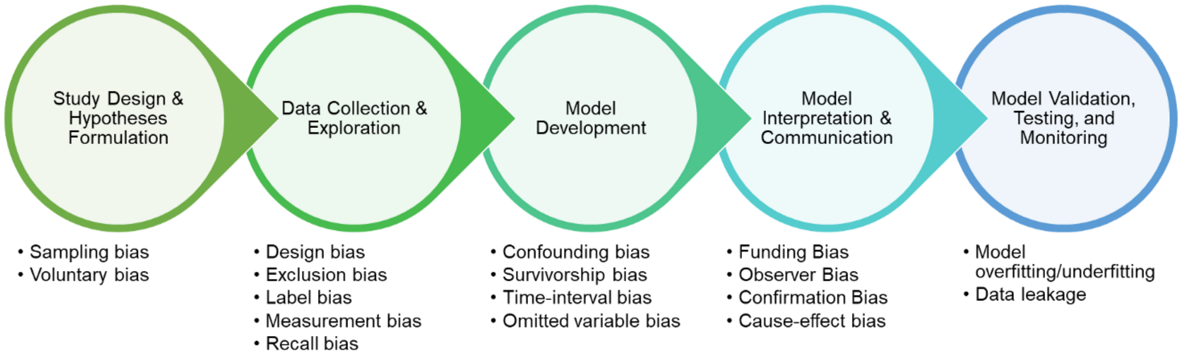


FIGURE 3: SOURCES OF AI BIASES IN EACH PHASE OF THE DEVELOPMENT PROCESS
(Source: Srivastava, 2021)

Model Development: This phase has forms of bias that are not common but can occur to when researchers do not carefully consider for this potential . Time-interval bias is a certain type of bias where a specific dataset only reflects a certain period of time in a year that can support a hypothesis. The bias can result in an AI algorithm that heavily privileges one period of time in a year while deprivileging another period of time in a year (Srivastava, 2021). An example of time-interval bias would be concluding that one form of swimwear is profitable because only summer months sales were included in the study. Omitted variable bias is another type of bias where a researcher does not include a specific variable that could result in a predictive machine learning model that relies on incorrect assumptions to make judgments. Confounding and survivorship bias are more common types of bias with the former meaning having confounders in the model (i.e., variables that are correlated with the response variable and the predictor variable), and the latter meaning that a researcher has inproperly picked certain variables that has "survived" a selection process.

Model Interpretation & Communication: The biases originating in the model development phase can carry over into this phase. Confirmation bias is a common type of bias where the researcher specifically looks for data and information that supports their beliefs. Funding and observer bias are similar to one another, where funding bias favors a model that supports the entity funding the project, and observer bias happens when researchers focusing on finding what they are seeking from the model outputs (Srivastava, 2021). Another bias that can occur in this phase is cause-effect bias, which is a common bias where the interpreter mistakenly believes that correlation implies causation.

Model Validation, Testing, and Monitoring: In this phase, model underfitting and overfitting are common issues that can reduce an AI algorithm's effectiveness in the real world. Underfitting occurs when there are not enough features being tested and the AI algorithm performs poorly on the training dataset as a result (Wilson, 2022). The AI algorithm has low statistical variance and high statistical bias, meaning that the AI algorithm has limited flexibility on the underlying pattern in the training set. Overfitting occurs when the AI algorithm provides a close-to-perfect fit to the training data, captures much of the noise contained in them and hence making the model unable to make accurate predictions for observations not included in the training set (Dietterich, 1995). This results in an algorithm that is unable to generalize and having high statistical variance and low statistical bias.

2.3 AI fairness

2.3.1 Ethical AI Principles

Many companies and organizations have used fundamental human rights to create ethical principles for AI systems. Finding and crafting ethical principles for AI systems can have a long-term effect on the development of the AI systems as it would provide the rationale for the systems' development, deployment, and societal use. Additionally, these principles can help create regulatory measures that may have not been considered previously and help interpret fundamental human rights into a socio-technical environment. There are four ethical principles that AI must respect in order to ensure that AI systems are properly developed, deployed in a safe way, and have ethical use: respect for human autonomy, prevention of harm, fairness, and explicability (O'Sullivan, 2021).

Respect for human autonomy means that humans who are interacting with the AI systems must be able to have control of their self-determination and be able to partake in the democratic process. Essentially, the AI system should not be unjustifiably subordinating, coercing, or manipulating a human to perform an action but rather augment and complement human skills. The interactions between humans and AI systems should leave opportunities for human choice as well as having human oversight of the AI systems. Additionally, the AI systems should support humans in work environments and work towards creation of meaningful work and contributions to society.

Prevention of harm means that the AI systems should not be causing harms or negatively affecting humans. The AI systems should not be detrimentally affecting a human's dignity along with their mental and physical integrity. AI systems that operate in an outside environment should be safe and secure for the natural environment and for all living beings and should also be technically robust and not open to malicious intentions from people. Special attention should be given to people who may be vulnerable to the development, deployment, and use of AI systems. Lastly, there needs to be additional attention to AI systems that can cause or make impacts from power or information.

At the stages of development, deployment, and use, all AI systems need to be considered **fair**. The developers and researchers behind the AI systems have to ensure that the AI systems has an equal and just distributions of benefits and costs and ensure that groups and individuals do not have suffer from unfair bias or discrimination. Additionally, equal opportunity for education, goods, services and technology should be a goal for AI systems. Another way that AI systems should be fair is for people to have the ability to voice against decisions made by an AI system and by the humans in charge of them. The humans behind the design and the humans in charge of the AI system must be identifiable and held accountable. Finally, the AI systems should not lead to people losing their fundamental right to choose.

When building AI systems, **explicability** is an important concept to allow for users to build and maintain trust with them. Explicability means to be transparent with the AI systems which includes the capabilities and purpose of the AI system along with the decisions it can potentially make. The reason why explicability is important is because if an AI system makes an erroneous or inaccurate decision and it leads to severe consequences, the people who suffer those consequences have the right to learn why the AI system made such a decision.

2.3.2 Algorithmic fairness

Before we discuss the development process of AI algorithms, it is imperative to define what algorithmic fairness is in AI algorithms. **Algorithmic fairness** is the field that involves heavily understanding and correcting biases that occur in AI algorithms. Researchers in this field consider causes of bias in data and algorithmics, develop methods to improved data collection and modelling methodologies to create fairer algorithms, and work to define and apply measurements of fairness (O'Sullivan, 2021). The past few years have seen numerous challenges in synthesizing one general definition of fairness. Several definitions has been proposed that cover a wide range of uses cases. At a high level, there is general agreement that an unfair algorithm is defined as an algorithm that makes decisions that are particularly skewed towards one or multiple groups of individuals (Verma and Rubin, 2018).

Within the field of algorithmic fairness, there are multiple ways to measure an algorithm's fairness, such as through fairness through awareness, counterfactual fairness, demographic parity, and equality of opportunity (Garg et al., 2020). The first method to measure fairness in an algorithm is a technique known as *fairness through awareness*. Fairness through awareness can be used when it is difficult to determine when the population of the study are in a "protected group" (group of variables that are categorical such as age, marital status, race, etc.) during the assessments of fairness and bias. Essentially, this methodology is used to assess fairness when there are not any protected attributes being explicitly used during the decision-making process of an AI algorithm. Another measure is *counterfactual fairness* which is used to assess fairness when the outputs of the protected variables (variables that are categorical such as age, marital status, race, etc.) are the same as that of the unprotected variables (variables that are not categorical). A third commonly used measure is *demographic parity* which states that the likelihood of a positive outcome from an AI algorithm should be the same regardless of whether the attributes are in a protected or unprotected group. Demographic parity has the advantage of being appropriate for most problems that are encountered in the real world; however, sufficient training data must be available. Finally, *equality of opportunity* is a fairness metric that checks whether, for a preferred label (one that confers an advantage or benefit to a group of individuals) and a given attribute, a classifier predicts that preferred label equally well for all values of that attribute. Table 1 summarizes the pros and cons of various fairness metrics (Zhong, 2018).

TABLE 1: PROS AND CONS OF VARIOUS FAIRNESS METRICS

Fairness Metrics	Pros	Cons
Fairness Through Unawareness	This method can be applied when it is not allowed or very hard to know if the populations are in the protected group during the assessments of fairness and bias	One cannot determine the optimal choice of threshold when there are no ground truth labels. The other observable attribute can contain discriminatory information and bias analogous to the protected attributes
Counterfactual Fairness	Rather than focusing on protected attributes, it allows us to consider and compensate the social biases that may affect the individuals	In practice, it is hard to reach a consensus in terms of which features to use for constructing the causal graphs, a main component of the counterfactual fairness measure.
Demographic Parity	It is appropriate for a set of applied problems	It cannot ensure fairness when one of a demographic group has minimal representation in the training data. It may lead to the loss of utility, especially when a prediction is related to the protected attribute
Equality of Opportunity	It makes up for the main conceptual weaknesses of Demographic Parity. It also can create classifiers with higher accuracy	In practice, using the measure may not help close the gap between two groups.

2.3.3 Achieving Fairness in AI Algorithms and Models

There are three approaches that are commonly used to improve the fairness of machine learning models: pre-processing, in-processing, and post-processing (O'Sullivan, 2021). *Pre-processing* algorithms utilize algorithmic solutions that preprocess data to remove discrimination before a machine learning model is built. *In-processing algorithms* develop a fair algorithm during the training of a machine learning model that allows the model algorithm to change the learning procedure if needed. *Post-processing* algorithms interpret the fine-tuned model with fairness-aware techniques.

Within pre-processing algorithms, there have been proposed preprocessing tools that can remove discrimination from datasets. The first tool is *massaging*, which is the process of changing labels of some objects in datasets to remove discrimination. However, this method requires researchers to know which labels to change because if the wrong labels are changed, then there may be little effect on the machine learning model. Another proposed tool is *reweighing* which assigns higher and lower weights to tuples in the datasets to give more preference to tuples that the machine learning model should try to replicate. Additionally, there have also been proposed sampling methods that can help improve pre-processing algorithms. One method is uniform sampling, which is based on the idea that all instances have the same probability to be selected. Another sampling method is stratified sampling, where instances are separated into a strata (defined by how much they account for the proportion of observations) and each strata has a certain probability to be selected.

For in-processing algorithms, there are a couple of techniques that are used to help machine learning models become more fairness-aware. These techniques generally either modify the training objective function or incorporate additional constraints. One approach to modifying the training objective function is to add a regularizer term (a penalty to a machine learning model's error function) which can control the bias-variance trade-off. This is particularly important because of the bias-variance trade-off in a machine learning model directly influences overfitting or underfitting, depending on the training data sets. Incorporating additional constraints seeks to minimize the loss from faulty predictions by having the regression variable subjected to several fairness constraints. This has the effect of helping the classifier variable reduce the prediction error made from the machine learning model.

2.3.4 Methods to Mitigate Bias

Bias in AI algorithms can manifest in several ways which makes it difficult to find a singular universal approach to eliminate the bias. Given this, and the fact that emerging AI methods are still being discovered, researchers and scientists have instead found ways to potentially mitigate the amount of bias that can develop, as seen in Figure 4. They have proposed quantitative assessments, business processes, monitoring, data review, evaluations, etc. These researchers and scientists have included two ground roles for mitigating bias in AI algorithms (Wilson, 2022). The first one is that the evaluation of an AI algorithm must be understandable and doable by someone who is not the primary developer of the system. This rule ensures that people with lower-level knowledge of an AI algorithm can understand it at a basic level (Srivastava, 2021). Additionally, there must be transparency of the input data being used in the algorithm. This ensures that there is no false or sensitive data being used by the algorithm. Below we summarize the methods to mitigate bias for each phase in the AI algorithm development process:

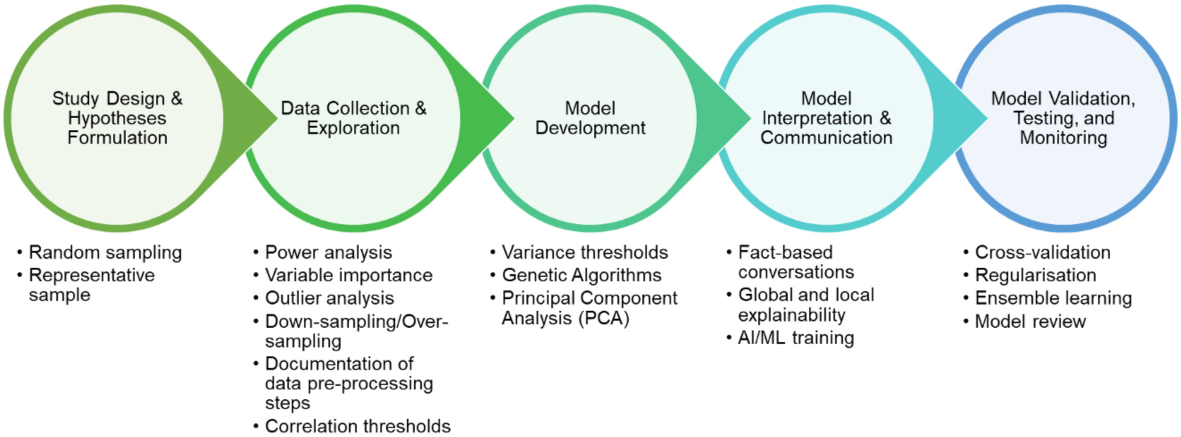


Figure 1: Commonly used methods to mitigate bias in each phase of AI Algorithms development process

(Source: Srivastava, 2021)

Study Design & Hypotheses Formulation: Researchers and statisticians have stated that it is important to focus on the design of the study when looking at the data and features. They also state to ensure that the sample dataset is representative of the population since that allows for more practical and better AI algorithms. Suppose that you were doing a survey to measure customer satisfaction with a food delivery system. You would need to ensure your dataset accounts for individuals from diverse age groups, both genders, diverse cultural, linguistic, and educational backgrounds, all geographic areas, and customers that respond to email, postal, and social media surveys. Additionally, it is recommended that a random and representative dataset is selected from a sample of respondents to ensure that each respondent has an equal chance of being selected in the study which would limit sampling, voluntary, and time-interval biases occurring in a study.

Data Collection, Pre-Processing, and Exploration: There are a multitude of tools and testing methods that can be used to limit bias occurring in this phase. The first is the use of a power analysis, which can allow a researcher to determine the smallest possible sample size to meet a certain alpha significance level. In the pre-processing phase of the study, researchers are expected to document all data cleansing and transformation steps. This allows for some types of biases to be avoided, such as exclusion bias (excluding certain features) and label bias (incorrectly labelling data). Also, Subject Matter Experts (SME) may be used to identify redundant features or use machine learning algorithms such as Random Forest to limit exclusion bias (Wilson, 2022). Regarding measurement bias, a simple way to mitigate it is to check for outliers and then calculate their degree of influence on outcome variables using methods such as Cook's Distance. Additionally, there could potentially be label bias within the datasets which can be resolved by balancing the datasets through down-sampling or over-sampling methods. Lastly, many researchers use techniques that consider pairwise correlation coefficients between model variables to account for confounding bias.

Model Development: Feature selection is the process in which researchers aim to develop accurate models by selecting the most appropriate features. Some machine learning or statistical models such as stepwise regression have incoporated an automated feature selection procedure but human judgement is still required. A commonly applied approach in the model development phase is to exclude features based variance thresholds, that is, features whose values do not vary much should not be used in the AI algorithm as they do not provide enough variance to explain the outcome variable. Principal Component Analysis and Genetic Algorithms are techniques used in this phase to limit many types of bias from occurring and damaging the results of the AI algorithms (Wilson, 2022). Principal Component Analysis attempts to reduce the number of features into components that can be expressed as a linear combination of one another. Genetic Algorithms are a type of search algorithm that use biological concepts such as mutation and natural selection principles to effectively select certain features from high-dimensional datasets.

Model Interpretation & Communication: When a model is being developed, it is important to ensure that researchers carefully examine the model outputs and provide appropriate interpretations. To ensure their audience understand all of the information being presented, the researchers should strive to utilize techniques that can improve transparency and model explainability. The first technique that should be used is global and local explainability. Global explainability is displaying a high-level model to discuss how the features inside of the collected data can influence a result. Local explainability is used to explain each observation with one feature at a time (Srivastava, 2021). Partial Dependence Plots are a type of global visualization that isolates one or two variables at a time to explain how they could have influenced a result which can help identify if relationship between the outcome variable and selected feature(s) are either linear or complex. Individual Condition Expectations (ICE) plots are a type of local visualization that analyzes the effect of a model's feature with the output feature meaning that the ICE plots "show separate predictions of the dependence of the outcome variable's values on the feature's value" (Srivastava, 2021). Another approach is using the Leave One Column Out (LOCO) which will restrain a single column and retrain an entire model to calculate the differences between prediction scores from both models. This can help determine whether an important column was left out in the model.

Model Validation, Testing, and Monitoring: There exists a plethora of techniques that can utilized in this phase to eliminate AI bias. Cross-validation is a popular technique that can be used to combat overfitting by using the initial training data to generate multiple split-tests to tune the AI model (Wilson, 2022). Regularization is a common type of technique that researchers use to simplify models. For example, early stopping is used to prevent model overfitting, limiting additional model runs as the accuracy in the model cannot be improved. Sometimes, a penalty parameter is incorporated into a model to assist in preventing model overfitting. Lastly, ensemble learning is another type of technique where researchers combine predictions from different models into one. Bagging, i.e., training many high accuracy AI models and then combining all their predictions to provide a final set of predictions for an "ensemble" model, allows for researchers to reduce model overfitting. Boosting attempts to tackle model underfitting by many weak learners and using the fact that sequential models will learn from previous models, creating one single strong model.

2.4 Approaches, Tools, and Software Used to Limit AI Bias

2.4.1 AI Fairness 360

AI Fairness 360 (AIF360) is an open-source Python toolkit developed by IBM that is specifically used to measure algorithmic fairness (Lin, 2021). The goal of the toolkit was to promote a deeper understanding of fairness metrics and mitigation techniques along with facilitating the transition of fairness research algorithms to an industrial setting. When developing AIF360, the researchers used datasets that were randomly divided into 50% training, 20% validation, and 30% test partitions. In addition to this, the researchers also divided bias mitigation algorithms into three categories: pre-processing, in-processing, and post-processing. Pre-processing algorithms can modify the training data, while in-processing algorithms are allowed to change the learning procedure for a machine learning model. Post-processing algorithms are never allowed to modify the training data or learning algorithm they use. For example, when the researchers were testing fair pre-processing algorithms, they computed fairness metrics on the training data before and after it is used to determine whether the algorithm had fairly utilized it without inadvertently placing more weight on a variable. Researchers were able to show that the pre-processing algorithms improved fairness after the transformation of the dataset. The research team was able to show, through intensive testing on these types of algorithms, that a pre-processing algorithm is the best option but if this option does not exist then a post-processing algorithm is most likely a good fit. The issues that came up when testing post-processing algorithms was that on average, it was a decent choice and in the worst cases, it did not improve the datasets.

Based off of the design of AIF360, the researchers and developers at IBM are attempting to improve all phases within an AI system's development. AIF360 utilizes three types of bias mitigation algorithms (pre-processing, in-processing, and post-processing) to illuminate to people using the software to look for potential biases within the Study Design & Hypotheses Formulation phase such as sampling or voluntary bias. As stated before, AIF360 will compute fairness metrics on the training data before and after the algorithm is trained with it. If the fairness metrics read that the training data lead to an algorithm that is biased and unfair, then AIF360 will point to design or sampling bias, allowing the researchers to look into their samples and see if they are representative of the population. Even after doing some preliminary data bias checking and bias mitigation, AIF360 will look into some model development bias, particularly confounding, omitted variable, and survivorship bias and mitigation techniques for those biases which can be seen in Figure 5.

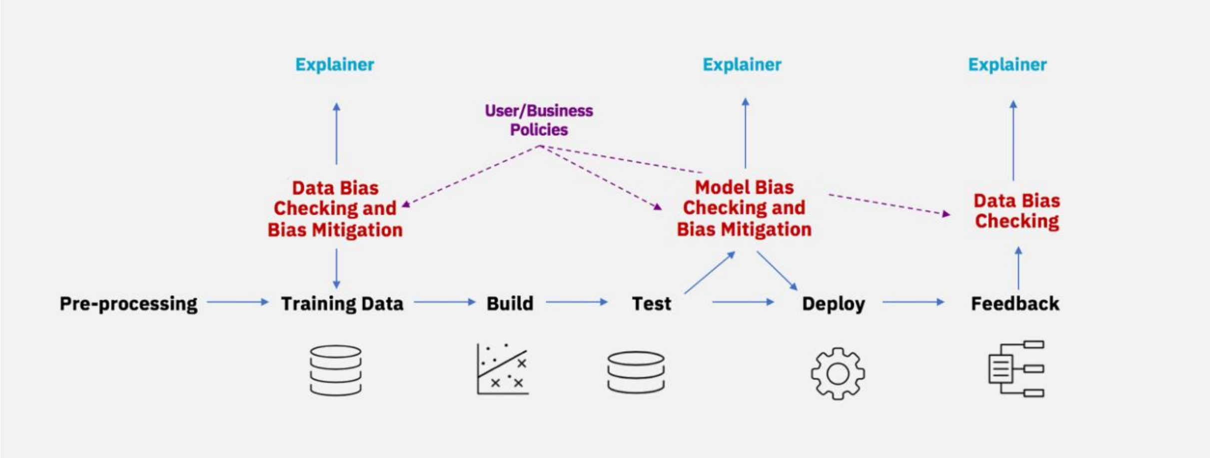


FIGURE 2: SUMMARY OF PROCESS OF AI FAIRNESS 360
(Srivastava et al., 2022)

2.4.2 Fairlearn

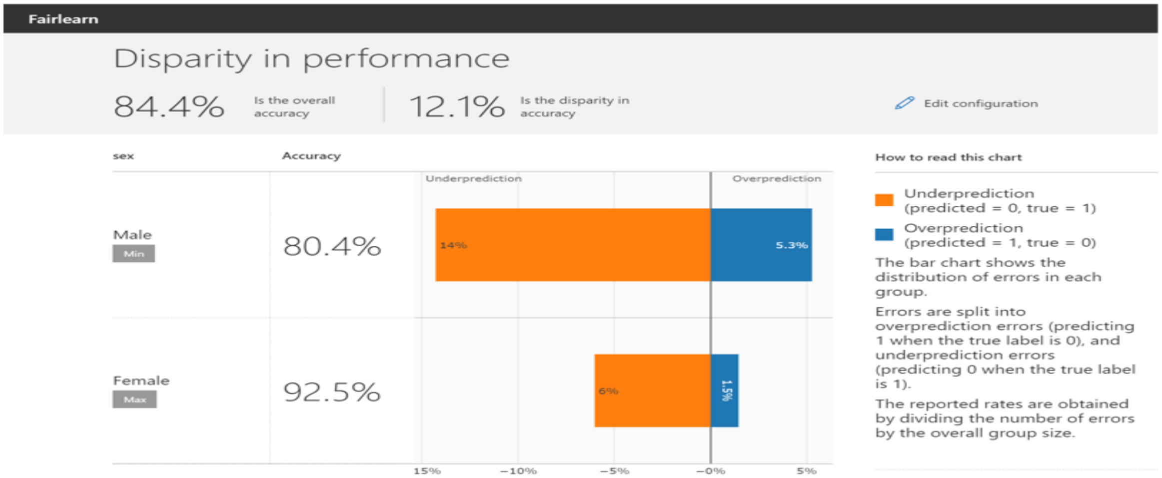


FIGURE 3: AN EXAMPLE OF MICROSOFT'S FAIRLEARN INVESTIGATING THE DISPARITY IN PERFORMANCE OF A MACHINE LEARNING MODEL WITH MALES AND FEMALES (Source: Bird et al., 2020)

Fairlearn is an open-source Python package made from Microsoft that allows for developers and data scientists to assess and improve the fairness of their machine learning model (Bird et al., 2020). Fairlearn assesses the fairness of machine learning models by using an interactive visualization dashboard and mitigation algorithms that allow for developers to understand the trade-offs between fairness and their systems performance. The interactive visualization dashboard gives developers an understanding of which groups of people could potentially be negatively affected by the machine learning models. To determine which groups of people, Fairlearn uses a variety of techniques such as demographic parity, equalized odds, and worst-case accuracy rate.

