Exploring Cost-effective Computer Vision Solutions for Smart Transportation Systems

Literature Review

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Literature Review on Smart Transportation Applications

Computer vision is reshaping the transportation industry and bringing its unique capabilities to the table to enable next generation smart transportation systems in many different ways. The state-of-the-art of IoT strategies and computer vision techniques is well-studied in the literature, some has already been tested and used for certain use cases, but this technology has not widely applied in the day-to-day operation to existing transportation infrastructures yet. A comprehensive review of both state-of-art and state-of-practices as well as gaps in terms of use cases and applications is needed. In addition, several major challenges that hinder further advances in computer vision-based smart transportation application development remain. This includes how to develop the transportation-specific computer vision techniques through advanced artificial intelligence (AI) and machine learning (ML) techniques; how to make use the outputs of the computer vision-based systems to enhance traffic safety and situational awareness; how to customize the solutions based on different objectives from the agencies and road users; how to improve the accuracy of these systems under conditions such as adverse weather; and finally, how to maintain the cost-effectiveness of these computer vision-based transportation solutions.

We conducted a multi-facet literature review that first examined the current use cases and transportation related applications that utilize the computer vision methodologies with a focus in urban areas, especially work zone and safety applications, and evaluated their applicability to various tasks of urban analytics, state of adoption, and limitations. The literature review then assessed if and how transportation equity is considered in the current state of adoption of computer vision/AI technology, for example, whether state-of-the-art object detection systems have equitable predictive performance on pedestrians with different skin tones.

Smart Transportation Applications Using Computer Vision

Many computer vision approaches have been introduced for vehicle detection. Based on these approaches, numeric research has been focusing on traffic counting and traffic monitoring, including density and speed estimation, congestion detection and so on. For example, Muhammad *(1)* created a simple vehicle counting system to help human in classify and counting the vehicles that cross the street. YOLOv3 was used for object detection and pre-trained model was applied using Common Objects in Context (COCO) dataset, a large-scale object detection, segmentation, and captioning dataset that has annotations for 80 different objects. The system achieved a detection accuracy as high as 96.96% with ‘motorcycle’ and ‘car’ being the most accurate and ‘truck’ and ‘bus’ being the worst accurate vehicle category. Most of the studies used a centralized detection system with a few utilizing edge computing. Liu et al. *(2)* proposed a two-tier edge computing based model for congestion and speed detection. They build their own video dataset using an IP-based camera. They also compared the edge and cloud schemes with the hybrid scheme (edge + cloud) and found that under good weather condition, the performance of the edge scheme is better than that of the cloud scheme while under bad weather condition (i.e., snowy), the performance of the cloud scheme is better than that of edge scheme.

Considerable development efforts have been made into autonomous driving using sensing technology and computer vision to find road obstacles and analyze the current traffic flow and surrounding conditions. Many review papers have been developed, for instance, *(3)* evaluated the technologies used to advance autonomous driving, including CNN, SSD, R-SNN, R-FCN and so on. The review paper identified that recurrent neural network (RNN) could be replaced by long-short term memory (LSTM) in terms of autonomous driving scenes because it could bring more efficiency. The authors tackled the existing works of these methods and concludes selected approaches to point their strengths and gaps. This study highlighted that since autonomous driving is fairly new to society, it is important to improve the weaknesses of scientific methods to help them become a safer option. Some studies focus on enhancing the 3D object detection. Peng et al. *(4)* introduced a a lightweight Instance-Depth-Aware (IDA) 3D Detection to approaching object detection in autonomous driving which accurately predicted the depth of the 3D bounding box's center by instance-depth awareness. Their method focused on objects and directly performs the instance depth regression and paid more attention on far-away objects by disparity adaptation and matching cost reweighting.