When using the dashboard, developers can select a variable like age or sex that will be used to assess the fairness of machine learning models while the performance metric will assess the performance of the machine learning model. Additionally, the dashboard allows for developers to compare the fairness and performance of different models to one another, letting the developer look more into trade-offs and determining a model that best fits their needs.

Fairlearn also has a feature to help developers improve the fairness of their AI systems and algorithms with their own unfairness mitigation algorithms. There are two types of these algorithms: postprocessing algorithms and reduction algorithms. With Fairlearn's postprocessing algorithms, there is no point to retraining the machine learning model that it is testing against; instead the postprocessing algorithms will transform the machine learning model's predictions so that they abide by the constraints placed by the fairness metric. Their reduction algorithms work differently from their postprocessing algorithms because the algorithm will iteratively re-weigh all of the data points in the machine learning model and then retrain the model after each re-weighting. When the algorithm does about 10 to 20 iterations, it will end up creating a machine learning model that satisfies the constraints laid out by the fairness metric while maximizing the model's performance. Another benefit from their reduction algorithm is the fact that it allows for training different variants of the same machine learning model that will make different trade-offs between fairness and model performance.

Based off of the available research done on the algorithms and overall design of Microsoft Fairlearn, Microsoft seems to be targeting to improve the Data Collection & Exploration phase of an AI system's development which includes design bias, exclusion bias, label bias, measurement bias, and recall bias. One distinct feature that Microsoft Fairlearn has over most of the software available used to limit AI bias is the ability to measure one variable at a time and analyze its fairness on a machine learning model and performance of the machine learning model. This would allow researchers to look back into the development of the AI system and determine if they could be experiencing some potential bias such as exclusion bias by excluding the importance of a variable in their AI system or design bias by using samples that do not truly reflect the characteristics of the population.

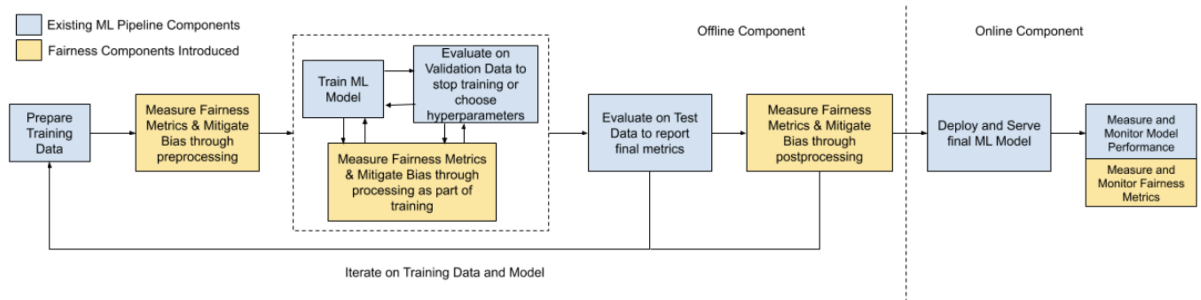
With Fairlearn's unfairness mitigation algorithms, Microsoft is attempting to improve all phases within the development of an AI system. It is not possible to determine which specific biases Fairlearn's unfairness mitigation algorithms attempt to eliminate since research does not exist on that but it is clear that Microsoft is attempting to cover some ground in each phases with their algorithms. The postprocessing and reduction algorithms take different approaches to cover some ground but once again there does not exist research to see which algorithms perform better on specific phases.

2.4.3 LinkedIn Fairness Toolkit

The LinkedIn Fairness Toolkit (LiFT) is a Scala/Spark library that can measure and investigate the bias in large-scale machine learning models and workflows (Vasudevan and Kenthapadi, 2020).

The measurement module inside of LiFT includes measuring biases in training data originating from flawed datasets, evaluating fairness metrics for machine learning models, and detecting statistically significant differences in their performance across different subgroups. Specifically on mitigation, LiFT includes a post-processing method for transforming model scores to ensure an equality of opportunity.

LiFT provides some advantages over Microsoft's Fairlearn and IBM's AI Fairness 360 with its



goals to achieving completely flexibility and scalability. Generally, fairness tools need to be usable as libraries for ad-hoc exploratory analyses and likely to be deployed in production machine learning workflows that are used on a daily basis because it should be easy to integrate these solutions to existing machine learning workflows to increase the adaption of AI systems by model developers. To address scalability, LiFT developers want their computations inside of LiFT to be performed over several nodes in a distributed computing environment because of advancements made in data parallelism over large datasets. The ultimate goal of LiFT is to provide an architecture for integrating bias measurement and bias mitigation into production machine learning systems that operate on datasets stored in distributed file systems. They also want to create a design for fairness toolkits that are flexible to use, integrate easily with existing machine learning workflows, and scale to large datasets.

Figure 4: Conceptual diagram of the LiFT System
(Source: Vasudevan and Kenthapadi, 2020)

LiFT's system architecture comprises of bias measurement and mitigation components that are integrated into different stages of a machine learning training regimen. Using Apache Spark, LiFT will provide compatibility for offline compute systems, machine learning frameworks, and cloud providers to achieve the best data parallelism and fault tolerance for the bias measurement and mitigation components. Before there is training done on the machine learning model, there are preliminary steps taken involving measuring metrics for representativeness, appropriate mitigation techniques, and label distribution across subgroups. Label distribution across subgroups is an important process to consider because it has the potential to unconver some potential leading biases within groups. The measures are made to help model developers know how representative the training data is across the different subgroups for the machine learning model.

During training is another stage where measurement and mitigation techniques are used to increase the performance of the machine learning model. Proper measurement and mitigation techniques can allow for accurate hyperparameters to create the right balance of fairness and model performance in the machine learning model. Additionally, niche tactics like black-box mitigation and in-processing methods can be integrated to help achieve optimal model performance and bias.

Finally, after training is the last stage which is used to measure fairness metrics on the training dataset and on post-processing mitigation methods. Fairness measurement post model training can compare predicted score distributions across different subgroups, compute aggregate metrics of unfairness/inequality, or directly compute performance metrics across different protected groups. It is important to do the final stage of training as it can be helpful to decide the appropriate tradeoffs for the machine learning model, or to iterate on with the training data and model.

3.0 ARTIFICIAL INTELLIGENCE IN TRANSPORTATION

Artificial intelligence has seen a tremendous amount of growth in its use from the U.S. Department of Transportation (USDOT) and across the transportation industry over the past few years. For example, some of the USDOT's administrations, such as the Federal Highway Administration (FHWA) and the Federal Railroad Administration (FRA), have been developing AI uses in video analytics, safety analysis, and anomaly detection for mission delivery. Additionally, the FHWA's Traffic Analysis Tools Program is investigating the use of AI in the creation of prediction techniques and evaluation tools. Other agencies, such as the Federal Transit Administration (FTA) and the Federal Motor Carrier Safety Administration (FMCSA), are investigating how AI can be used to help citizens.

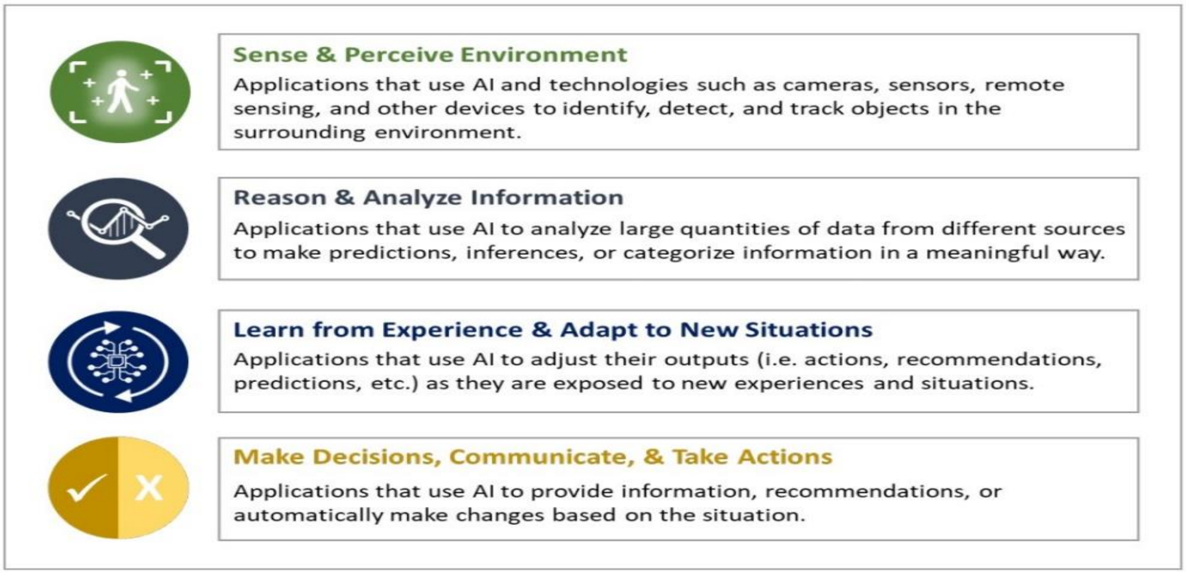


FIGURE 5: USE CASES FOR AI APPLICATIONS
(Source: Walker, 2020)

The United States Department of Transportation (USDOT) and its Intelligent Transportation Systems Joint Program Office (ITS JPO) have outlined in their strategic plans the implementation of emerging, innovative, and enabling technologies in the national transportation system (Sheehan, 2022). With this plan, the ITS JPO has established that research in AI has become a main priority for local and state agencies for addressing transportation issues. The USDOT has said that they plan to engage with the emerging utilization of AI in transportation in two key ways: enabling the integration of AI into safety-critical domains and adopting and deploying AI-based tools to improve the delivery of enterprise functions.

AI is starting to be used for ITS. In general terms, AI is defined as processes that can "replace or enhance human tasks or create new capabilities that humans cannot perform." In addition, AI can understand its surrounding environment, reason and analyze information, use experience and adapt to new situations even without human interaction, and make decisions and execute its own actions. Within AI are numerous subfields and techniques such as machine learning, using data to discover patterns and make decisions without human interaction, and natural language processing, a technique that parses, processes, and analyze human language. After drafting and finding credible AI definitions, using natural language processing and machine learning, prioritizing the definitions with four ranks: relevance, clarity, inclusivity, and simplicity, and with USDOT feedback, a new definition of AI for ITS was created that aligns with U.S. government definitions of AI. The new definition asserts that AI can be "used to replace or augment actions of field, handheld and remote sensing devices, connected and automated vehicles, TMC operators, transit and freight operators, decision makers, and travelers and that AI can be placed in any system entity (vehicle, mobile device, management center, etc.) or be placed in many entities in a system (Sheehan, 2022)."

In this section, we discuss the potential benefits of AI applications in transportation, barriers to these applications, and the ethical and equity considerations. We also discuss some existing AI applications in transportation, focusing on traveler decision support tools, transportation system management and operations, transit operations and management, and asset management.

3.1 Potential Benefits of AI Applications in Transportation

As with any new technology, artificial intelligence (AI) has the potential to transform industries and revolutionize systems and processes. To understand what this would entail for the transportation industry, it is important to outline the key goals that underlie the development of transportation systems. These goals will guide the discussion of how AI can be implemented to augment existing practices and establish new ones. As the US Department of Transportation lays out in its Strategic Plan (FY 2022-2026), its strategic goals include: safety, economic strength and competitiveness, equity, climate and sustainability, transformation, and organizational excellence. In addition to these strategic goals, the DOT's top three priorities are safety, infrastructure, and innovation. These goals and priorities will guide the discussion regarding how AI can benefit the existing transportation system.

3.1.1 Operational and Organizational Benefits

Increased Efficiency

The key operational and organizational benefits that AI provides include cost reduction, increased efficiency, process automation, and positive externalities such as improved environmental outcomes. Increased efficiency can be seen both on a micro scale in terms of individual processes and on a macro scale in terms of overall systems. One example of this on a macro scale is the use of dynamic scheduling algorithms to improve urban traffic flow; by using neural network models to predict passage times of vehicles at intersections, network communication can be harnessed to reduce congestion at intersections (Lv et al, 2021). Additionally, intelligent public transport systems can leverage real time data by monitoring road conditions and provide optimized routes to shorten travel time. On a global scale, not only transportation systems but entire value chains could be transformed by the idea of the Physical Internet (PI) (Nikitas et al, 2020). The physical internet integrates AI with hardware components in system elements such as containers and hubs to allow for optimal decision making across logistics systems (Nikitas et al, 2020).

Reduced Costs

Along with these improvements in efficiency come decreases in costs. For example, in addition to route optimization based on road conditions, public transportation can be optimized through demand responsiveness (Abduljabbar et al, 2019). This would provide door-to-door convenience to users at lower costs compared to taxi services (Abduljabbar et al, 2019). Operational costs can be reduced through the use of text mining to handle customer complaints and using demand forecasting tools to optimize inventory costs (Okrepilov et al, 2022). AI can also be used to monitor infrastructure conditions to reduce maintenance and repair costs (Okrepilov et al, 2022).

Environmental benefits

Around the world, the transportation sector is the primary source of emissions (Shaheen and Lipman, 2007). Therefore, this is clearly one area in which there is room for significant improvement in terms of total environmental impact. The improvements in efficiency and cost through the use of AI solutions have many positive externalities for the environment. For example, implementing better traffic flow solutions using network routing and connected automated vehicles has the potential to improve on fuel savings and thereby decrease emissions (Hasan et al, 2019). Additionally, moving away from car ownership and towards shared automated vehicles has the potential to decrease congestion by decreasing the total number of vehicles on the road (Hasan et al, 2019). These reductions in vehicle numbers have the added benefit of reducing the need for vast parking spaces, thereby allowing for improvements in land use and green cover even in urban environments (Rigole, 2014).

3.1.2 Benefits to Travelers

Safety

A key consideration in transportation is passenger safety - from the time they depart to the time they arrive at their destination. Combining geographic information systems tools with artificial neural network predictive models allows the forecasting of high crime risk areas along the transportation chain in urban areas (Kouziokas, 2017). This knowledge is vital for implementing increased safety measures in these areas. Additionally, physical safety can be enhanced through the Internet-of-Vehicles (IoV) (Boukerche et al, 2020). IoVs are able to perceive and communicate information pertaining to the surrounding environment to adapt to ongoing road and traffic conditions (Boukerche et al, 2020). Technologies such as these have the potential to reduce fatalities for both passengers and pedestrians alike.

Accessibility

One group that could benefit from the integration of AI into transportation systems in the disabled community. Several steps of the travel cycle - including journey planning, purchasing tickets, finding services, boarding, and navigation among other steps (Hezam et al, 2023) - can be improved for users through AI technologies. Cooperative traffic signal assistance can improve street mobility for disabled users through harnessing computer vision (Yang et al, 2022). Through object recognition and pose estimation, non-motorized users can have their needs met by traffic infrastructure: they can receive extended time at intersections, or receive updates through personal devices (Yang et al, 2022). Additionally, LiDAR technology can be used in conjunction with AI to allow for the rapid assessment of sidewalk infrastructure to determine whether it is in compliance with ADA regulations (Ai and Tsai, 2016). Computer vision can be integrated with haptic feedback technology to create wearable devices for disabled persons to better navigate environments (Boldini et al, 2021).

Convenience

In addition to cutting costs on an operational level, smart planning, scheduling, and optimization technologies have the potential to deliver significant time saving for passengers. For example, timetable synchronization and optimization for high-speed rails can lead to enhanced system robustness by minimizing total delay time across the system and minimizing passenger wait time at stations (Yin et al, 2020). AI powered traveler information systems can reduce stress by providing users with information about routes to optimize for factors such as travel time and fuel consumption, in addition to traveler preferences in path selection (Adler and Blue, 1998). Furthermore, traveler experience could be enhanced for tourists in a number of ways such as: smart recommendations of destinations and amenities based on anticipated needs; enhanced navigation and language query services using natural language processing; and shared information through social networks (Tsaih and Hsu, 2018).

3.2 Barriers to AI applications in transportation

While it has been made evident that AI has vast potential to aid in the improvement of transportation systems, there are also a plethora of barriers that must be evaluated. The three major categories that have been identified are: technological, human capital, and ethical considerations. Knowledge gaps in these areas may limit our ability to fully harness AI technologies in transportation systems as they exist today. The goal of this report is to examine the existing barriers to adoption and thereby identify the current needs of the transportation industry in terms of these three broad categories. Clearly defining the problem statements in this manner is the first step towards developing solutions to individual problems and frameworks to streamline decision making and operational policies for AI implementation.

3.2.1 Technical Barriers

Training AI models for practical applications in transportation often require large amounts of data, which may not be available across transportation agencies. Although the growing availability of big datasets in recent years offered by both non-profit organizations (e.g., Open Street Map) and for-profit companies (e.g., INRIX, RITIS, Waze, Streetlight, and HERE) makes it less of a concern, some other issues remain. For example, state and local transportation agencies have been using different types and sources of data, making it difficult for AI systems proven to be effective in one place to be readily transferable to other cities or regions. Also, it is often challenging for transportation agencies to identify the data needed to support a given AI application as well the instructions and communication facilities required to collect such data. Therefore, despite the increasing amount of data being collected and stored by transportation agencies, they may face the need to constantly acquiring new data. But the decision to invest in additional resources for data collection often raises the question of whether the investment is worthy and if the application of AI using such data will bring unforeseen risks.

In many cases, AI applications in transportation requires significant infrastructure investments such as smart sensors, video cameras, and other internet-of-things facilities. Building and maintaining such infrastructure can be challenging for some local transportation agencies, especially those without sufficient financial resources and staff capacity. Moreover, the increased data storage required to collect and maintain the collected data can poses a challenge. Cybersecurity is another concern as sensitive data are being collected and stored.

3.2.2 Barriers in Training and Human Capital

The development of AI systems in transportation require investments in human capital in addition to technical infrastructure. It is people that are responsible for the development, maintenance, and management of AI systems and their integration with transportation systems. Understanding the demands for human capital with regards to AI implementation more broadly is a stepping stone towards understanding the specific demands within the field of transportation.

Public Perception

Understanding the perceptions held by the general public is an important first step towards dissecting the barriers in the way of training and human capital development. This is because the perceptions that people hold can shape everything from their willingness to learn about AI to their ability to make tangible policy changes. Furthermore, public concerns can translate into regulatory action if the public sentiment is strong enough (Fast and Horvitz,2017). One longitudinal study done in the US analyzed New York Times articles over the past 30 years to determine the level of discourse surrounding AI, and found that there has been a sharp increase since 2009 (Fast and Horvitz, 2017). While attitudes have generally become more optimistic over time, there are also concerns such as those pertaining to loss of control, ethical issues, and negative impacts on work (Fast and Horvitz, 2017). Another study found that some of the positive associations that people have with AI include innovation, technological processes, environmental protection, and a positive future (Hilgarter and Graning, 2020). However, the study also noted some perceived challenges including job losses, acceptance and awareness, privacy, cost, reliability, and legal challenges (Hilgarter and Graning, 2020).

There has been some research done about the perceptions of experts in the field, and the role that they play in perpetuating public discourse about AI (Neri and Cozman, 2020). It was found that when experts perpetuate messages of risk, it is usually in the context of counterfactual scenarios rather than in the context of real life incidents (Neri and Cozman, 2020). In general, experts can take on the role of being a pragmatist, an antagonist, or an enthusiast (Neri and Cozman, 2020). Furthermore, expanding the scope from transportation to urban planning on a broader scale, a Twitter study done in Australia found that 66% of the content related to AI was positive in nature (Yigitcanlar et al, 2020). The discourse included keywords related to AI such as robotics, drones, automation, digital twins, block chain, and machine learning, as well as planning concepts such as sustainability, cybersecurity, innovation, construction, governance, and transportation (Yigitcanlar et al, 2020). Some of the key concerns held by the Australian public include cybersecurity, ethics, loopholes, and the elderly population (Yigitcanlar et al, 2020).

In addition to these views, the development of ChatGPT has contributed to new emerging attitudes in recent times. While public sentiment is generally positive, it has decreased since the technology's debut (Leiter et al, 2023). Additionally, while it is viewed as an opportunity for scientific development, it is seen as a threat in the domains of ethics and education (Leiter et al, 2023). Students believe that fears of ChatGPT may be blown out of proportion, and think that the technology should be embraced as it could potentially aid learning (The Learning Network, 2023). However, some students fear that it could inhibit learning by hindering motivation and limiting creativity and critical thinking skills (The Learning Network, 2023). Perceptions of risks and benefits also vary across user group. Higher risks are perceived by those who are liberal, educated, more interested in politics and science, and knowledgeable about ChatGP. Those with high levels of interest, personal relevance, and knowledge regarding new technologies tended to recognize its benefits. As a whole, Americans do not seem to view language model technologies such as ChatGPT as of groundbreaking importance, while they do view AI developments in medicine and agriculture as major advances in those fields (Funk et al, 2023).

General Demands for Human Capital for AI Implementation

The emergence of Industry 4.0 has presented new trajectories for the development of human capital across industries. While there are multiple models of Industry 4.0, it can be characterized by technical, economic, and demographic transitions (Klingenberg et al, 2022). The key technical development is the emergence of cyber-physical systems: systems which connect physical production processes with internet, computer, and AI technologies (Klingenberg et al, 2022). The economic transition is characterized by changes in market structures and business models, and the demographic transition is characterized by changes in the quantities and types of labor demanded (Klingenberg et al, 2022). While there are rising concerns regarding job loss due to increased automation, it is likely that jobs would change in function rather than disappearing completely (OECD).

With this understanding of the broader societal transition, we can better explore the specific roles of human capital. Three broad skill sets can be identified - cognitive skills, emotional skills, and behavioral skills (Singh et al, 2022). Cognitive skills include AI related skills such as machine learning and natural language processing, data management and analysis skills, and programming skills in languages such as Python, SQL and C++ (Samek et al, 2021). Additionally, workers need to know how to extract data from a variety of sources, and have knowledge of computer fundamentals such as logic, data structures and algorithms (Johnson et al, 2021). Interdisciplinary skills and competencies as found in the field of data science are also highly relevant (Samek et al, 2021). The necessary socio-emotional skills include communication, teamwork, problem solving, presentation, creativity, and planning among others (Samek et al, 2021). In addition to these broader skills, domain knowledge in the specific field of implementation is beneficial (Chung, 2022). Hybrid skill sets which combine a variety of these skills and others are vital for workers (Johnson et al, 2021).

3.3 AI ethics and equity considerations

While there are extensive debates about the ethical implications and equity considerations when it comes to artificial intelligence in general, we are still left with limited answers. This is especially true in the realm of transportation. Arriving at an appropriate ethical framework requires comprehensiveness and consistency, as well as a thorough assessment of the value tradeoffs in place. Various corporations and governments have their own ethical principles, but the effectiveness of the guidelines rely on the underlying technological and human limitations in place. Additionally, when assessing social impact, there is a necessity to consider the broader social impact of a given technology.

3.3.1 Ethical Frameworks

Ethical frameworks provide different lenses through which we can view ethical dilemmas. They are not necessarily prescriptive in nature, but rather provide a set of tools by which problems can be analyzed and conclusions can be drawn. The ethical framework of choice for most AI practitioners is utilitarianism (Goldsmith and Burton, 2017). As a form of consequentialism, utilitarianism is an outcome focused approach to ethics. It favors the greatest good for the greatest number of people ("Utilitarianism"). The benefit of this framework for AI practitioners is the ability to arrive at a more ethically comprehensive position (Goldsmith and Burton, 2017). However, it is important that practitioners be familiar with other major frameworks as well to arrive at not only a comprehensive, but also a holistic ethical position. The deontological framework focuses on adherence to rules and ensuring that actions are in accordance with the law (Goldsmith and Burton, 2017). One conceivable problem with this approach for AI is that there is currently limited legislation in this realm. Any attempts at interpreting existing legal codes in search for a solution would lead different actors to different conclusions (Goldsmith and Burton, 2017). Alternatively, the virtue ethics framework focuses on cultivating character and "virtues" and pushes actors to consider how AI could shape society at large (Goldsmith and Burton, 2017).

While these ethical frameworks are certainly a good starting point to establish ethical guidelines for the use of AI in the field of transportation, they are far too broad to produce a system of quantitative metrics by which the impacts of AI technologies can be assessed. To gain a better understanding as to how this can be done, we can turn to other sectors to gain a method by which such a system can be developed. Healthcare is one such sector in which there are a plethora of benefits to adopting a data-driven approach enabled by AI, but there are also many risks associated with AI adoption. These risks can be broken down into epistemic concerns (those associated with the evidence required for a given situation), normative concerns (those associated with potential outcomes), and overarching concerns (those related to the system at large) (Morley and Floridi, 2020). These concerns mirror some of the major concerns associated with AI adoption in transportation.

Rather than addressing these concerns with statutory obligations, there is a need for the creation of a robust regulatory system (Morley and Floridi, 2020). This holds true for the application of AI across sectors given the very nature of the technology - it is driven by algorithms, not formulas. Since the technology is not black and white, a relevant regulatory system would need to be able to embrace the many shades of gray in between.

Another salient feature of how the healthcare system uses AI technology is the focus on the end user and protecting the individual (Morley and Floridi, 2020). Identifying this key stakeholder can be a challenging task in the field of transportation because while the end user is indeed important, there are far reaching consequences for all stakeholders throughout the system. This is where a multi-level analysis of both stakeholders and the algorithm's life cycle could be beneficial (Morley and Floridi, 2020). This multi-level analysis approach is also used in the insurance market, which implicitly considers the overarching concepts of transparency, fairness, and equality among other broadly established data principles (Mullins et al, 2021). In the education sector, an intersectional approach has been undertaken to understand the intersection between algorithms, data, and analytics in the context of ethics and equity (Holmes et al, 2022).

3.3.2 Ethics and Equity in Transportation

While understanding ethical frameworks in a broad sense is a useful starting point to dissecting the ethics and equity involved in incorporating AI into transportation systems, it is also key to understand the specific ethical considerations in the field of transportation. The discourse surrounding equitable outcomes in transportation are abundant, and the purpose of this section is to highlight a few key issues in transportation ethics and equity to be put in the context of artificial intelligence.

One aspect of transportation that is inextricably related with ethical implications is mobility. According to The Ethics of Mobilities, mobility is inherently linked to freedom. Looking at this idea through Orlando Patterson's model of freedom as personal, sovereign, and civic, (Bergmann and Sager, 2016) developed an understanding of mobility that is linked to these concepts. Personal mobility is concerned with the body and micro abilities and disabilities; sovereign mobility is relational - it looks at the people, institutions, and systems in power that could promote or restrict mobility; civic mobility is a means of assembly and is concerned with networks of exchange. Numerous factors such as gender, disaster and crisis, conflict, and the environment can influence each of these levels of mobility. The authors recommend that the impacts of mobilities on public life are evaluated, and that governance be ensured in situations where there are competing freedoms of mobility.

Transportation safety is another key area in which ethical considerations are crucial. One prominent model of assessing transport safety is the Cost-Benefit Analysis (CBA) model (Basta, 2013). Falling under the utilitarian framework, it assesses the various costs and benefits associated with a given decision. It is generally used in transportation planning because the costs and benefits are generally well known, there are models available for forecasting, and it is value "neutral" compared to methods such as Multi-Criteria Analysis (MCA) which assigns weights to attributes. However, there are challenges associated with this model as well. The quality of the models and estimates is not always reflective of reality, quantifying risk can be difficult, and the distribution of risks are not always taken into account. One specific technique that is used in CBS is calculating a person's willingness to pay (WTP) for a reduction to risk to estimate the value of a statistical life (VOSL). However, these estimates are highly dependent on the level of risk and corresponding monetary valuation, and fluctuations can lead to high variation in results. Risk is also subject to perception - people are not always accurate in their assessment of risk. Finally, distribution effects are not accounted for as those with different income levels are likely to have different abilities to pay for risk reduction and to have different values of time. This model reveals the challenge of balancing market-oriented policy making and equity concerns in transportation planning.

Discussions on transportation equity are often grounded on principles of distributive justice (Anciaes and Thomopoulous, 2014). As opposed to utilitarian frameworks which focus on maximizing benefit, justice ethics approaches also look at who is benefiting. Unequal distributive effects in the transportation system can translate to inequalities in distributive effects in downstream socioeconomic outcomes. The justice ethics approaches proposed by John Rawls and Amartya Sen argue for individuals' access to primary goods. Transportation access is a means of achieving this. Therefore, limited access to mobility can limit access to economic and social participation. Those who do not have the ability to purchase a car are unable to take advantage of highway infrastructure, and this can be compounded when public transit is out of reach for socioeconomic minority groups. There is also an uneven distribution of negative effects. For example, pollution caused by traffic does not impact everyone proportionally. These challenges can be addressed through either horizontal or vertical equity. Horizontal equity would be associated with similar levels of access across groups, while vertical equity would prioritize disadvantaged individuals.

The integration of AI into transportation systems has the potential to either alleviate or worsen existing inequities. Many AI applications have the capacity to improve the accessibility, fairness, dependability, and affordability of transportation services for traditionally underserved travelers. Examples include AI-driven citizen engagement, routing and wayfinding tools for pedestrians, payment assistance facilitated by AI, and AI-powered assistive robots for individuals with disabilities. However, rather than addressing the needs of underserved communities and marginalized communities, the current focus of AI applications in transportation predominantly revolves around enhancing driver assistance systems, addressing traffic congestion, and automating infrastructure assessments.

So far, limited research has focused on the equity implications of deploying AI technologies across sectors. In the field of transportation, AI-enabled applications may lead to inequitable outcomes despite good intentions. For instance, a data-driven, AI-informed roadway maintenance decision-making procedure can cause the road infrastructure in disadvantaged neighborhoods to receive less investments; this happens when a lack of data results in lower ranking of transportation facilities that are less well maintained, which are more commonly found in marginalized communities. Also, AI-based decision-support systems can lead to policies and decisions that leave out of the needs of certain population groups if they are underrepresented in the data used to support decision-making.

3.3.3 Establishing Guidelines

Various bodies have established guidelines for handling the development and use of AI systems. One of the most notable examples is the European Union. In terms of regulatory action, the EU has identified six key areas of focus: ethics; liability; connectivity, intellectual property and flow of data; standardization, safety and security; education and employment; and institutional coordination and oversight (Ruiner et al, 2018). Data protection was found to be the key argument for regulation, and transportation was found to be a key domain for regulation (Ruiner et al, 2018). The High-Level Expert Group (HLEG) on Artificial Intelligence have also recommended guidelines for AI. The group focuses on trustworthy AI - AI that is lawful, ethical, and robust (*Ethics Guidelines for Trustworthy AI*, 2019).

The key ethical principles include respect for human autonomy, prevention of harm, fairness, and explicability (*Ethics Guidelines for Trustworthy AI*, 2019). Additionally, their seven requirements for trustworthy AI include: human agency and oversight, technical robustness and safety, privacy and data governance, transparency diversity, non-discrimination and fairness; societal and environmental wellbeing, and accountability (*Ethics Guidelines for Trustworthy AI*, 2019). Some of the broader strategy goals include boosting technological and industry capacity, preparing for socio-economic changes, and establishing ethical and legal frameworks (Ulnicane, 2022). These goals would be accompanied by an increase in collaboration across EU member states (Ulnicane, 2022).

Apart from the efforts made by governmental agencies and regulatory bodies, corporations have their own sets of guidelines for AI development. Facebook's five pillars include: privacy and security, fairness and inclusion, robustness and safety, transparency and control, and accountability and governance (*Facebook's Five Pillars of Responsible AI*, 2021). Microsoft's principles include: fairness, transparency, inclusiveness, accountability, reliability and safety, and privacy and security (*Responsible and Trusted AI*, 2023). In general, corporations tend to model their guidelines after the business-oriented FAST principles - Fairness, Accountability, Sustainability, and Transparency (Attard-Frost et al, 2022). Another study found that the key ethical principles include transparency, justice and fairness, non-maleficence, responsibility, and privacy.

3.3.4 Challenges

While these various ideas provide some guidance regarding AI, there are several critiques of the existing work. For one, the existing EU guidelines are often a patchwork of guidelines from other regulatory frameworks, thereby adding little to existing law (Veale and Zuiderveen Borgesius, 2021). The scope of the regulation can also be rather broad, leading to prohibitions that are either fantastical or ambiguous in nature (Veale and Zuiderveen Borgesius, 2021). The existing guidelines are also strongly influenced by industry interests, leading to deliberately vague guidelines and "ethics washing" (Ulnicane, 2022). These practices could actually lead to more deregulation in the future (Veale and Zuiderveen Borgesius, 2021).

Additionally, new developments in the field of AI have demonstrated some potential gaps in existing frameworks. A key example is how the deployment of ChatGPT revealed problems with the European Union's AI Act (Sharma, 2023). The act relied on a harm principle to prohibit certain uses of AI (Veale and Zuiderveen Borgesius, 2021). For instance, social scoring systems or systems that are manipulative in nature would be prohibited as they could cause harm to individuals and to society (Veale and Zuiderveen Borgesius, 2021
). However, these are examples of systems that are designed for specific use (Sharma, 2023). ChatGPT is a general-purpose model that can be used for a variety of purposes - some of which might cause harm, such as generating phishing materials (Sharma, 2023). In an attempt to mitigate any harm, there is a push to minimize risk, but it could be difficult to regulate a general-purpose technology such as ChatGPT without also diminishing the effectiveness of the solution (Sharma, 2023). This situation reveals the difficulty in balancing the need for regulation with the goal of technological development.

For regulation to be effective, people must be willing to accept independent AI decisions and respect the autonomy of AI systems (Ruiner et al, 2018). Without this level of trust, there could be higher rates of neglect in practice when using these systems (Ruiner et al, 2018). While this conundrum demonstrates the need for effective regulation, it also demonstrates the hurdle of human acceptance.

3.3.5 Discussion of Ethical AI Guidelines and Regulations

It is evident that the existing guidelines pose a plethora of problems that must be overcome in order to effectively regulate the development of AI. The guidelines proposed by the EU tend to be too narrow, and heavily restrict technological development. While limiting certain technologies such as social scoring systems may be justified on the grounds of limiting harm, extending limitations of general purpose technologies could severely hinder adoption. This attempt to regulate AI across all industries is idealistic as each industry faces its own unique challenges when it comes to ethics and equity. On the other hand, guidelines proposed by corporations are far too broad to have any tangible impact when it comes to curbing harm. Principles such as "justice and fairness" are difficult to empirically define to achieve desirable outcomes. If corporations are allowed to self-regulate when it comes to technology, this may leave consumers vulnerable. Given these two extremes, it is evident that finding a middle ground could lead to a desirable outcome. The problem, however, lies in the fact that most lines in the sand would be arbitrarily defined.

Since current regulations which rely on an approach that stems from regulating the technology itself seem to be limited in their ability to achieve their desired outcomes, a new system must be established. One potential solution could involve a domain-centric approach to governance rather than a technology-centric approach. This method would involve regulating industries based on the desired ethical outcomes within a particular field. For example, in the realm of transportation, AI could be regulated in terms of its ability to mobility, safety, and accessibility, and then technological concerns such as privacy and security could be tested for after this preliminary assessment of the system. This two-step system would allow industries to have control over their domain specific requirements to ensure ethical practice, while also adhering to national or international guidelines to meet standard technological requirements.

3.4 Applications of AI in the Transportation Industry

The AI for ITS Program has loosely defined categories to help provide a framework for researchers and AI developers to explore applications that leverage AI. In some of the categories, there have been some AI-enabled applications that have been deployed into the real world while others are still in research and development. This paper focuses on four particular categories of importance to equity in AI implementation: traveler decision support tools, transportation systems management and operations, transit operations and management, and asset management. Table 2 below provides a brief overview of some existing AI applications in these areas.

TABLE 2: SUMMARY OF AI APPLICATIONS IN TRANSPORTATION

Application Area	Examples	Phase of Development
Traveler Decision Support Tools	Traffic prediction; estimated times of arrival (ETA); airline arrival times; air traffic control support; itinerary choice models	Concept phase & development phase
TSMO	Traffic management centers (TMC); integrated transportation management systems (ITMS); incident detection; adaptive ramp metering	Concept phase, development phase, & prototype phase
Transit Operations and Management	Transit signal priority (TSP); bus & rail scheduling; vehicle route planning; fare enforcement	Concept phase & development phase *(fare enforcement in prototype)*
Asset Management	Track maintenance & inspection, rolling stock inspection; pavement condition detection; signage inspection; curve safety detection	Concept phase, development phase, & prototype phase

3.4.1 Traveler Decision Support Tools

Traveler Decision Support Tools is the category that uses AI information about a transportation network, including the route and mode travel, transit status, mobility services, pricing information, and incentive-based data (Walker, 2020). Essentially, the AI-enabled applications inside of this category would help travelers of all functional abilities be able to plan their trips to fit their preferences.

The use of cellular data for traffic prediction and routing algorithms has demonstrated substantial growth in the past five years, with a summary of the use of cellular traffic prediction showing a large increase in research of 88 publications or conference proceedings in these applications. Machine learning and deep learning models represent a majority of the research in this space (Jiang, 2022). A variety of models are presented in this summary, and future research seeks to evaluate methods for the deployment of the technology in practice. An example of deployment of this technology has occurred with Google Maps, who partnered with DeepMind to improve traffic prediction and estimated times of arrival (ETA) using machine learning technology. The model adopts graph neural networks to represent road segments, which are subsequently grouped into "supersegments" that operate under predicted and pre-observed travel patterns. Figure 9 presents a diagram of the model relative to a simplified road network. The use of this method has improved ETA predictions by Google Maps by up to 50 percent in urban environments (Derrow-Pinion, 2021; Jiang, 2022).

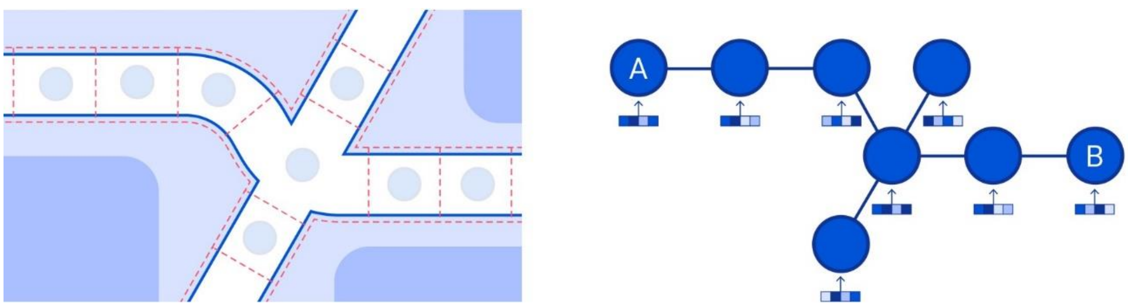


FIGURE 6: GRAPH NEURAL NETWORK FOR GOOGLE MAPS ETA PREDICTION

AI technology has also been applied to airlines and flight arrivals, notably on the consumer side for predictions of flights delays. Given the complexity of the national airspace system, there has been research into the application of AI for traveler demand and support using such technologies and models. Internally, AI may serve numerous uses for the airline, and has been suggested as applicable in areas to reduce congestion both in the air and in airports. AI may be used to identify and predict surface congestion in airports, analyze air traffic control speech, and detect irregularities (referred to as irregular operations or IROPs) in flight paths and taxiing (Tien, 2022). Figure 10 shows an example of AI/ML applications to alert air traffic controllers on potential conflicts given voice and surveillance data. The potential technology would be able to identify given clearances, observe safety risks, and coordinate various inputs to better advise controllers.

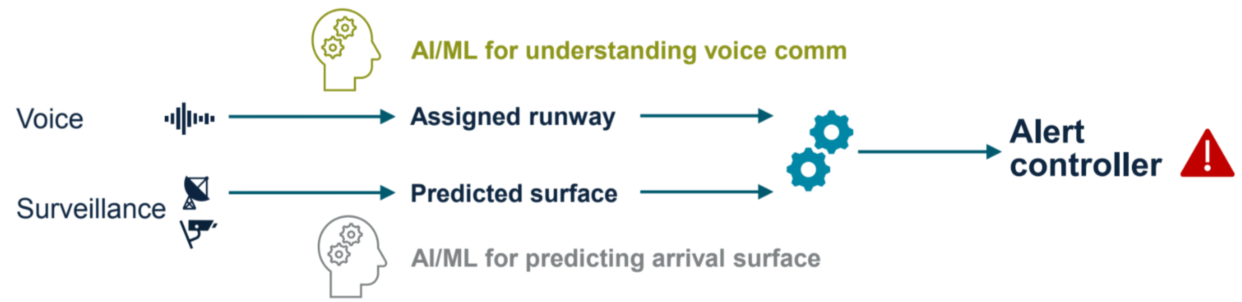


FIGURE 7: SURFACE SAFETY APPLICATIONS FOR AI FOR AIRPORTS

Further research has developed more specifics on these predictions, such as in a study that sought to analyze irregular airline operations using artificial intelligence. The study applied AI due to its ability to manage varied and diverse inputs, including flights schedules and weather patterns, to model delays and predict "meltdown" events as a result of inputted factors. The product produced an IROPs alert when such meltdowns were predicted by midday, and was able to provide a prediction of cumulative delays over the rest of the day (Sherry, 2022).

For air passengers, research on the use of AI for consumer products and applications is motivated by a desire to improve the traveler experience through tools and technologies based on better, more efficient algorithms. However, much of the work in the practice has revolved around reinforcement learning models, and AI applications in the space remain more theoretical. For instance, an algorithm using reinforced learning has developed for itinerary choice model applications for travelers. This model provides greater flexibility by adopting a variety of system metrics and inputting competition characteristics among different airlines. (Abdelghany, 2012). The importance of flight delays, too, in customer satisfaction has prompted research into predicting flights delays on non-traditional and low-cost airlines. A study on long-term system memory (LSTM) modeling for flight delays produced reliable results, and was also applicable to both large and smaller or regional airlines (McCarthy, 2019).

3.4.2 Transportation Systems Management and Operations

Transportation Systems Management and Operations (TSMO) refers to operational improvements and technologies to maintain and improve performance of transportation infrastructure rather than capacity expansion. For AI applications, TSMO implementation seeks to optimize the performance, efficiency, and reliability of a multimodal infrastructure system through real-time and dynamic systems and services.

Some state and regional traffic management centers (TMCs) have implemented AI technology to incorporate an ever-increasing number of sensors and inputs into the transportation management process. At the Southern Nevada TMC, a conglomeration of four transportation agencies overseeing roadway operations in the region. The cloud-based system "Waycare" sought to improve cross-agency collaboration and data sharing among the four agencies, providing a more streamlined service with improved sensors for locating and tracking incidents. The system was developed with a structured implementation approach, focusing on incident detection and response capabilities among the four agencies. The algorithm processes inputs including automatic vehicle locators, incident-response dispatcher applications, and tracking software. Studies of the AI system have suggested that there has been a twelve-minute decrease in incident response times in the Southern Nevada region since piloting the Waycare system in 2017. Additionally, the Delaware Department of Transportation (DelDOT) has implemented multiple measures to incorporate AI into its Integrated Management System (ITMS) system through its AI-ITMS program (discussed in an upcoming section).

More specific TSMO applications of AI are being piloted in the incident detection space, using artificial intelligence to identify traffic incidents. A study on using aggregated traffic data for incident detection in Iowa developed the Traffic Incident Management Enabled by Large-data Innovations (TIMELI) system. The system utilizes INRIX data, a large database of purchased traffic data covering primarily state highways and interstates, and AI algorithms to identify incidents (Barichello and Knickerbocker, 2017). Further studies of the algorithm developed a threshold computing algorithm that is able to input large-scale, real-time data inputs to detect incidents in Iowa (Chang, 2019). These analyses present an important step in the future application of artificial intelligence in the data processing for management and operations.