One of the vital application areas in smart transportation is accident detection. Ijjina et al. *(5)* developed a neoteric framework for detection of road accidents using road-traffic CCTV surveillance footage. This work was evaluated on vehicular collision footage from different geographical regions under various ambient conditions such as harsh sunlight, low visibility, daylight hours, snow and night hours. The dataset includes accidents in various ambient conditions such as harsh sunlight, daylight hours, snow and night hours. All videos were compiled from YouTube and were around 20 seconds. Their proposed framework was able to detect accidents correctly at a 71% detection rate with 0.53% false alarm rate on the accident videos. Another interesting research *(6)* used eye blink detection system based on object tracking and machine learning to alert drivers with high efficiency. Authors used real life dataset of drivers when they are commuting to a certain destination. This system had an efficiency of 80%, which means it could detect about 8 eye blinks in 10 actual blinks.

Various studies have also been conducted on parking occupancy detection using computer vision. Traditional approaches for parking occupancy detection include background subtraction and hand-crafted feature (e.g., edges, color, texture) extraction *(7)*. Single shot detector (SSD) *(8)*, You Look Only Once (YOLO) *(9)* and its subsequent versions, and CNN-based frameworks *(10)* have achieved state-of-the-art accuracies in image classification and object detection. For instance, Acharya and Yan *(7)* used deep Convolutional Neural Networks (CNNs) trained from public datasets (PKLot) and a binary Support Vector Machine (SVM) classifier to achieve outdoor parking occupancy detection. The detection accuracies of the model are reported to be 99.7% and 96.7% for a public dataset and for a new dataset generated by the authors. Amato et al. *(11)* developed a solution for visual parking space occupancy detection using a deep CNN model robust to light condition changes, presence of shadows, and partial occlusions. The authors tested two CNN architectures, mAlexNet and mLeNet, based on *(10)* and *(12)* and reported an overall accuracy 82.9% on CNRPark, and 90.4% on PKLot dataset using mAlexNet. Bulan et al. *(13)* presented a video-based real-time on-street parking occupancy detection system using background subtraction, motion detection, and occlusion detection. To eliminate unreliable frames and regions for vehicle detection, they applied occlusion detection based on the position of a foreground blob with respect to a parking region. The parking occupancy detection method performs in real time with a 91% average detection accuracy for each camera. The authors stated that the video-based approach could replace the in-ground sensor approach since the former has a higher detection accuracy than that of in-ground sensors in San Francisco.

A natural value-added option to on-street parking occupancy detection is to perform illegal parking detection simultaneously. For example, Bulan et al. *(13)* integrated parking angle violation detection, parking boundary violation detection, and exclusion zone violation detection, into their parking occupancy detection model. Other than fixed traffic or surveillance cameras, Gkolias and Vlahogianni *(14)* developed data science models to detect empty on-street parking spaces in urban networks based on in-vehicle cameras. Ranjan et al. *(15)* introduced StreetHAWK that leverages the rear camera of a dashboard mounted smartphone to identify potential parking violations. Other value-added features can be considered for adoption, such as bus or bike lane occupancy and violation detection. In the literature, most studies focus on parking lot usage detection *(7, 11, 16-19)* but illegal parking detection is mostly needed on-street. Only a few studies *(13, 14)* have tested for on-street parking occupancy of curb lanes. Previous studies have often relied on moderate to high resolution videos (over 480p) and consecutive video frames (>1 frame per second (fps)) *(15, 17, 20-22)* and many models use vehicle tracking *(17) (20, 21, 23)* for event detection. Since public traffic surveillance cameras suffer from low image resolution and frame rate, an effective solution that accounts for this feature is needed.