There have also been indications of TSMO applications in adaptive ramp metering for freeway and interstate locations. Adaptive ramp metering refers to a corridor-wide management scheme to account for variability in congestion both upstream and/or downstream of the ramp meter location. Advancements in adaptive ramp metering and the applications of computer algorithms have taken place since the late 1990s, albeit not including artificial intelligence in the algorithm design. In Washington state, a “fuzzy logic” ramp metering algorithm has been in place along Interstate 5, with more variable inputs given the imprecise and incomplete nature of traffic congestion (O’Brien, 2000). More recently, the California Department of Transportation (Caltrans) has developed more advanced ramp metering algorithms along major corridors in the state. These advancements include multi-corridor ramp metering, which inputs traffic data from parallel corridors in a system referred to as Coordinated Ramp Metering (CRM). Further adaptive ramp metering algorithms seek to apply AI in California to optimize the ramp metering algorithms (Pande, 2018).

3.4.3 Transit Operations and Management

Transit operations and management, often described as a subset of TSMO strategies, refers to specific operational enhancements that improve mobility and performance of transit systems. While transit infrastructure often requires significant investment, operations and management strategies seek to use technology to optimize and enhance services, often in conjunction with other improvements such as traveler support systems and roadway-focused TSMO strategies. Given the technology focus of such strategies, artificial intelligence has begun to play a growing role in operational enhancements for a variety of transit networks.

Transit signal priority (TSP) refers to the optimization of traffic signals on roadway corridors to prioritize transit vehicle service. In essence, traffic signals are modified in deference to bus or other transit routes along a corridor, improving travel times and reducing delay at signalized intersections. While TSP has been previously used in a “passive” strategy that usually seeks to optimize general green-time along a corridor, “active” TSP implementation actually detects oncoming vehicles and adjusts signal time accordingly. TSP can provide significant improvements to bus travel times and delay reduction along corridors; however, the application may require significant technology investments and/or infrastructure improvements such as queue jumps. Queue jumping is a bus-only road lane that allows buses to bypass vehicular queues at intersections or make necessary turns across travel lanes.

AI improvements to transit signal priority have begun pilots and evaluations, bolstered by the technology-focus of this application. In San Jose, California, Intelligent Transit Signal Priority (iTSP) finished a pilot program in 2022 on a high-volume corridor with the goal of improving bus travel times and delay along the roadway. The system utilized a cloud-based AI approach, where buses were fitted with radio-based GPS devices that were linked to traffic signals along the corridor, as shown in Figure 11. Rather than signals being activated upon vehicle arrival, the system optimized signal phasing based on vehicle locations along the corridor from a birds-eye perspective. The system also sought to improve cross-street travel times, a common issue associated with transit signal priority along primary arterials. As a result, intersection delay for buses was reduced by 19-45 percent, and benefits were observed for bus travel time and eventual turning movements.

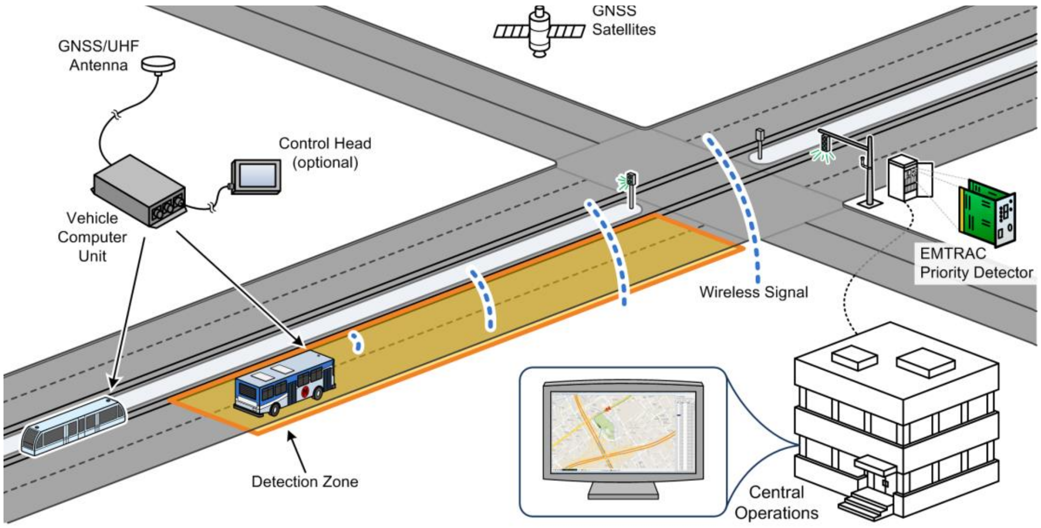


FIGURE 8: TRANSIT SIGNAL PRIORITY (TSP) SYSTEM.
(SOURCE:EMTRAC, 2017)

The predictive capabilities of artificial intelligence have also been researched with regards to bus arrival times (BAT) modeling to better estimate and design bus schedules and provide traveler information. A study summarizing artificial intelligence-based models developed in the literature is summarized in Figure 12 (Singh and Kumar, 2022). The models include deep machine learning models that take in a variety of inputs including bus location, weather conditions, active bus travel times, and passenger information.

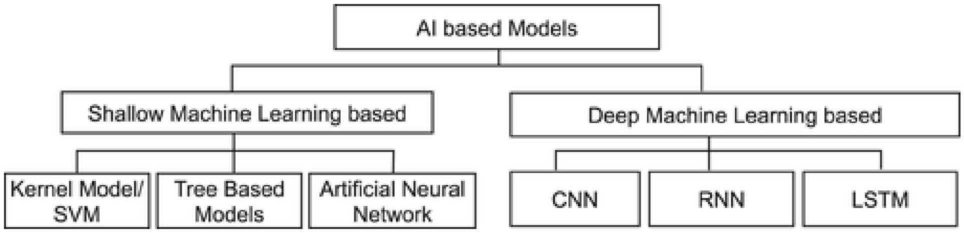


FIGURE 9: SUMMARY OF BUS ARRIVAL TIME AI MODELS (SOURCE: SINGH AND KUMAR, 2022)

However, actual applications of artificial intelligence for these predictive algorithms for operational enhancements remain in progress. A primary focus of these algorithms would be in transit scheduling, especially for modes such as buses with more variability in travel times compared to fixed-guideway systems such as rail, or to better account for historical or predicted variability in schedules. For example, a machine learning model was trained to be able to detect the ”robustness” of train timetables – the performance of the schedule against delays – based on provided schedule and system information (Müller-Hannemann, 2022).

Beyond scheduling, opportunities for AI application exist in transit routing as well, referring to the optimal design of transit routes on a complex roadway network. The simple “vehicle routing problem”, or the optimal routing of vehicles given fixed parameters, has been expanded to a more dynamic system for possible transit applications. Various models and proposals have been considered for this problem. For instance, a proposal of dynamic bus routing, as opposed to fixed bus routes, developed a modified Max-Min Ant System to optimize passenger transport based on minimal travel times. Figure 13 presents a simplified version of the passenger layout used to develop this algorithm (Dimitriu et al, 2020). It is important to note that the applicability of such system, especially communicating such systems to users would be a challenge for implementation.

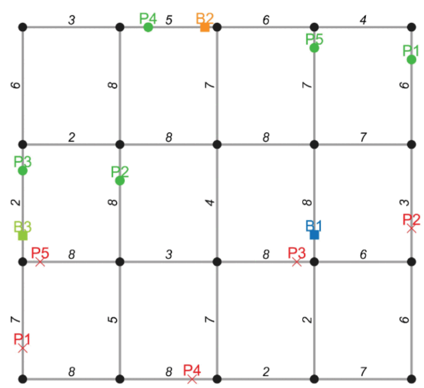


FIGURE 10: PASSENGER LAYOUT AND ROAD NETWORK FOR DYNAMIC BUS ROUTING MODEL

Another example study on dynamic vehicle routing applied a simulated annealing-genetic model to test against an urban environment of supermarkets. The model classified users into static and dynamic classes based on needs, then quantified the optimization model using vehicle costs, vehicle capacity, and regional classification, among other considerations. This model was then able to develop an optimal route network for the urban environment (Ge and Jin, 2021). The location of bus stops, too, is a topic of other literature. A GIS-based model sought to develop a model to optimize bus stop relocation based on service level, existing conditions, traffic conditions, and safety considerations. The study used AI-based partial swarm optimization (PSO) and genetic algorithm to create this model, and then applied it to an urban environment (Shatnawi et al, 2020). There have also been studies of bus routing modeling applied to school bus services (Avilés-González et al, 2020) and campus bus routing (Noor et al, 2021).

Vehicle scheduling and vehicle routing, especially, have been the subject of recent studies on equity considerations for the use of such algorithms. Transit frequency, for instance, is of particular importance for equitable access to services that transit provides. A study evaluating bus frequency and employment uncertainty found that transit frequency is of increasing importance for lower-income populations, and transit-dependent populations both receive greater benefit from robust transit service yet carry more burden from inconsistent service (Ferguson et al, 2012). Other research suggests that economic costs should be balanced with social equity and environmental quality to reduce total cost of a transit network. This specific research modeled a transit network routing system based on modal equity (transit time versus car time) and spatial equity (difference of modal equity across regions) to develop an objective function to evaluate overall equity (Myeonghyeon et al, 2019). Further equity studies have been evaluated for school bus routing, given its unique importance to educational access (Banerjee et al, 2019; Liu et al, 2022).

With the ability of AI to better handle broader data inputs, fare enforcement is another application area of increasing importance to transit agencies. In Barcelona, for example, computer vision technology has been piloted in conjunction with AI-based software to alert ticket inspectors of suspected fare evasion. Figure 14 provides images of a ticket inspector interface (left) and visual representation of suspected fare evasion (right), commonly referred to as “tailgating” (“DETECTOR”, Awaait). Future computer vision applications have been observed for fare enforcement on buses, where fare collection is often taken off-board the bus to reduce boarding times due to on-board collection. Image recognition and cloud-based video monitoring, while not using advanced artificial intelligence yet, presents another example of such application (Burgos-Prada et al, 2021).

FIGURE 11: DETECTOR FARE ENFORCEMENT SYSTEM

However, there are numerous ethical considerations with regards to both computer vision technology and fare enforcement. A recent TCRP report discusses ongoing issues with the increasing using of data and automation for fare enforcement, particularly with regard to preexisting conditions of discrimination in fare enforcement. The report describes potential data challenges due differences in use of public transport by certain groups, limited reliability of census data to the unspecified origin point of transit users, and disparate deployment of enforcement personnel. Due to these potential pitfalls, it recommends baselining fare evasion data by demographic groups to mitigate the impact of disparities in fare evasion and enforcement (Wolfgram et al, 2022).

3.4.4 Asset Management

For transportation infrastructure, asset management (or TAM, transportation asset management) refers to the processes and systems used to maintain and upgrade physical infrastructure during its lifecycle. Thus, the goals of TAM systems are to keep transportation systems in safe and good operation and balance costs of maintaining, operating, and maintaining these facilities. Given the use of asset management in a variety of sectors, AI applications have also occurred for transportation-specific uses to promote more optimized and efficient asset management. Asset management is also a significant investment for agencies and practitioners due to the large amounts of data collection and variety of data types for proper TAM systems (Allen et al, 2019).

The use of technology in the maintenance and inspection of track, rolling stock, and related rail infrastructure has been extensively documented in the literature, and these technologies include adjacent research field to AI including pattern recognition and evolutionary computing (Bešinović, 2021; Tang, 2022). For instance, the use of non-destructive techniques – the ability to determine internal and external fatigue along the entire cross-section of the rail – already has adopted many technologies to promote safety and automation. These techniques include ultrasonic inspection, magnetic flux leakage inspection, and the use of electric currents (Gong et al, 2022). AI has been applied to some of these newer inspection techniques to determine internal cracks within the rail due to repeated contact stress. For instance, an artificial neural network was applied to the alternating current field measurement (ACFM) for rail inspection, where a one-directional alternating current is induced in the rail and observing changes in the observed magnetic field where non-uniformities occur. The magnetic field data is inputted into a multilayer perceptron neural network, as diagrammed in Figure 15, then the ACFM response to clustered cracks is observed. The neural network is trained using validated simulation data to observe cracking, and was validated against untrained data (Rowshandel et al, 2018).

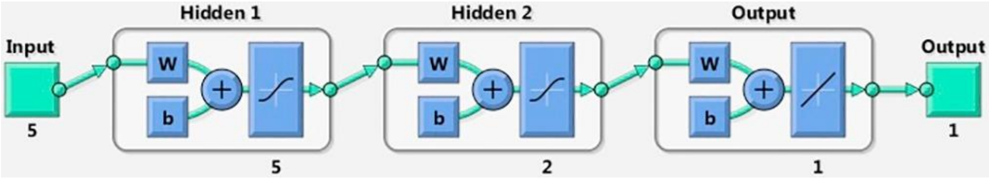


FIGURE 12: MULTILAYER PERCEPTRON NEURAL NETWORK FOR ACFM TECHNIQUE
(Source: Rowshandel et al, 2018)

There are examples of existing technologies also automating rail inspection, seeking to reduce the need for manual inspection and improve safety. For example, Tetra Tech has developed RailAI, a “boxcar” system that travels within a normal train to actively detect track irregularities. The system is entirely autonomous, and uses “AI-powered onboard processing” using sensors that detect fatigue in the rail, ties, and track geometry (“RailAI”, 2021). Additional examples of using computer vision for asset management in the roadway space are also in development. For instance, the technology has been developed to assess curve safety to optimize targeted investments and for automated pavement condition detection in conjunction with 3D laser technology (Tsai, 2023).

3.5 Case Study: Delaware Department of Transportation’s Integrated Transportation Management System

As part of the case study, the research team reached out to the Delaware Department of Transportation (DelDOT). The team interview the DelDOT TMC Operations Manager as well as an outside consultant (BlueHalo) contracted by DelDOT as part of their AI efforts. The team gratefully acknowledges participation of the interviewees.

The DelDOT has developed and implemented multiple measures to incorporate artificial intelligence into its Integrated Transportation Management System (ITMS) since 2019. Over three years, DelDOT has applied AI and machine learning technologies to three primary areas - control, monitoring, and information – which seek to mitigate the impacts of anomalies on Delaware’s transportation network and improve system performance. These technologies build upon existing ITMS plans that have been in place since 1997, with similar goals of reducing congestion and costs while improving performance and safety. This new traffic operations management system has been called AI-TOMS (Artificial Intelligence Traffic Operations and Management System).

3.5.1 Benefits

DelDOT has indicated a long-term goal to develop a potentially “autonomous” traffic decision center for the state transportation network. However, in the short ter it also expects to experience general benefits on information and decision support through AI implementation. DelDOT believes that AI may improve detection and day-to-day operations of the transportation management center (TMC) as increased automation is implemented at the agency.

The system has already realized benefits with regards to short-term traffic flow predictions, and it is able to use recently-recorded traffic data to predict traffic volumes for up to an hour in the future. Furthermore, there are expected future benefits in queue estimation and congestion prediction that are already being tested using camera data. DelDOT has also begun using Bluetooth data and existing loop detectors for vehicle reidentification, where vehicles can be tracked through the network based on non-visual data. These results have shown promising accuracy using video footage as validation.

3.5.2 Challenges

The development of AI at DelDOT has faced three primary challenges, which it has also suggested as affecting the transportation industry at large: workforce requirements, AI compatibility, and media and public perception around AI technology. DelDOT has also identified organizational collaborations as a potential challenge for other agencies in their adoption of AI technology. However, Delaware already has a centralized, single-organizational control over its transportation system. This centralization includes state ownership over the majority of roadways and the transit agency (DART) and a centralized signal system for over 90 percent of traffic signals. This preexisting structure has served as a benefit to more optimized and streamlined AI development, limiting interagency collaboration challenges.

According to DelDOT, workforce challenges have been experienced both from staffing and knowledge in maintaining increasingly complex transportation systems. Understaffing at DelDOT, as with other public agencies, has limited the personnel available for testing and software development. Furthermore, there exists a training and knowledge need for personnel to maintain and operate the AI system upon further implementation.

On the development side, many tools at the disposal of DelDOT are not AI-compatible and do not provide the necessary application programming interfaces (APIs) to consume data or receive instructions. This has required increased sensor deployment, and subsequent cost, to allow the development of a system that can provide data for AI development. DelDOT already had programs in progress for more technology and sensors on its transportation network (such as 500+ miles of fiber optic cable), but it has been limited in some cases by older infrastructure that cannot be adapted to the AI system.

Media and public perception around AI technology has also posed a challenge for AI implementation at DelDOT. General concerns about increased data and technology, in addition to public knowledge of the nature of artificial intelligence, have been and will continue to be an ongoing education and outreach need to provide support for continued AI development.

3.5.3 Hardware and Infrastructure Needs

DelDOT has an in-house software development team that has been working towards AI implementation in collaboration with BlueHalo, an outside contractor. This team already has previous software experience in developing a mobile app for the agency. With regards to hardware and computational resources, DelDOT has opted to install server clusters in the TMC rather than investing in cloud storage due to the critical nature of the transportation network. The agency needs full operations and control under an array of disruptions, adverse conditions, and/or disconnections that would be inhibited by the inherent risks of cloud storage. Nonetheless, these hardware resources are necessary for the high capacity for machine learning processes and AI training.

The following sensor infrastructure has been previously published by DelDOT as examples of current and expected inputs into the AI-based system:

1. Weather Data Collection: provides updated weather conditions on network
2. Traffic Flow Data Collector: provides speed, traffic volume, and roadway occupancy data
3. Bluetooth Data Collector: provides travel time
4. High Resolution Data Collector: provides speed and volume
5. Traffic Cameras: provides vehicle counts, traffic volume, and speed
6. WAZE/HERE Data Collector: provides estimated travel times and traffic incidents; additional app metric provides pothole information for maintenance purposes
7. Social Media Data Analytics: provides traffic incident data
8. Simulation Server: inputs solutions and measures of effectiveness

3.5.4 Performance and Evaluation Metrics

For vehicular traffic, DelDOT relies primarily on travel time, delay, and throughput to gauge the effectiveness of the AI system. For transit performance, DelDOT expects to use on-time frequency of scheduled services and is developing safety metrics for more vulnerable users, particularly with regards to “dilemma zone” incursions (discussed in subsequent section). As their AI efforts expand, additional metrics are likely incorporated into performance evaluation.

3.5.5 Equity Considerations

Considering algorithm biases, DelDOT has primarily focused on broadening data collection methods in order to reflect the demographics of the transportation network more accurately. For example, DelDOT has collaborated on the use of Bluetooth data, which can be a valuable data source for traffic volumes. However, concerns about the penetration of such Bluetooth receivers have led DelDOT to build models that reflect this disparate impact. DelDOT has also adopted three test sites that reflect a range of geographic and traffic flow characteristics: (1) an urban arterial-freeway corridor near Wilmington, (2) a suburban arterial corridor with transit vehicles and connected and autonomous vehicles, and (3) a tourist corridor near the Atlantic coast beaches.

Focusing on vulnerable road users, specifically bicycle and pedestrian traffic, is an ongoing equity consideration for DelDOT. In order to promote increased safety for these users, there is work to develop dilemma zone protection using artificial intelligence to minimize dangers posed to all users. The dilemma zone, referring to the location where drivers may decide to either stop or continue at the onset of a yellow light, is a significant safety concern for signalized intersections. DelDOT hopes that such protections and algorithms may improve safety, particularly for vulnerable users that must interact with signalized road intersections.

The system has also sought to prepare for and mitigate the effects of climate change on Delaware's transportation network. For instance, a project is in development to use artificial intelligence for flood prediction and response, of importance to the state given that much of the network lies at or near sea level. These concerns are due to be exacerbated by rising sea levels, and exert greater impacts on coastal regions. While these projects are not currently being trialed, they are in development for future implementation for the AI system.

4.0 SURVEY OF TRANSPORTATION PROFESSIONALS' VIEW ON AI APPLICATIONS IN TRANSPORTATION

4.1 Background and survey design

The current AI applications in transportation are mostly driven by technology developers and early adopters who are typically more receptive to innovation and eager to explore the potential of new technologies. Since AI is still a new and emerging technology, there is still much to explore regarding the implications of deploying AI systems to transform current transportation planning and engineering practices. The potential of AI systems to advance transportation goals and the full extent of AI's impact on the transportation sector are yet to be explored. As the transportation community navigates the path forward, it can expect to engage in ongoing debates and discussions concerning the benefits of AI, the challenges of its implementation, and the ethical and equity implications that arise. As the case of ChatGPT demonstrates, these discussions are likely to evolve over time as our understanding of AI, its capabilities, and its impacts on transportation deepens.

As such, it is critical to continuously collect data to understand transportation professionals' perceptions of AI as well as their willingness and capacity to leverage AI systems to transform the current practice. How the transportation community as a whole perceives AI and its efficiency and equity impacts will significantly affect whether and how fast these technologies are adopted by transportation agencies. Also, the current level of awareness and knowledge of AI technologies and AI applications in transportation would determine their readiness to manage AI systems being deployed in the real world.

Accordingly, we designed a survey to investigate how transportation professionals perceive AI, the potential impacts of AI, major barriers to AI adoption, and the equity and ethical concerns of AI. The survey also asks about respondents' knowledge of and training in AI. Finally, it asks some questions about equity and ethical considerations for AI applications in transportation. The survey consists of a total of 25 questions, divided into four sections: respondents' perception of AI's impact on transportation, respondents' knowledge level and training in AI, respondents' perception of AI's equity and ethical concerns, and respondents' sociodemographic and economic information. Since AI and transportation are both broad concepts that can be defined broadly, the following definitions are provided in the survey:

- **Artificial Intelligence (AI)** refers to processes that make it possible for systems to replace or augment routine human tasks or enable new capabilities that humans cannot perform. AI enables systems to: (1) sense and perceive the environment, (2) reason and analyze information, (3) learn from experience and adapt to new situations, potentially without human interaction, and (4) make decisions, communicate, and take actions.
- **Transportation** mainly refers to transportation planning and engineering practices that facilitate the movement of people and goods.

4.2 Data collection

A pilot survey was conducted among a small group of respondents, whose feedback was incorporated into the final survey. Our survey target includes a wide range of transportation professionals working in both public and private sectors, regardless if they actively engage in conducting AI-related work or not. Specifically, to engage professionals working in the public sector, the research team has gathered a list of email addresses consisting of state DOT, city DOT, metropolitan planning organization, and transit agency employees. For each agency, we collected the email addresses of two to three individuals who serve in leadership positions related to research and innovation, planning/engineering, and civil rights. Our hope was that these individuals may forward the survey to their colleagues (see survey promotion email below). To engage professionals working in the private sector, we have mainly relied on personal networks. We have also advertised the survey on the TMIP listserv. Several local chapters of the Institute of Transportation Engineers (e.g., Florida Puerto Rico District ITE), several Transportation Research Board Standing Committee (e.g., AED50), as well as the transportation planning division of the American Planning Association, helped advertise the survey on social media or through email newsletters. Finally, to maximize participation from minority transportation professionals, we have contacted the leaders of the local chapters of the Conference of Minority Transportation Officials.

The PI sent out the following email to potential respondents:

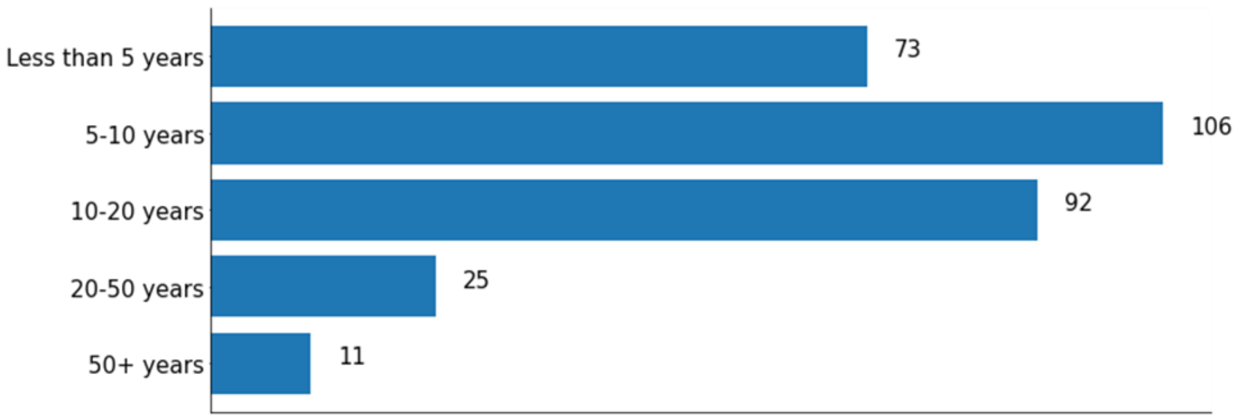
> *"I am writing to ask for your help with a survey study titled "Promoting Equitable AI in Transportation." My research assistants and I found your email address through your institutional website.*
>
> *Artificial intelligence (AI) is quickly changing transportation, but the equity and ethical impacts of AI are not yet well understood. The USDOT-funded STRIDE University Transportation Center is conducting a survey on how transportation professionals perceive AI, the potential impacts of AI, major barriers to AI adoption, and the equity and ethical concerns for AI.*
>
> *As a member of the transportation community and regardless of your level of expertise with AI, your inputs are critical to us. The results of the survey will be used to develop a practical guide to help transportation professionals navigate AI and promote equitable AI applications in transportation.* ***If you would like to participate in this 10-min survey, please click on the link below****:*
>
> *https://ufl.qualtrics.com/jfe/form/SV_9mq3E4Uc3rJMIR0*
>
> *Also,* ***we would very much appreciate it if you can circulate this email to other transportation professionals such as your colleagues****. Thank you so much for your time and help!"*

The survey collection efforts happened between January 2023 to May 2023. No incentives were provided for survey participation. In the end, we have collected a total of 354 responses, among which 275 are complete responses. In the following section, we present the results of the survey responses. Due to the survey topic on AI and the survey distribution approach discussed above, the survey sample is skewed toward highly educated individuals in leadership position. Compared to the general population, these individuals are disproportionately male, White, and have higher household income. More details on the survey respondents are provided in the next section.

4.3 Survey results

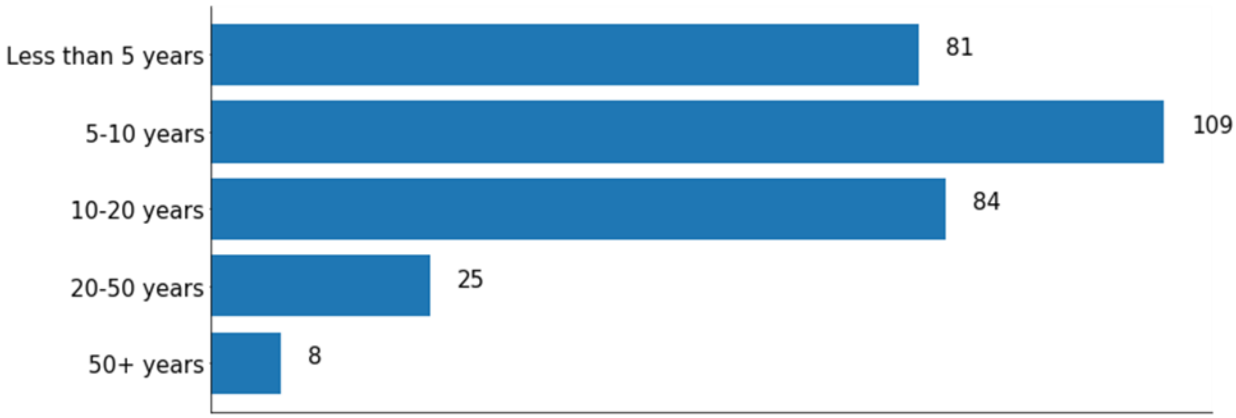
4.3.1 The Potential of AI to Transform Transportation Practices

Q1. AI will be widely adopted by U.S. states, regions, and cities/towns for transportation planning and engineering practices within the next:



About 24% of respondents think that it is less than 5 years, about 35% of respondents think that it is within 5-10 years, about 30% respondents think that it is within 10-20 years, about 8% of respondents think that it is within 20-50 years, and about 4% of respondents think it would be more than 50 years.

Q2. AI will alter the *day-to-day practices* of transportation planning and engineering within the next:

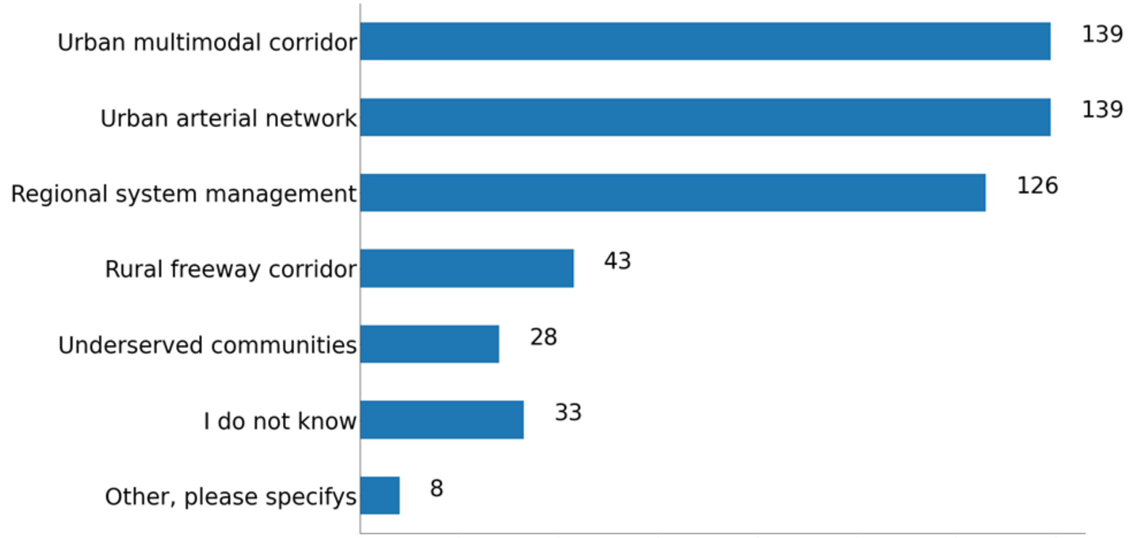


About 26% of respondents think that it is less than 5 years, about 36% of respondents think that it is within 5-10 years, about 27% of respondents think that it is within 10-20 years, about 8% of respondents think that it is within 20-50 years, and about 3% of respondents think it would be more than 50 years.

Q3. In your opinion, which of the following has the most potential for AI applications (select up to three options)?

In this question, respondents are asked to select up to three applications that AI has the most potential for. The results shows that "Advanced driver assistance systems," "Automated driving systems," and "Transportation systems management and operations" are the most selected options. In other words, respondents think there is more potential for AI applications in vehicle automation and driving assistance than in transportation planning and engineering.

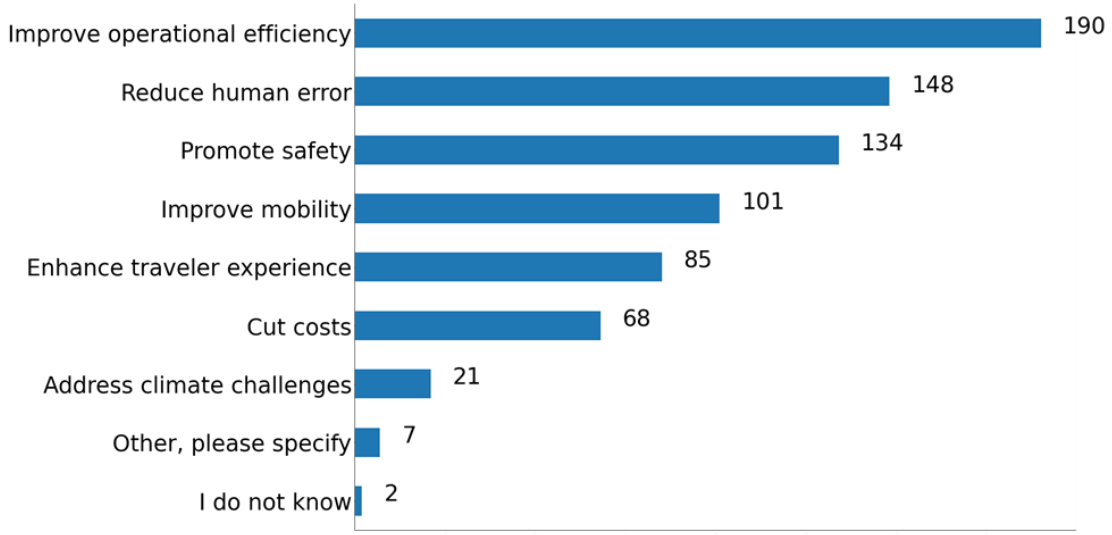
Q4. In your opinion, which of the following **spatial contexts** have the most potential for AI applications (select up to two options)?



Most respondents pick selections "Urban arterial network", "Urban multimodal corridor", and "Regional system management". It is evident that respondents think that AI would be applied in the urban and higher developed area rather than rural and undeserved areas.

4.3.2 Main Benefits and Barriers Associated with AI Adoption in Transportation

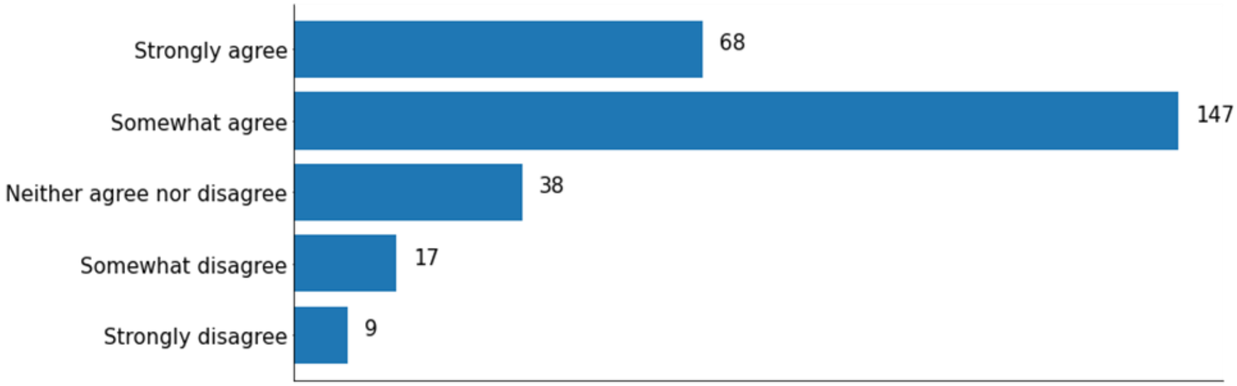
Q5. Which of the following do you perceive as the biggest **AI-enabled benefit** in transportation (select up to three options)?



The most selected options include "Improve operational efficiency", "Reduce human error", and "Promote safety". Only 3% respondents perceive that AI can address climate challenges.

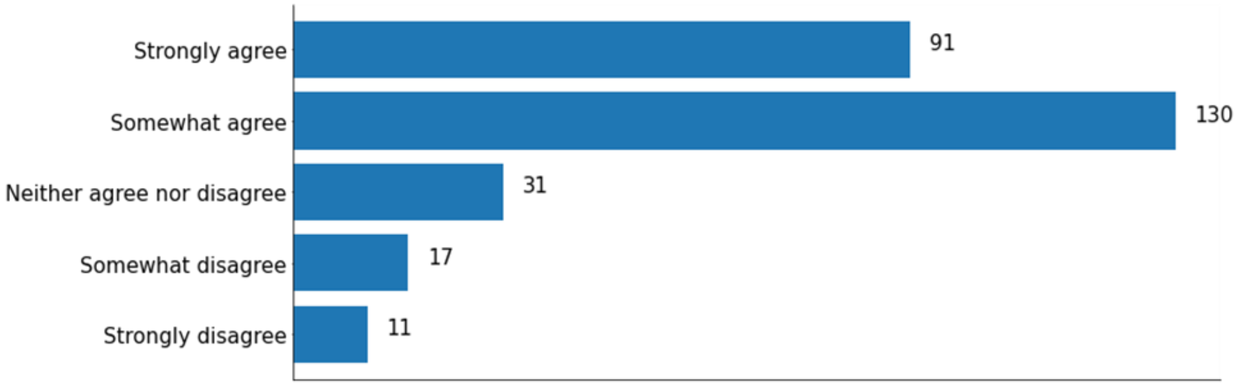
Q6. To what extent do you agree with the following statements?

AI can lead to more efficient transportation services and cost-savings



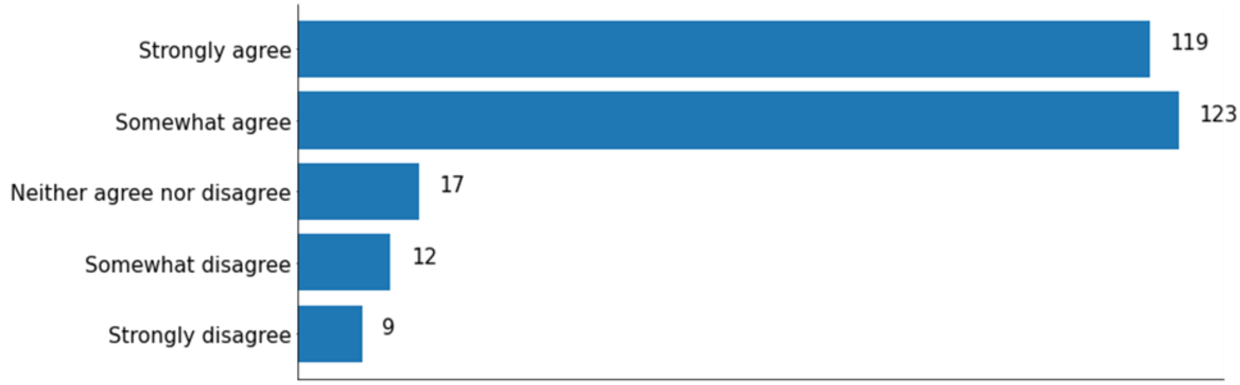
Here respondents are asked to what extent they agree with the idea that AI can lead to more efficient transportation services and cost-savings. About 53% of respondents feel somewhat agree, about 24% of respondents think strongly agree, about 14% of respondents think neither agree nor disagree, and only about 6% and 3% of respondents think somewhat disagree and strongly disagree. Therefore, most respondents think AI can lead to more efficient transportation services and cost-saving.

AI can help transportation agencies make smart, data-driven decisions



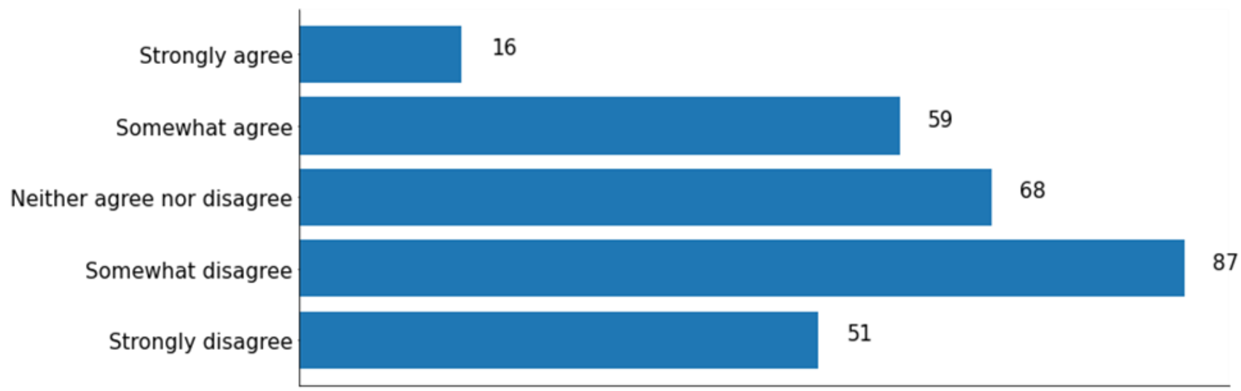
Here respondents are asked to what extent they agree with the idea that AI can help transportation agencies make smart, data-driven decisions. About 46% of respondents feel somewhat agree, about 32% of respondents think strongly agree, about 11% of respondents think neither agree nor disagree, and only about 6% and 4% of respondents think somewhat disagree and strongly disagree. The results suggest that most respondents agree the idea that AI can help transportation agencies make smart, data-driven decisions.

AI can automate routine tasks and improve labor productivity



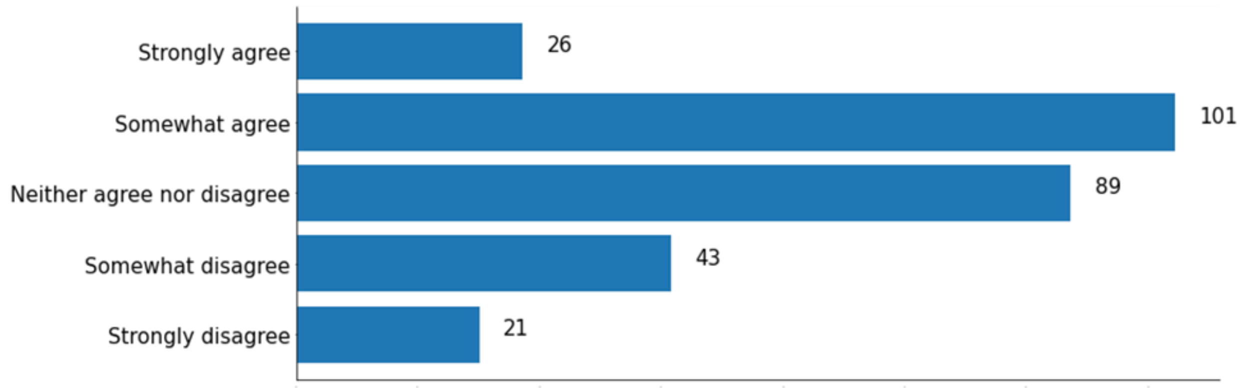
Here respondents are asked to what extent they agree with the idea that AI can automate routine tasks and improve labor productivity. About 44% of respondents feel somewhat agree, about 42% of respondents think strongly agree, about 6% of respondents think neither agree nor disagree, and only about 5% and 3% of respondents think somewhat disagree and strongly disagree. It is evident that most respondents support the point of view that AI can automate routine tasks and improve labor productivity.

AI can remove bias in government decision-making processes



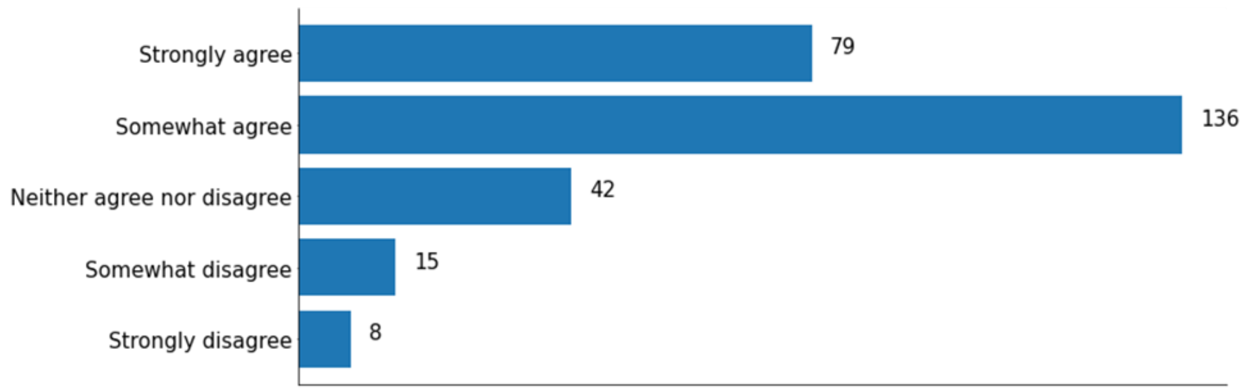
Here respondents are asked to what extent they agree with the idea that AI can remove bias in government decision-making processes. About 31% of respondents choose somewhat disagree, about 18% of respondents reckon strongly disagree, about 24% of respondents think neither agree nor disagree, about 21% and 6% of respondents think somewhat agree and strongly agree. The results show that most respondents lack confidence that AI can remove bias in government decision-making processes.