Besides vehicle detection, enhancing the safety of vulnerable road users (VRUs) is also of critical importance to achieving the objectives of USDOT's National Roadway Safety Strategy (NRSS), and vision zero goals. According to data from the National Highway Traffic Safety Administration (NHTSA), in 2020 there were 10,626 traffic fatalities in the United States at roadway intersections, including 1,674 pedestrian and 355 bicyclist fatalities. These fatalities at intersections represent 27% of the total of 38,824 road traffic deaths recorded in 2020. Previous detection methods for VRUs, especially pedestrians, mainly using infrared sensors, radar sensors, thermal imaging, microwave sensors and so on. Figure 1 shows the evolution of pedestrian detection technologies and vision-based detection system showed an increasing trend in recent years. More details about pedestrian detection deployment can be found in the interactive timeline and map visualizations developed by the C2SMART research team for USDOT Intelligent Transportation Systems Joint Program Office (ITSJPO) at *https://www.itskrs.its.dot.gov/decision-support*. Besides the general VRU detection application, some studies also extended the use case to social distancing measuring or pedestrian intention predictions *(24, 25)*. Zuo et al. *(24)* developed a reference-free video-to-real distance approximation-based urban social distancing analytics. Their method measured pedestrian distancing and density at crosswalks and sidewalks in complex urban environment to quantify social distancing to better understand the new norm of urban mobility amid COVID-19 pandemic. Wang et al. *(25)* added a Temporal Attention (TA) to the encoding and decoding layers of the Generative Adversarial Network (GAN) to improve pedestrian intention prediction. Such prediction can be further incorporated into various applications such as jaywalker detection and cooperative perception. Review of the literature also revealed that only a few studies centered on detecting people with mobility aids. Kollmitz et al. *(26)* collected of over 17,000 annotated images from a hospital in Frankfurt, Germany and developed a model to detect people with mobility aids to benefit robots operating in hospitals. Their dataset contained five classes, including pedestrian, person in wheelchair, pedestrian pushing a person in a wheelchair, person using crutches, and person using a walking frame. The study only focused on indoor environment and its performance on outdoor environments such as crosswalks is unknown.