AI can facilitate the discovery of solutions to improve transport equity



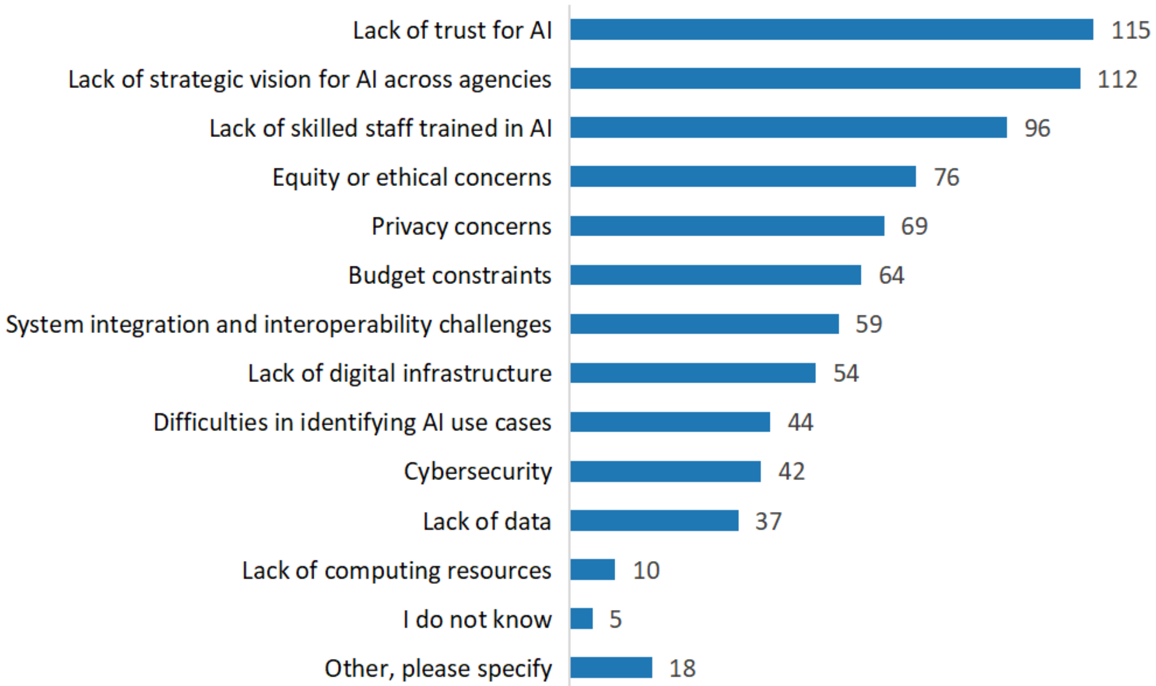
Here respondents are asked to what extent they agree with the idea that AI can facilitate the discovery of solutions to improve transport equity. About 36% and 9% of respondents choose somewhat agree and strongly agree, about 32% of respondents think neither agree nor disagree, only about 15% and 8% of respondents think somewhat disagree and strongly disagree. Overall, the results are somewhat mixed, with slightly more respondents agreeing that AI can facilitate the discovery of solutions to improve transport equity.

AI can improve traveler experience with personalized recommendations/services



Here respondents are asked to what extent they agree with the idea that AI can improve traveler experience with personalized recommendations/services. About 49% and 28% of respondents choose somewhat agree and strongly agree, about 15% of respondents think neither agree nor disagree, only about 5% and 3% of respondents think somewhat disagree and strongly disagree. In other words, most respondents agree that AI can improve traveler experience with personalized recommendations/services.

Q7 In your opinion, which of the following are **major barriers** to widespread AI adoption in transportation (select up to <u>three</u> options)?

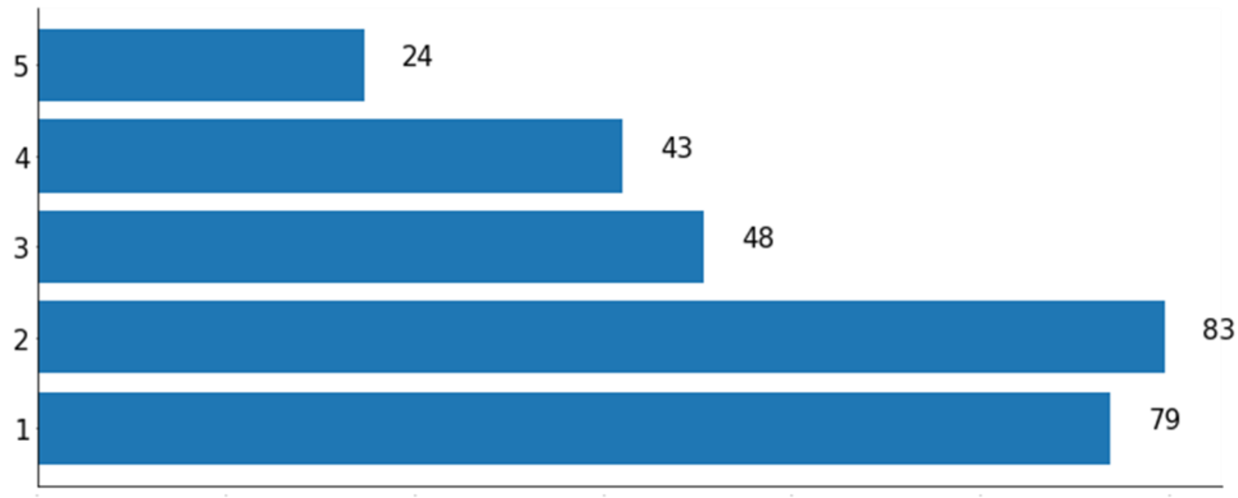


In this question, respondents are asked to select up to three major barriers that hinder widespread AI adoption in transportation. The most selected options include "Lack of trust for AI," "Lack of strategic vision for AI across agencies," and "Lack of skilled staff trained in AI". The resource and technical barriers such as "Lack of computing resources" and "cybersecurity" are not regarded as the main barriers among the respondents.

4.3.3 Transportation Professional's AI Knowledge Level

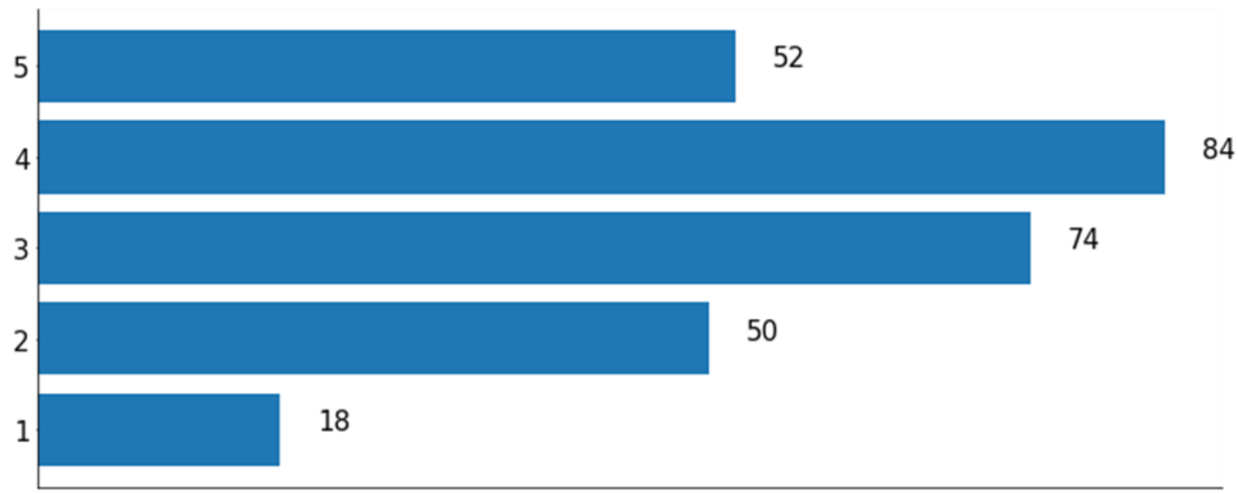
Q8 On a scale of 1-5, please indicate your level of knowledge in each of the following (with 1 indicating "no knowledge" and 5 indicating "expert-level knowledge").

Computer programming (e.g., Python/R/Java/SQL)



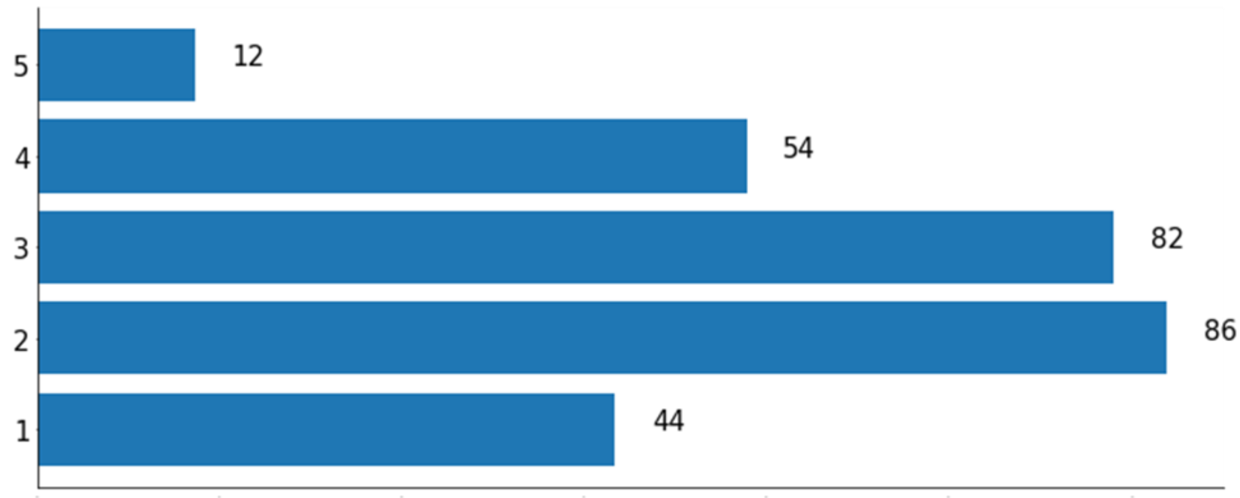
Almost 60% of respondents have no or little knowledge in computer programming.

Mathematics and statistics (linear algebra, regression, hypothesis testing)



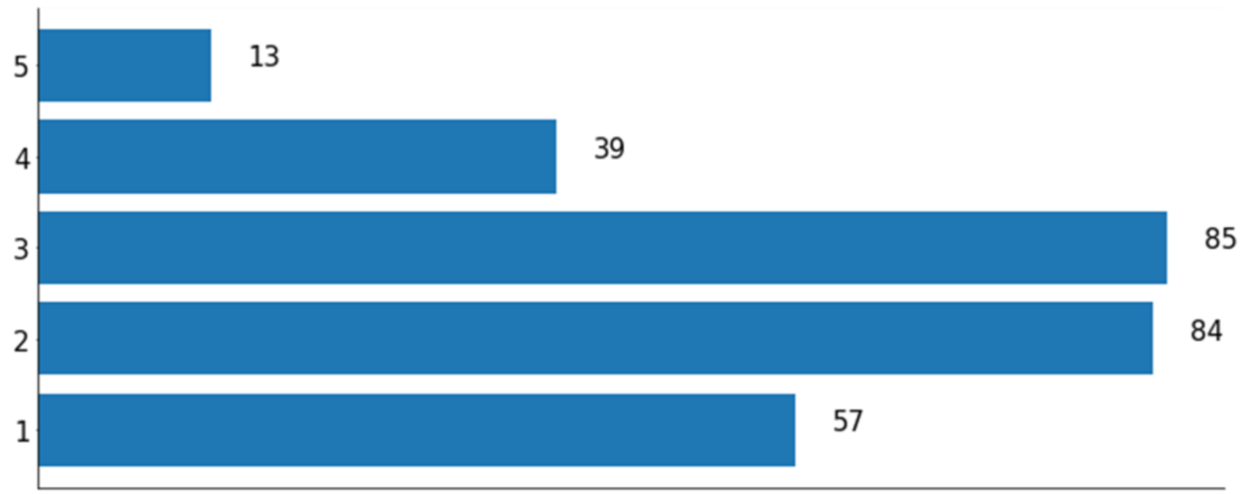
Most respondents reported that they have medium- to high-level of knowledge at mathematics and statistics.

Data and Computer infrastructure (data structures, database management systems, cloud computing, cybersecurity)



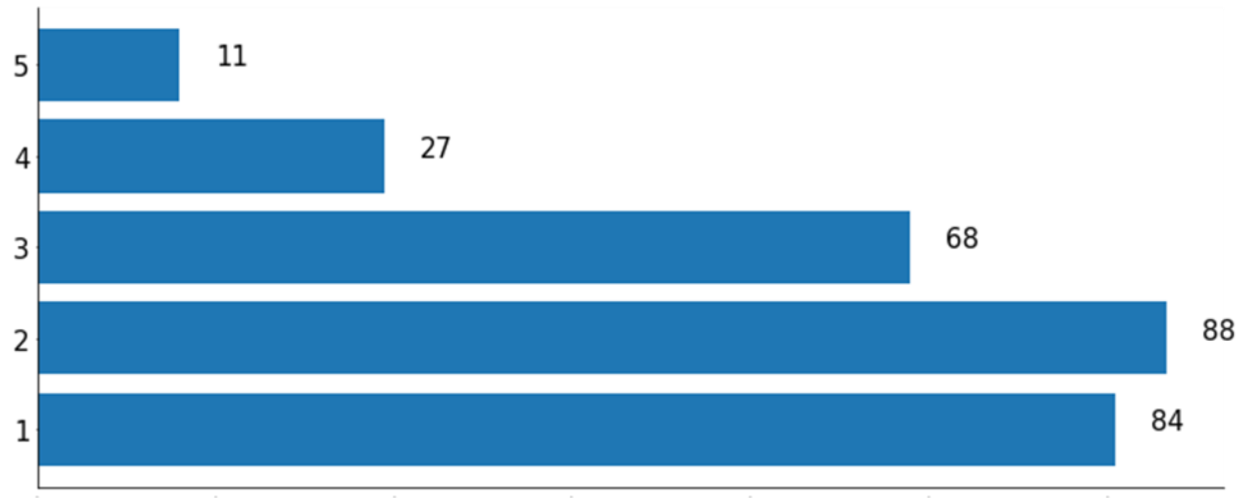
Most respondents have medium level of knowledge about data and computer infrastructure.

AI concepts (machine learning, deep learning, neural networks, reinforcement learning)



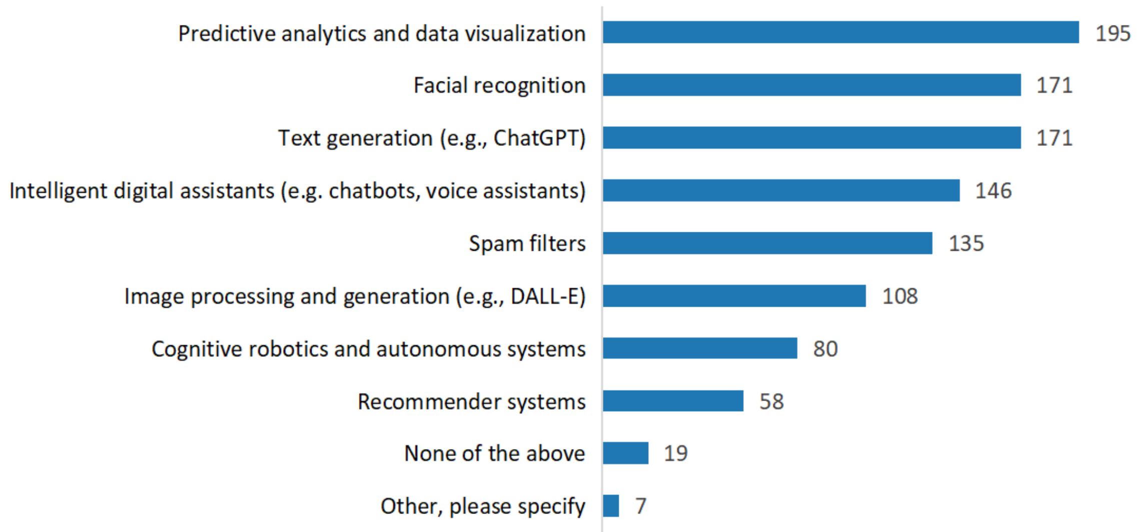
The results suggest that most respondents have low- to medium level of knowledge in AI concepts (machine learning, deep learning, neural networks, reinforcement learning).

AI technologies (computer vision, natural language processing, robotic systems, predictive analytics)



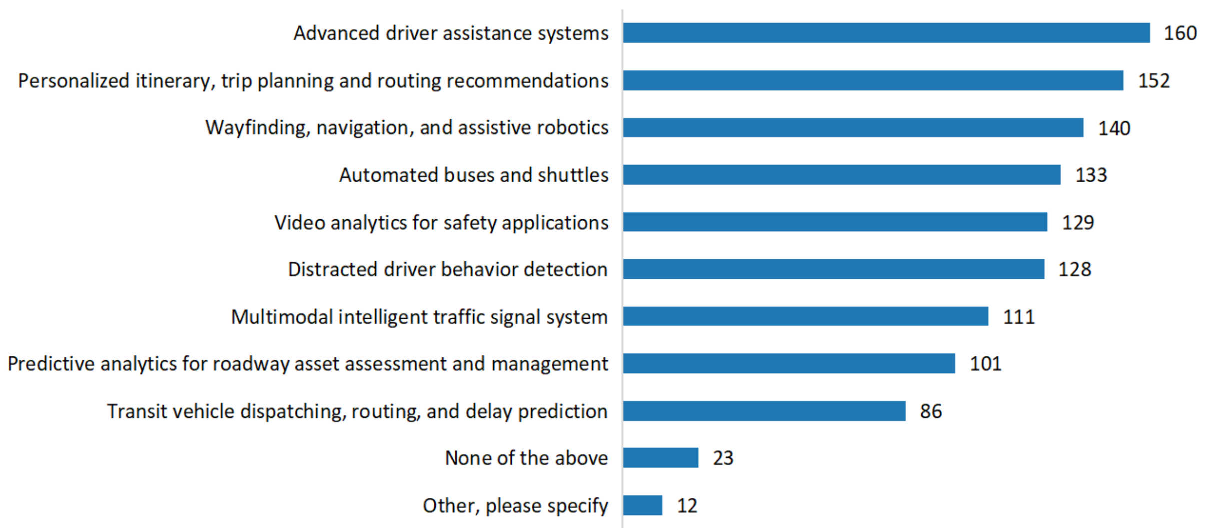
Most respondents have low- to medium level of knowledge of AI technologies.

Q10. Which of the following *general* AI applications are you familiar with? (select all that apply)



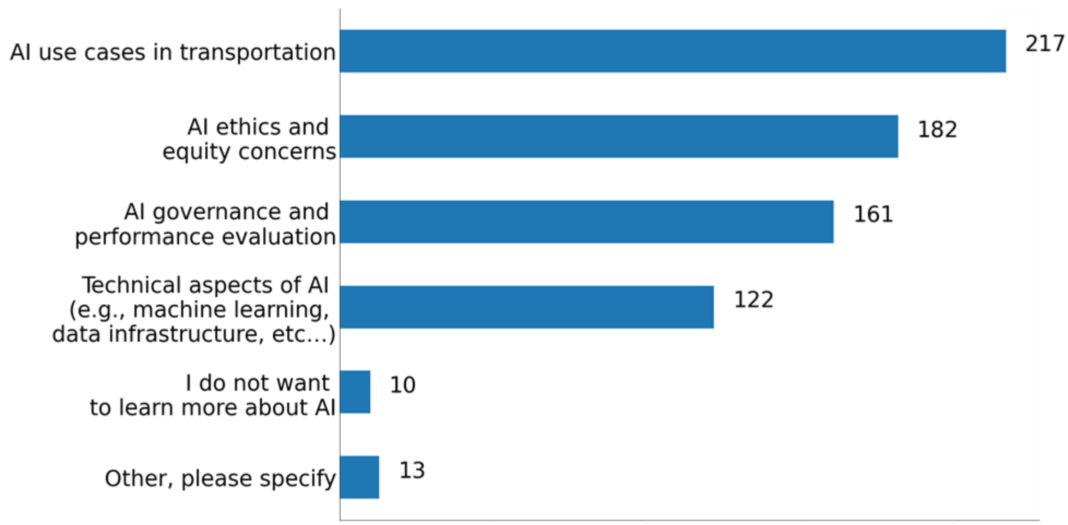
In this question, respondents are asked to select the general AI applications that they are familiar with. The most selected options include "Predictive analytics and data visualization", "Text generation (e.g., ChatGPT)", "Facial recognition", and "Intelligent digital assistants (e.g., chatbots, voice assistants)". Interestingly, only 5% of respondents selected "Recommender systems" even though they have experienced the targeted ads promoted to them based on their browser history.

Q11. Which of the following *transportation* AI applications are you familiar with? (select all that apply)



In this question, respondents are asked to select the transportation AI applications that they are familiar with. The most selected options include "Advanced driver assistance systems", "Personalized itinerary, trip planning and routing recommendations", and "Wayfinding, navigation, and assistive robotics." Compared to the general AI applications, the responses are much more evenly distributed, indicating a greater level of familiarity with transportation AI applications overall among the survey respondents.

Q12. Which of the following AI topics do you hope to learn more about? (select all that apply)

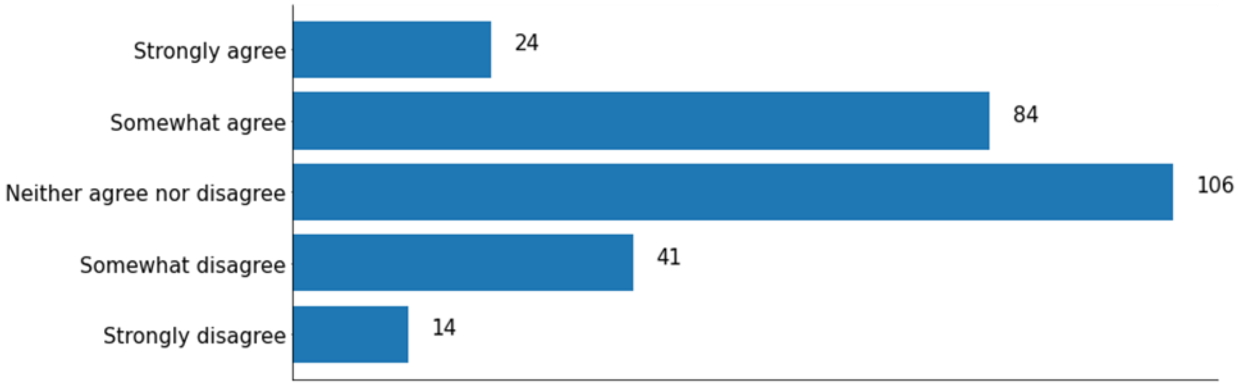


In this question, respondents are surveyed what AI topics they hope to learn more about. About 31% respondents choose "AI use cases in transportation", 26% respondents choose "AI ethics and equity concerns", 23% respondents choose "AI governance and performance evaluation", and 17% respondents choose "Technical aspects of AI (e.g., machine learning, data infrastructure, etc.)"