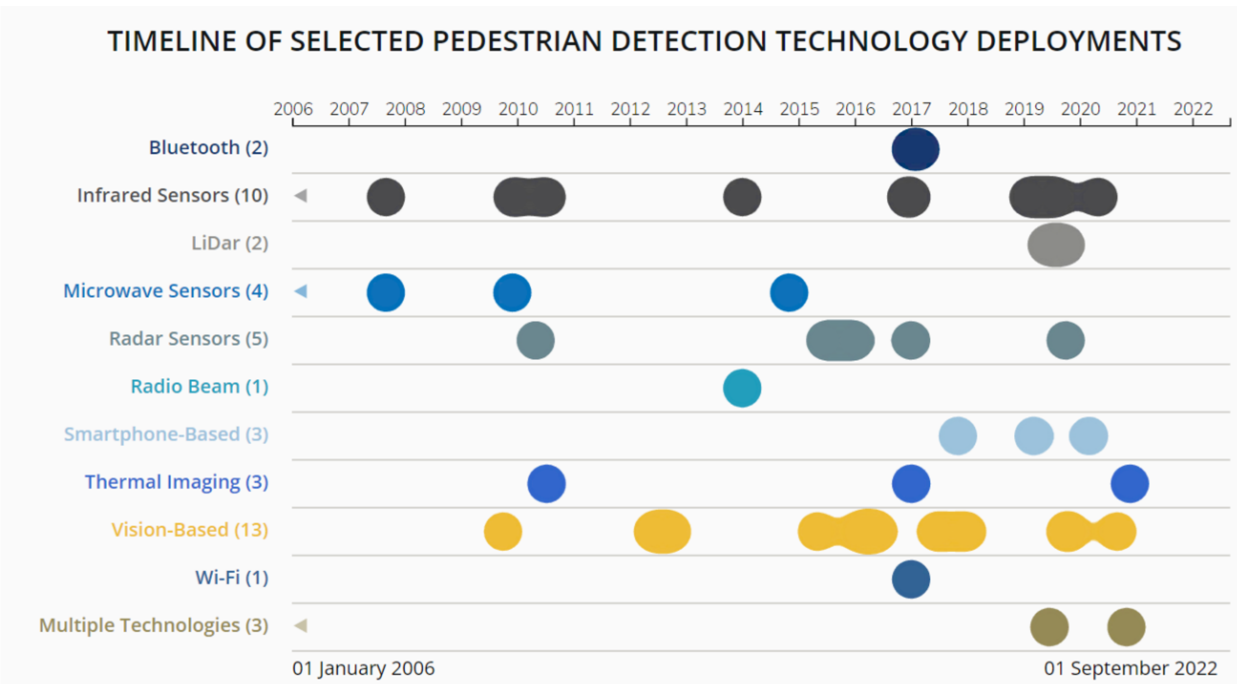

Figure 1. Timeline of selected pedestrian detection technology deployments

The literature review also revealed that progress has been made in computer vision, but mainly on pedestrians and vehicles. Computer vision for other use cases, such as work zone detection, is still very limited. Most existing studies focus on off-street work zones or a single type of work zone object (e.g., traffic cones). In addition, almost all of the existing literature emphasized that the main challenge for work zone detection is the scarcity of publicly available, large-scale, domain-specific, annotated dataset of work zone imagery. For example, Nath and Behzadan *(27)* used a CNN model that laid out a framework for detecting the most common types of off-street construction objects, namely, buildings, equipment, and workers (Figure 2 (a)). They recognized the lack of publicly available annotated work zone imagery dataset and introduced a systematic approach to visual data collection through crowdsourcing and web-mining and annotating the dataset for AI model training to overcome the limitation. The results showed that models perform best when trained on combined (crowdsourced and web-mined) data. They collected 3,500 images with 11,500 work zone objects and tested both YOLO-v2 and -v3. The study found the best-performing model is YOLO-v3, which had a 78.2% mAP. Duan et al. *(28)* also stated that the lack of large-scale, open-source dataset for the construction industry limited the development of computer vision algorithms as they are often data-hungry. This study developed a new large-scale work zone image dataset, Site Object Detection dAtaset (SODA), which was collected from the real construction site and contained 15 types of object classes categorized by workers, materials, machines, and layout. A total of 19,846 images including 286,201 objects were mined and annotated. Their model achieved a maximum mAP of 81.47%. They also suggested field data acquisition could adopt methods such as using drones, handheld monocular camera shooting, and construction site monitoring video. The limitation of this dataset is it is mainly for off-street work zones and may not be suitable for detecting work zones that occur on the roadways. A recent study conducted by Katsamenis et al. *(29)* used Yolov5 for traffic cone detection using a training dataset of 500 traffic cones images (Figure 2 (b)). The data used in this paper was collected and manually annotated under the framework of the H2020 HERON project. The results showed that the proposed computer vision model could achieve a 91% accuracy in detecting traffic cones. However, work zones, especially urban work zones often composed by multiple types of construction objects and has no standard work zone set up, single object type detection may not be as effective as expected in such cases. This demands the needs of building and sharing a comprehensive publicly available, domain-specific, annotated dataset of urban work zone (on urban streets and sidewalks) imagery.

(a) Work zone detection for off-street sites *(27)* (b) traffic cone detection *(29)*

Figure 2. Examples of work zone detection research

Additionally, we found most of the existing studies rely on specific cameras while a few of them utilized existing intelligent transportation systems (ITS) infrastructures such as closed-circuit television (CCTV) cameras (5, 24, 30).

Table *1* synthesizes some of the most recent literature on smart transportation applications using computer vision. While not exhaustive, it provides a representative sample of recent research efforts.

Table 1 Summary of recent literature on smart transportation applications using computer vision

Study	**Year**	**Application(s)**	**Goal**	**Method**	**Training image dataset publicly available?**
(31)	2019	Traffic monitoring, Traffic count	Propose a vision-based traffic monitoring system detect the number of vehicles that monitors the density of the roads.	Haar feature based Adaboost classifier and virtual	No