4.3.4 Ethical and Equity Considerations of AI Applications in Transportation

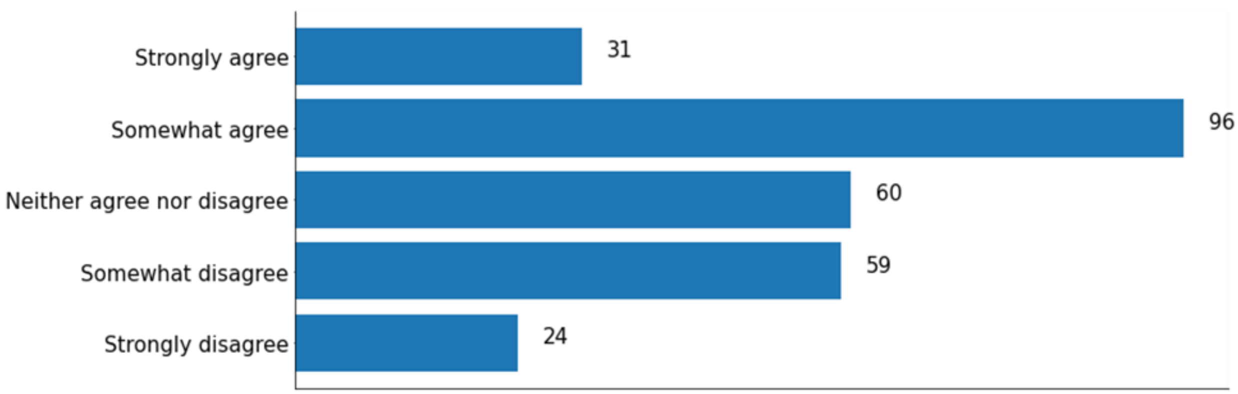
Q13. To what extent do you agree with the following statements?

I believe that AI algorithms will exaggerate inequalities in transportation.



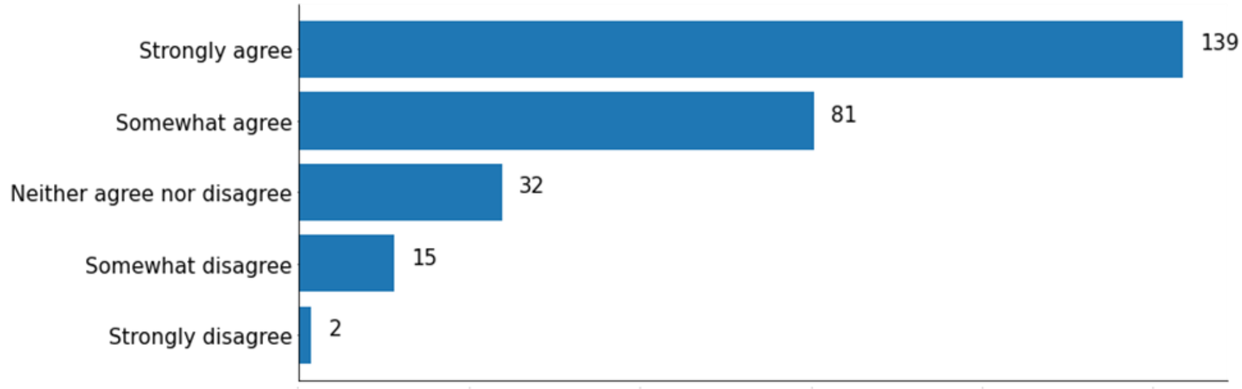
The most selected option is “neither agree or disagree,” which indicates a neural view on how AI will shape transportation equity. Moreover, compared to those who disagree, a slightly higher proportion of the respondents agree that AI algorithms will exaggreate inequalities in transportation.

Applying AI in transportation decision-making will reduce transparency.



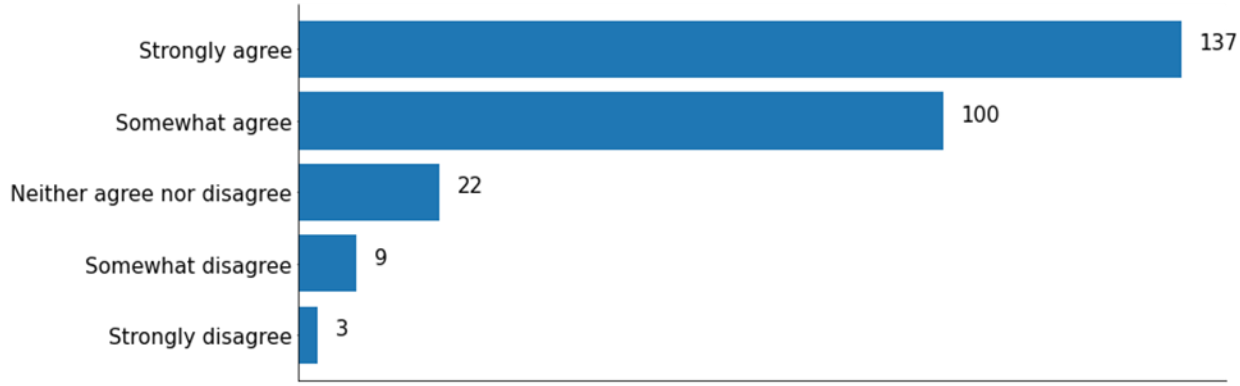
While the results are mixed, a slightly higher proportion of the respondents agree that applying AI in transportation decision-making will reduce transparency compared to those disagree.

Community engagement is important when developing AI transportation systems.



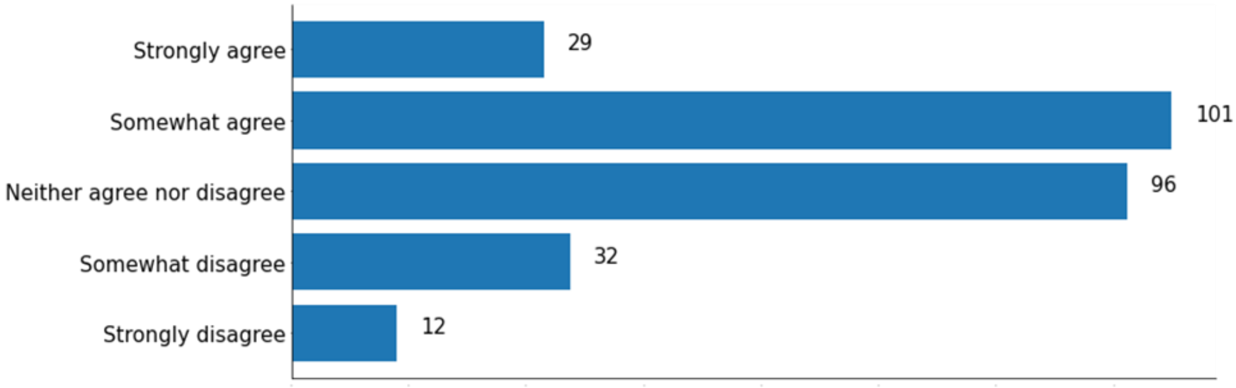
An overwhelming majority of the respondents agree that community engagement is important when developing AI transportation systems.

There is limited understanding of AI ethics in the transportation community.



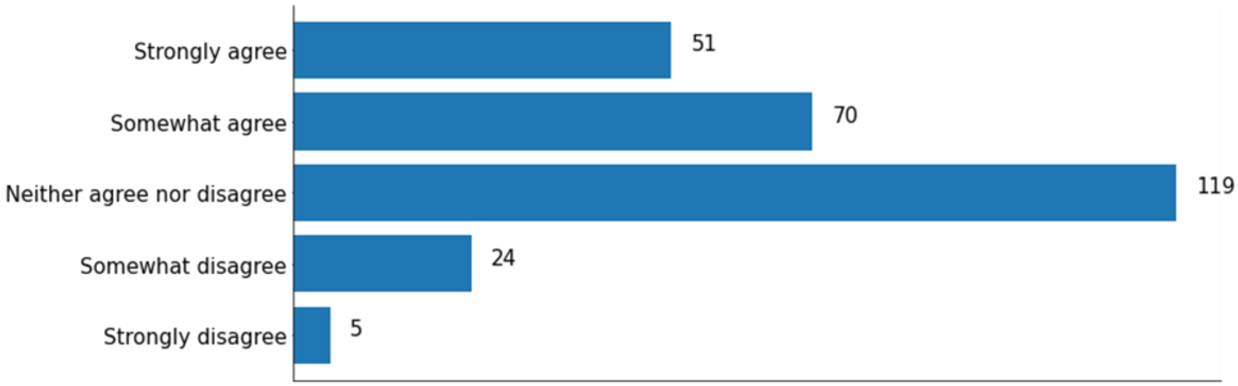
An overwhelming majority of the respondents agree that there is limited understanding of AI ethics in the transportation community.

Proper use of AI can help reduce social inequality.



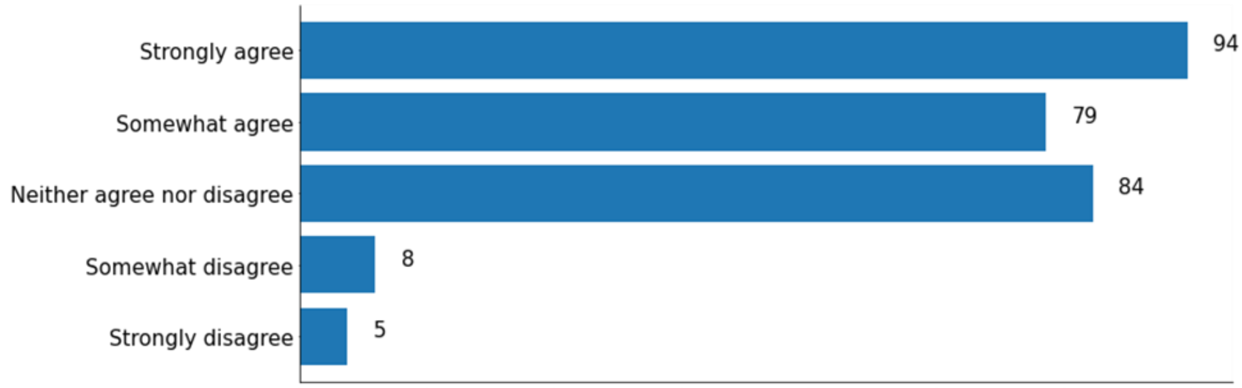
Close to half of the respondents strongly or somewhat agree that proper use of AI can help reduce social inequality, whereas the rest have varying degrees of doubts.

The data used in AI applications are often not representative of the population.



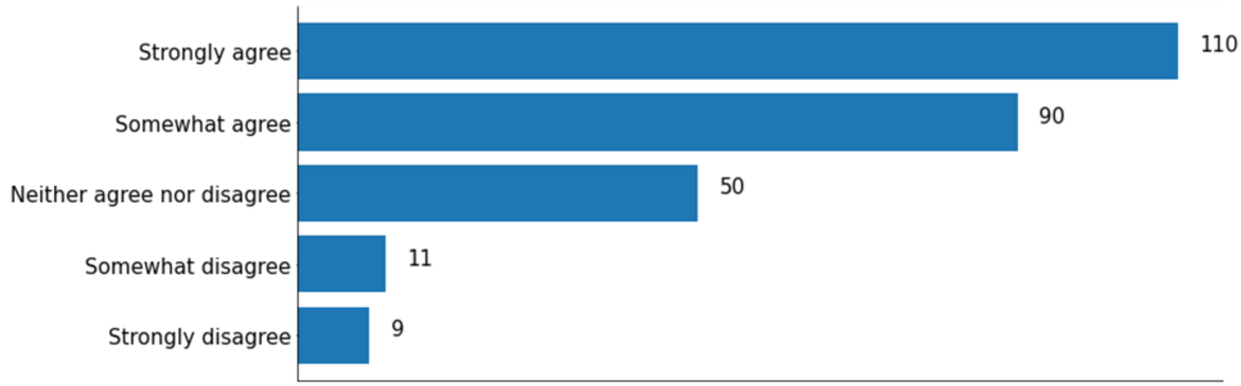
The most selected option is "neither agree or disagree," which indicates a neural view on this topic. Moreover, compared to those who disagree, a slightly higher proportion of the respondents agree the data used in AI applications are often not representative of the population.

The current AI development and deployment progress has not done enough on engaging communities and the disadvantaged populations.



Most respondents agree that the current AI development and deployment progress has not done enough on engaging communities and the disadvantaged populations. Note that about 31% of the respondents are neural about the statement.

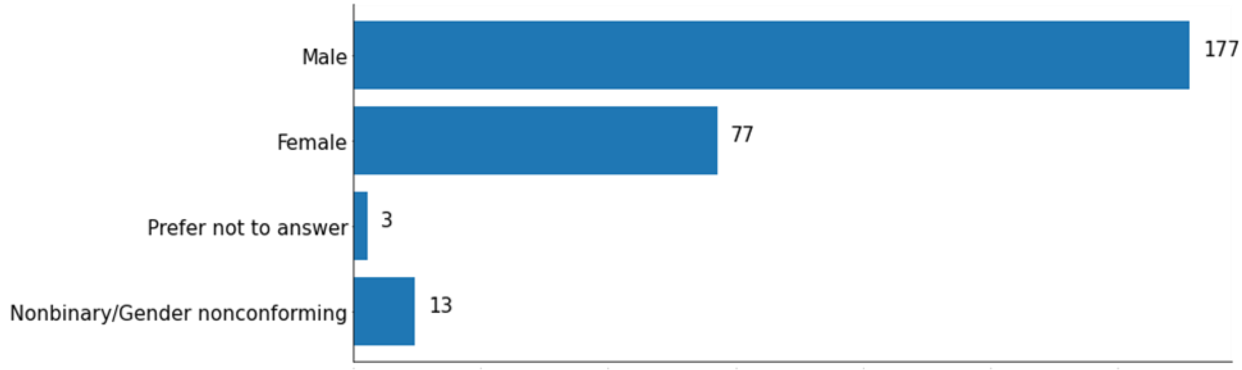
Biased datasets used for developing AI systems will lead to social inequalities.



The majority of respondents agree that the current AI development and deployment progress has not done enough on engaging communities and the disadvantaged populations. About 31% of the respondents are neural about the statement.

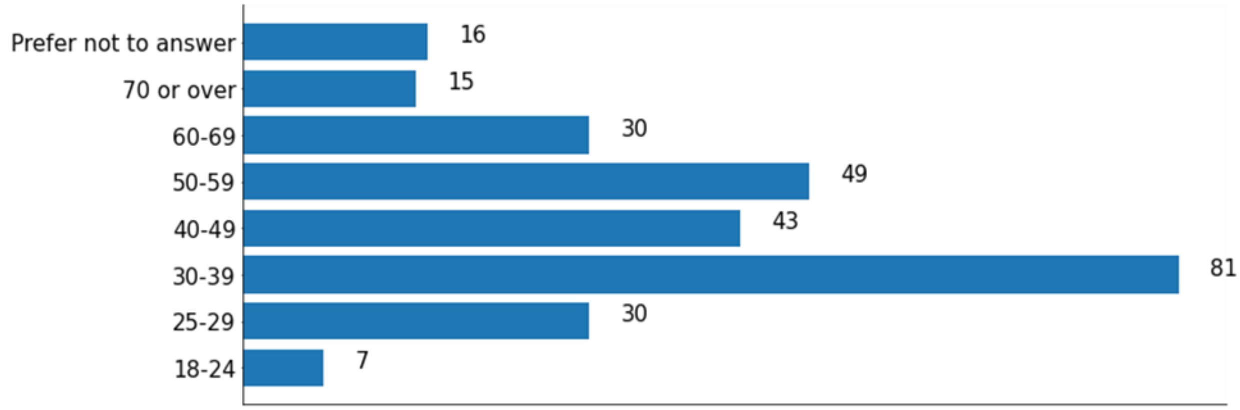
4.3.5 Sociodemographic Characteristics of Survey Respondents

Q15 Are you a:



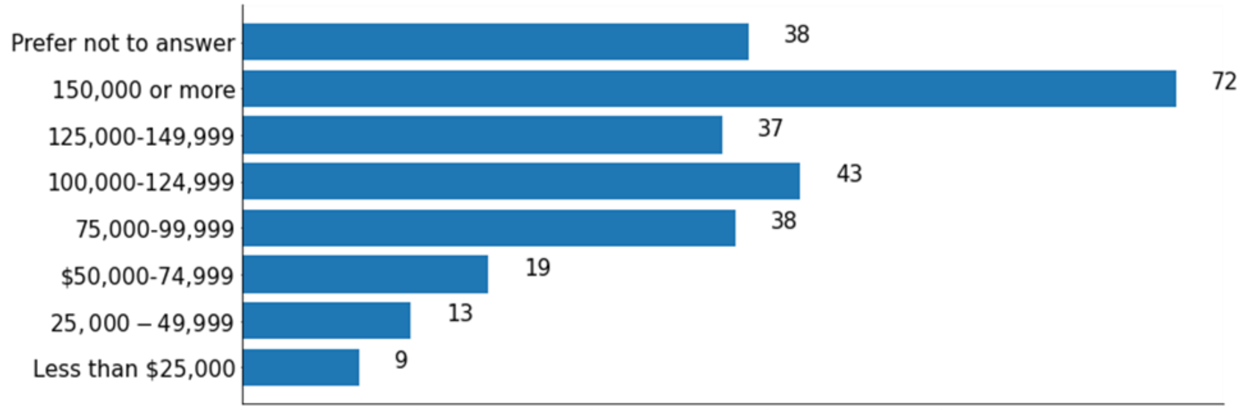
The proportion of male respondents (66%) is much higher than that of female respondents (28%).

Q16 What is your age?



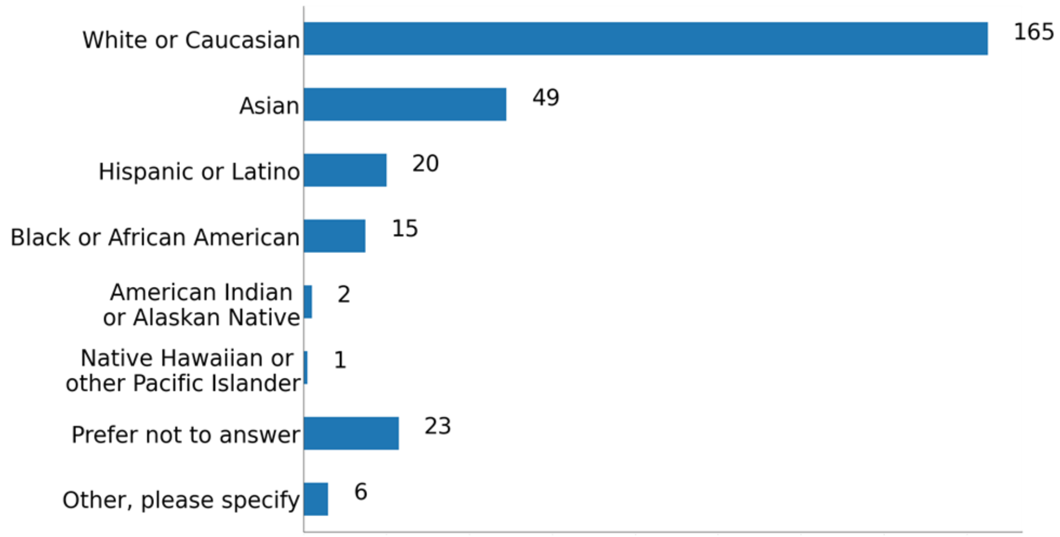
About 30% of the respondents are 30-39 years old, which the largest age group in our sample. It is followed by people who are 40-49 years old and 50-59 years old, who make up 16% and 11% of the respondents, respectively.

Q17 Which category best represents your annual household income in the past year?



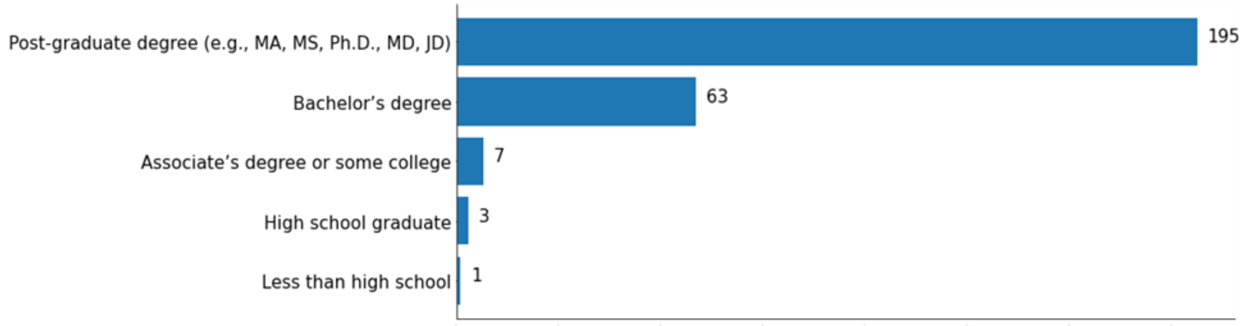
The household income of the respondents in our survey sample is higher than the general population. Most respondents have a household income of $75,000 or above, and those having a household income of $150,000 or more constituting the largest income group. This likely results from our survey distribution approach: as discussed above, we contacted individuals in leadership positions when reaching out to state and local transportation agencies, and so these individuals (who tend to have higher income) are likely to be disproportionately represented in our survey.

Q18 *Which race/ethnicity best describes you?*



Most respondents are White or Asian, with White respondents comprising 59% of the sample. While we have devoted extensives efforts to engaging minority professionals (e.g., reaching out to all local chapters of COMTO), they are underreprented in our sample.

Q19 What is your highest educational level?



An overwhelming majority of respondents have a Bachelor's degree or above, and about 72% of respondents have a post-graduate degree (e.g., MA, MS, Ph.D., MD, JD).

4.4 Summary of Survey Results

The survey results indicate that most respondents believe that AI will be widely adopted in transportation planning and engineering practices within the next 5-20 years. There is particular optimism regarding the potential for AI applications in advanced driver assistance systems, automated driving systems, and transportation systems management and operations. Respondents also perceive more potential for AI in urban and developed areas compared to rural and underserved areas.

The major benefits of adopting AI in transportation, as perceived by respondents, include improved operational efficiency, reduced human error, and enhanced safety. Respondents largely agree that AI can lead to more efficient transportation services, cost-savings, and data-driven decision-making. They also believe that AI has the potential to automate routine tasks and improve labor productivity. However, there is some skepticism regarding AI's ability to remove bias in government decision-making processes and address social inequalities.

The main barriers to widespread AI adoption in transportation, as perceived by respondents, include the lack of trust in AI, insufficient strategic vision for AI across agencies, and a shortage of skilled staff trained in AI. Interestingly, resource and technical barriers such as computing resources and cybersecurity were not seen as the primary challenges.

Transportation professionals have varying levels of knowledge in different AI-related domains. While respondents generally have limited knowledge of computer programming and AI concepts, they possess a higher level of familiarity with mathematics and statistics. Furthermore, their knowledge of data and computer infrastructure falls mostly in the medium range. Respondents expressed strong interest in learning more about AI use cases in transportation, AI ethics and equity concerns, and AI governance and performance evaluation.

There is widespread agreement among respondents that community engagement is crucial in the development of AI transportation systems and that biased datasets used for AI development can contribute to social inequalities. Many respondents also express concerns for AI algorithms to potentially exacerbate inequalities in transportation and reduce transparency in government decision-making processes. Furthermore, they believe that there is currently a limited understanding of AI ethics in the transportation community.

The survey sample predominantly consists of male respondents and the largest group of respondents falls within the 30-39 age range. The income distribution skews towards higher household incomes, likely due to the survey's focus on engaging individuals in leadership positions. The majority of respondents possess at least a Bachelor's degree, with a significant proportion holding post-graduate degrees.

4.5 A Related Survey: Urban Planner's View of AI

Dr. Tom Sanchez has recently conducted a similar survey that focuses on how urban planners perceive AI, which has generated useful insights that complement the current study. Therefore, we provide a brief summary of the results from the survey here.

The objective of the survey was to assess the current understanding, experiences, and perspectives of urban planners about artificial intelligence (AI). We were interested in drawing from a broad range of planners, whether actively engaged in using AI techniques or not. Therefore, we surveyed all current members of APA and received approximately 400 completed surveys. The survey consisted of ten questions that ranged from self-reported levels of knowledge about AI, perceived levels of appropriateness for several sub-areas of planning, the likelihood of adopting AI tools, and respondent demographic characteristics.

Survey respondents mentioned transportation-related analysis as the top potential area for AI applications (see Figure 16). Transportation tends to have more data available and bounded planning questions compared to other types of planning issues. The second most frequently mentioned area is plan review. This is likely a suitable application because of its routine nature that is associated with rule-based analysis. Like transportation, data analysis (including big data) and demographic analysis are well-suited to potential AI applications due to the quantitative nature of the questions being addressed. Other application areas like environmental, land use, and zoning have significant spatial dimensions that are appropriate for AI types of analysis as well.

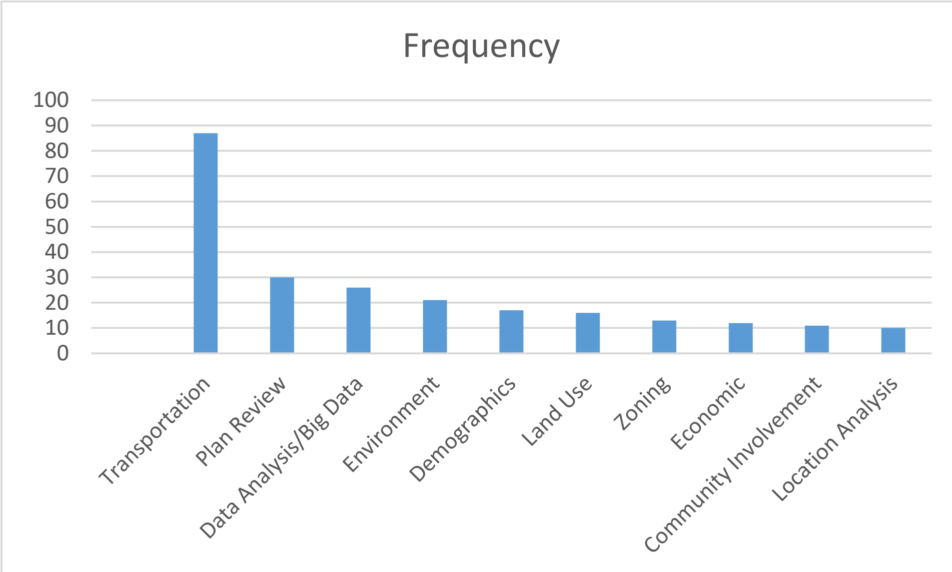


FIGURE 13: TOP 10 AREAS MENTIONED AS SUITABLE FOR AI APPLICATIONS

In addition, survey respondents provided approximately 14 additional comments about particular areas within transportation where they felt AI could have the most impact:

- Areas where there are large amounts of data such as land use, traffic, economics where AI can aid experts with data automation, integration, and analysis
- Transportation planning as it evolves into smart mobility planning
- Land Use data collections and traffic data collection on the road network
- Travel demand modeling (transportation)
- Transportation and land-use
- Transportation, land use scenarios
- Transportation and public parking
- Transportation - incorporation of autonomous vehicles
- Transportation and greenhouse gas emissions
- Transportation planning can greatly benefit from AI, especially in regards to ridership (e.g. counting the number of passengers that enter a train automatically), self-driving vehicles, and identifying circulation patterns and intensity
- Transportation modeling
- Travel demand modeling, micro and macro. The field is long overdue and needs to be indicated to deal with all of the AVs, mixed use construction, and active transportation modes coming online
- Transportation (autonomous vehicles) and logistics (delivery); land surveying
- Transportation planning and regular processes

Overall, these 14 comments refer to the potential use of AI in transportation planning and related fields such as land use, traffic, and logistics. The areas where AI can aid experts include data automation, integration, and analysis, particularly using large data sets. Other areas where survey respondents think AI can be beneficial include smart mobility planning, travel demand modeling, transportation and land-use scenarios, autonomous vehicles, and greenhouse gas emissions. Additionally, transportation modeling and micro and macro travel demand modeling are important fields that can benefit from AI.

5.0 CONCLUSION AND DISCUSSION

5.1 Conclusion

The rapid development of AI technology is changing many fields, including transportation. AI applications in transportation can bring many benefits including, but not limited to, enhancing the efficiency of operation, reducing traffic congestion, saving costs, etc. However, AI adoption in transportation also face many challenges, including technical barriers such as the need for large amounts of data and infrastructure investments, the lack of skilled personnel, and the public's concerns about AI's negative impacts.

The transportation industry has been increasingly incorporating AI applications in various areas. We have reviewed AI applications in four domains: traveler decision support tools, transportation systems management and operations, transit operations and management, and asset management. Overall, AI systems offer significant potential to improve efficiency, traveler experience, and safety. While some applications are already deployed in the real world, others are still in the research and development phase. Continued advancements in AI technology are expected to drive further innovation and implementation in the transportation sector.

Our survey of transportation professionals generated rich insights regarding how the current transportation workforce perceives Artificial Intelligence (AI), its potential impacts, and the major barriers to widespread AI adoption. Most respondents believe that AI will be widely adopted in transportation planning and engineering practices within the next 5-20 years. The major benefits of adopting AI in transportation, as perceived by respondents, include improved operational efficiency, reduced human error, and enhanced safety. Respondents largely agree that AI can lead to more efficient transportation services, cost-savings, and data-driven decision-making. They also believe that AI has the potential to automate routine tasks and improve labor productivity. However, there is some skepticism regarding AI's ability to remove bias in government decision-making processes and address social inequalities.

There is widespread agreement among respondents that community engagement is crucial in the development of AI transportation systems and that biased datasets used for AI development can contribute to social inequalities. A significant percentage of respondents also express concerns for AI algorithms to potentially exacerbate inequalities in transportation and reduce transparency in government decision-making processes. Furthermore, they believe that there is currently a limited understanding of AI ethics in the transportation community.

Finally, in our ongoing work, we have segmented respondents based on their latent attitudes toward the impacts of AI applications in transportation and investigated the factors associated individuals' latent attitudes. The preliminary results suggest that how people perceive AI differs from how they perceive autonomous vehicles. Even though autonomous vehicles are a major domain for AI applications, we observe some differences. Notably, while studies often identify gender differences in attitudes towards autonomous vehicles, we find that gender is not a significant factor in determining latent class membership. However, consistent with the existing literature that suggests a strong link between people's age and their acceptance of new technology, we find that respondents' perception of AI's impacts on transportation correlates with their age. Our survey results suggest that, compared to people aged 40 or above, younger professionals are much more likely to hold more positive views on AI. These results suggest that older adults should be the primary target for education and outreach efforts if AI applications in transportation continue to grow in significance and will likely impact all aspects of transportation. More detailed results will be presented in future publications resulting from this project.

5.2 Discussion

Workforce development

Our research suggests the need for a transition in educational systems. Rather than the existing model of initial qualification, there is a need for continuous knowledge accumulation and training. Instead of being replaced by AI, workers will likely need to be increasingly familiar with emerging technologies as the industry moves towards human-machine coexistence as it has in previous industrial revolutions. While this new model can benefit young workers and those who are well trained, those with lower educational levels and aging populations are left vulnerable. Therefore, it is important that emerging systems of education and human resources management take into account the requirements of this changing landscape.

To address these challenges, we can consider two groups of interest: current students, and current workers in the labor force. In a collegiate setting, there is an increasing need for all students to be familiar with big data and artificial intelligence, regardless of academic discipline. There is a gap in cross-program offerings and a divide between theory and practice. To address these challenges, co-curricular and extracurricular activities and programs such as apprenticeship programs, career fairs, industry led workshops, and mentoring programs could be potential solutions. As for the existing labor force, mid-career workers and low earners are at particular risk. Here, employer-led training is a key avenue for skill development, but employers may be reluctant to invest in workers’ portable skills. In these cases, there is a need for public funding and programs through community colleges, intermediary and sectoral programs, and school based vocational training and apprenticeships.

To ensure widespread implementation of AI in appropriate contexts for maximum benefits, it is essential to implement ongoing education and training programs aimed at better equipping the transportation workforce. Our survey results suggest that despite the generally high educational attainment among surveyed transportation professionals, their self-reported understanding of AI remains relatively limited. This knowledge gap poses a dual risk: it may result in misguided decision-making regarding AI applications, and, given the swift advancements in artificial intelligence, individuals lacking in AI proficiency may miss out on potential advantages and face the threat of job displacement.

The consequence of inadequate AI knowledge levels among transportation professionals extends beyond personal risks to encompass heightened societal costs. To tackle this challenge effectively, there should be a strategic emphasis on targeted AI education. Notably, our observations reveal that transportation professionals under the age of 40 are unlikely to exhibit AI skepticism but may lean towards AI pessimism due to their insufficient AI knowledge. Consequently, efforts should concentrate on bolstering incomplete or inadequate AI training, bridging the divide between AI theory and practical application. For older professionals, whose perceptions of AI may be outdated or stereotypical, the imperative lies in updating and augmenting their knowledge base. To achieve this, prioritizing professional workshops or conference sessions that showcase successful AI use cases becomes crucial. In doing so, we can enhance the understanding and acceptance of AI among transportation professionals of all age groups, fostering a more informed and progressive industry.

Future research directions

We identify the following major research directions:

First, *investigate sources of data biases that can make AI applications augment transport inequality.* Data are the key to all AI applications. Data bias can arise from many sources. Commonly recognized data biases include the lack of data points for certain population groups (e.g., racial minorities and low-income people), lack of geographic representation (e.g., data are not collected from some marginalized communities), and lack of timely data (i.e., available data are outdated) and temporally granular data (e.g., researchers cannot break down the data by time of day). It is critical for transportation researchers and practitioners to understand where various sources of data bias may arise and to identify approaches to mitigate these biases. Additional case studies of AI applications in various contexts would be instrumental.

Second, identify potential AI applications that can address community transportation needs. Existing AI applications in transportation are mostly motivated by intentions such as improving existing data collection and modeling practices, reducing costs, and improving efficiency. AI technologies also have the potential to improve transportation equity by addressing pressing community needs. At present, however, few studies have conducted in-depth community engagement to examine what essential transportation needs can be fulfilled by AI technologies; to our best knowledge, the closest studies are those that focus on how autonomous vehicles can improve accessibility for disadvantaged communities and the public attitudes toward AI technologies.

Third, keep track of transportation professionals' knowledge of and attitudes toward AI applications in transportation. How the transportation community as a whole perceives AI and its efficiency and equity impacts will significantly affect whether and how fast these technologies are adopted by transportation agencies around the world. Building on this project, future research should seek to understand the factors influencing respondent attitudes toward AI beyond demographics and basic knowledge. Using qualitative methods like interviews or focus groups can reveal insights into skepticism or neutrality towards AI in transportation. Also, it's crucial to explore how different AI education programs may impact these attitudes and the role of organizational culture. Comparative analyses of transportation professionals from diverse backgrounds can uncover regional variations. As the transportation sector evolves, understanding how organizations can foster innovation while addressing employee concerns is vital. Experimental design can assess the impact of interventions like workshops on AI literacy. A comprehensive approach considering psychological, organizational, and cultural dimensions is essential for fully understanding AI acceptance in transportation and developing effective integration strategies.

Finally, develop a practical guide for transportation professionals. In response to a growing interest in understanding AI technologies and in deploying them in various transportation domains, a practical guide is needed for transportation professionals to promote equitable AI applications.

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7.1 APPENDIX A - Acronyms, abbreviations, etc.

Acronyms	Definition
AI	Artificial Intelligence
TSMO	Transportation Systems Management and Operations

7.2 APPENDIX B – Survey Instrument

Transportation AI and Equity - Professionals

In this survey, **Artificial Intelligence (AI)** refers to processes that make it possible for systems to replace or augment routine human tasks or enable new capabilities that humans cannot perform. AI enables systems to: (1) sense and perceive the environment, (2) reason and analyze information, (3) learn from experience and adapt to new situations, potentially without human interaction, and (4) make decisions, communicate, and take actions. **Transportation** mainly refers to transportation planning and engineering practices that facilitate the movement of people and goods.

Q1 AI will be widely adopted by U.S. states, regions, and cities/towns for transportation planning and engineering practices within the next:

- ○ less than 5 years (1)
- ○ 5-10 years (2)
- ○ 10-20 years (3)
- ○ 20-50 years (4)
- ○ 50+ years (5)

Q2 AI will alter the *day-to-day practices* of transportation planning and engineering within the next:

- ○ less than 5 years (1)
- ○ 5-10 years (2)
- ○ 10-20 years (3)
- ○ 20-50 years (4)
- ○ 50+ years (5)

Q3 In your opinion, which of the following have the most potential for AI applications (select up to <u>three</u> options)?

- ▢ Advanced driver assistance systems (1)
- ▢ Automated driving systems (11)
- ▢ Asset management and road condition monitoring (5)
- ▢ Cybersecurity (8)
- ▢ Transportation systems management and operations (2)
- ▢ Traveler decision support tools (7)
- ▢ Travel demand forecasting and planning (3)
- ▢ Trip planning and itinerary recommendations (4)
- ▢ Transit/paratransit operations and management (6)
- ▢ Other, please specify (9)

____

- ▢ ⊗I do not know (10)

Q4 In your opinion, which of the following **spatial contexts** have the most potential for AI applications (select up to <u>two</u> options)?

- ☐ Urban arterial network (1)
- ☐ Urban multimodal corridor (2)
- ☐ Regional system management (3)
- ☐ Rural freeway corridor (4)
- ☐ Underserved communities (5)
- ☐ Other, please specify (6) ____
- ☐ ⊗I do not know (7)

Q5 Which of the following do you perceive as the biggest **AI-enabled benefit** in transportation (select up to <u>three</u> options)?

- ☐ Promote safety (1)
- ☐ Improve mobility (2)
- ☐ Enhance traveler experience (3)
- ☐ Address climate challenges (4)
- ☐ Cut costs (5)
- ☐ Improve operational efficiency (6)
- ☐ Reduce human error (7)
- ☐ Other, please specify (8) ____
- ☐ ⊗I do not know (9)

Q6 To what extent do you agree with the following statements?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
AI can lead to more efficient transportation services and cost-savings (1)	○	○	○	○	○
AI can help transportation agencies make smart, data-driven decisions (2)	○	○	○	○	○
AI can automate routine tasks and improve labor productivity (3)	○	○	○	○	○
AI can remove bias in government decision-making processes (4)	○	○	○	○	○
AI can facilitate the discovery of solutions to improve transport equity (5)	○	○	○	○	○
AI can improve traveler experience with personalized recommendations/services (6)	○	○	○	○	○

Q7 In your opinion, which of the following are **major barriers** to widespread AI adoption in transportation (select up to three options)?

- ☐ Lack of strategic vision for AI across agencies (1)
- ☐ Difficulties in identifying AI use cases (2)
- ☐ Lack of skilled staff trained in AI (3)
- ☐ Lack of data (4)
- ☐ Lack of digital infrastructure (5)
- ☐ Lack of computing resources (6)
- ☐ Lack of trust for AI (7)
- ☐ Budget constraints (8)
- ☐ Privacy concerns (9)
- ☐ Equity or ethical concerns (10)
- ☐ Cybersecurity (11)
- ☐ System integration and interoperability challenges (12)
- ☐ Other, please specify (13) ____
- ☐ I do not know (14)

Q8 Please let us know if you have any additional comments regarding the future of AI, its potential benefits, and challenges for implementing AI applications in transportation.

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Q9 On a scale of 1-5, please indicate your **level of knowledge** in each of the following (with 1 indicating "no knowledge" and 5 indicating "expert-level knowledge").

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Computer programming (e.g., Python/R/Java/SQL) (1)	○	○	○	○	○
Mathematics and statistics (linear algebra, regression, hypothesis testing) (2)	○	○	○	○	○
Data and Computer infrastructure (data structures, database management systems, cloud computing, cybersecurity) (3)	○	○	○	○	○
AI concepts (machine learning, deep learning, neural networks, reinforcement learning) (4)	○	○	○	○	○
AI technologies (computer vision, natural language processing, robotic systems, predictive analytics) (5)	○	○	○	○	○

Q10 Which of the following *general* AI applications are you familiar with? (select all that apply)

- ☐ Predictive analytics and data visualization (1)
- ☐ Cognitive robotics and autonomous systems (2)
- ☐ Text generation (e.g., ChatGPT) (3)
- ☐ Image processing and generation (e.g., DALL-E) (4)
- ☐ Recommender systems (5)
- ☐ Intelligent digital assistants (e.g., chatbots, voice assistants) (6)
- ☐ Facial recognition (7)
- ☐ Spam filters (8)
- ☐ ⊗None of the above (9)
- ☐ Other, please specify (10) ____

Q11 Which of the following *transportation* AI applications are you familiar with? (select all that apply)

- ☐ Video analytics for safety applications (1)
- ☐ Predictive analytics for roadway asset assessment and management (2)
- ☐ Multimodal intelligent traffic signal system (3)
- ☐ Distracted driver behavior detection (4)
- ☐ Advanced driver assistance systems (5)
- ☐ Personalized itinerary, trip planning and routing recommendations (6)
- ☐ Wayfinding, navigation, and assistive robotics (7)
- ☐ Automated buses and shuttles (8)
- ☐ Transit vehicle dispatching, routing, and delay prediction (9)
- ☐ ⊗None of the above (10)
- ☐ Other, please specify (11) ____

Q12 Which of the following AI topics do you hope to learn more about? (select all that apply)

- ☐ Technical aspects of AI (e.g., machine learning, data infrastructure, etc…) (1)
- ☐ AI use cases in transportation (2)
- ☐ AI governance and performance evaluation (3)
- ☐ AI ethics and equity concerns (4)
- ☐ Other, please specify (5) ____
- ☐ I do not want to learn more about AI (6)

Q13 To what extent do you agree with the following statements?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I believe that AI algorithms will exaggerate inequalities in transportation	○	○	○	○	○
Applying AI in transportation decision-making will reduce transparency	○	○	○	○	○
Community engagement is important when developing AI transportation systems	○	○	○	○	○
There is limited understanding of AI ethics in the transportation community	○	○	○	○	○
Proper use of AI can help reduce social inequality	○	○	○	○	○
The data used in AI applications are often not representative of the population	○	○	○	○	○
The current AI development and deployment progress has not done enough on engaging communities and the disadvantaged populations	○	○	○	○	○
Biased datasets used for developing AI systems will lead to social inequalities	○	○	○	○	○

Q14 Please let us know if you have any additional comments regarding the **equity and ethics** of using AI in Transportation.

____

Q15 Are you a:

- ◯ Male (1)
- ◯ Female (2)
- ◯ Nonbinary/Gender nonconforming (3)
- ◯ Not listed (4) ____
- ◯ Prefer not to answer (5)

Q16 What is your age?

- ◯ 18-24 (1)
- ◯ 25-29 (2)
- ◯ 30-39 (3)
- ◯ 40-49 (4)
- ◯ 50-59 (5)
- ◯ 60-69 (6)
- ◯ 70 or over (7)
- ◯ Prefer not to answer (9)

Q17 Which category best represents your annual household income in the past year?

- ○ Less than $25,000 (1)
- ○ $25,000-$49,999 (2)
- ○ $50,000-$74,999 (3)
- ○ $75,000-$99,999 (4)
- ○ $100,000-$124,999 (5)
- ○ $125,000-$149,999 (6)
- ○ $150,000 or more (7)
- ○ Prefer not to answer (9)

Q18 Which race/ethnicity best describes you?

- ▢ American Indian or Alaskan Native (1)
- ▢ Asian (2)
- ▢ Black or African American (3)
- ▢ Hispanic or Latino (4)
- ▢ Native Hawaiian or other Pacific Islander (5)
- ▢ White or Caucasian (6)
- ▢ Other, please specify (7) ____
- ▢ Prefer not to answer (9)

Q19 What is your highest educational level?

- ◯ Less than high school (1)
- ◯ High school graduate (2)
- ◯ Vocational or technical training (3)
- ◯ Associate's degree or some college (4)
- ◯ Bachelor's degree (5)
- ◯ Post-graduate degree (e.g., MA, MS, Ph.D., MD, JD) (6)

Display This Question:
If Q19 = Associate's degree or some college
Or Q19 = Bachelor's degree
Or Q19 = Post-graduate degree (e.g., MA, MS, Ph.D., MD, JD)

Q20 What is the field of study for your academic degree(s) (e.g., Civil/Transportation Engineering, Urban Planning, Geography, etc.)?

____

Q21 What type of organization do you currently work at?

- ▢ I am a student (1)
- ▢ Academia (2)
- ▢ Government or public agency (DOT, MPO, County, City, Transit Agency, etc.) (3)
- ▢ For-profit private sector (4)
- ▢ Non-profit organization (5)
- ▢ Other, please specify (6) ____

Q22 What is your areas of expertise in transportation? Please select all that apply.

- ▢ Administration and management (1)
- ▢ Data and information technology (2)
- ▢ Policy, planning, and forecasting (3)
- ▢ Traffic operations and management (4)
- ▢ Public transportation, pedestrian, and bicyclists (5)
- ▢ Safety and human factors (6)
- ▢ Pavements, Materials, Maintenance and Preservation (7)
- ▢ Bridges, structures, and transportation facilities (8)
- ▢ Research and Innovation (9)
- ▢ Other, please specify (10) ____
- ▢ ⊗My area of expertise is not in transportation (11)

Q23 Please let us know if you have any additional comments regarding the use of AI applications in Transportation. Your comments may pertain to the contents of this survey or may come from your own experience as a professional in transportation.

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7.3 APPENDIX C - Summary of Accomplishments

Date	**Type of Accomplishment**	**Detailed Description**
01/2020	Conference Paper	Zhao, X., Liu, X., Yan, X. (2020). Modeling demand for ridesourcing services in the City of Chicago: A direct demand machine learning approach. Proceedings of Transportation Research Board 99th Annual Meeting, Washington, DC.
01/2020	Conference Presentation	Xu, Y., Yan, X., Liu, X., Zhao, X. (2020) Applying Interpretable Machine Learning to Identify Key Factors Associated with Ride-Splitting Adoption Rate and to Model Their Nonlinear Relationships. Transportation Research Board 99th Annual Meeting, Washington, DC.