				detection lines (VDL)	
(2)	2021	Traffic monitoring (speed estimation & congestion detection)	Propose a two-tier edge computing based model for congestion and speed detection	Gaussian Mixture Model and Global Foreground Detection	No
(1)	2020	Traffic counting	Aim to create a simple vehicle counting system to help human in classify and counting the vehicles that cross the street.	YOLOv3 & counting using coordinates or location of the vehicles	Yes
(32)	2020	Traffic counting	Develop a video-based system that can be used to count the road traffic, and it does not disturb traffic flow	Background extraction	Yes
(33)	2022	Traffic Counting	Develop small, location-specific object detection models for traffic counting without needing manual data labeling	location specific models	Yes
(30)	2020	Traffic counting	Incorporate an intelligent traffic light controlling system using an algorithm that consumes real data from closed-circuit television (CCTV) cameras	Neural network-based models	Yes
(34)	2020	Pedestrian detection	Develop an accurate computer vision-based system to track and count passengers for both indoor and outdoor scenarios.	Support vector machine (SVM) classifier and histograms of orientated gradient descriptor	Yes
(24)	2021	Pedestrian detection/Social distancing	Measure pedestrian distancing and density to quantify social distancing to better understand the new norm of urban mobility amid the pandemic	Reference-free distance measure algorithm & YOLOv3	No
(25)	2022	Pedestrian intension estimation	Add a Temporal Attention to the encoding and decoding layers of the Generative Adversarial Network to improve pedestrian intention prediction	Generative Adversarial Network based on Temporal Attention (TA-GAN)	Yes
(26)	2019	People with disabilities	Detect people with mobility aids to benefit robots operating in indoor environment such as hospitals.	Deep convolutional neural network (CNN)	Yes
(35)	2022	Parking management/Illegal parking	Develop a computer vision–based data acquisition and analytics approach for curb lane monitoring and illegal parking impact assessment	YOLOv3 & Mask R-CNN	Yes
(36)	2018	Parking management	Develop data science models for the detection of empty on-street parking spaces in urban road networks based on data provided by invehicle cameras	CNN	Yes
(27)	2020	Work Zone Detection (off-street)	Detect consturction objects at off-street construction sites	YOLOv2/v3	Yes
(28)	2022	Work Zone Detection (off-street)	Develop a large-scale off-street construction site image dataset	YOLOv3/v4	Yes
(29)	2022	Work Zone Detection (Traffic cone only)	Detect construction buildings, equipment, and workers	YOLOv5	Yes
(37)	2021	Autonomous driving	Eevaluate the technologies used to advance autonomous driving, including CNN, SSD, R-SNN, and R-FCN.	CNN	Yes
(4)	2020	Autonomous driving	Introduces Instance-Depth-Aware (IDA) 3D Detection as to approaching object detection in autonomous driving which	IDA 3D Detection	Yes

			accurately predicts the depth of the 3D bounding box's center by instance-depth awareness		
(3)	2020	Autonomous driving	Review and develop advanced technologies for the visual sensing system of autonomous vehicles from standard computer vision to event-based neuromorphic vision	CNN & Neuromorphic-vision algorithms	Yes
(5)	2019	Accident Detection	Develop a neoteric framework for detection of road accidents using road-traffic CCTV surveillance footage	Mask RCNN	No
(38)	2020	Accident detection	Detection of workers and heavy vehicles, three-dimensional (3D) bounding box reconstruction, depth and range estimation in the monocular 2D vision, and 3D spatial relationship recognition.	CNN	Yes (for COCO) No (for KITTI)
(6)	2017	Accident detection	Develop an eye blink detection based alert system with high efficiency.	Eye blink detection	No
(39)	2019	Flood management/monitoring	Present a systematic review of the literature regarding IoT-based sensors and computer vision applications in flood monitoring and mapping	Artificial Neural Networks and so on	Yes

Equity and Fairness in AI-based Transportation Solutions

Technological development happens fast and is constant; no sooner is an innovation developed than it is being iterated and evolved. In broad strokes, this is good news: it means that we are always getting faster, safer, more efficient, and more sustainable. But within the field of mobility, compared to traditional transportation solutions, these new innovations rarely evaluate equitable impact across populations, leaving some groups behind or, in the worst cases, constructing unforeseen barriers. These negative impacts are not necessarily the result of malicious intent but rather are due to the lack of an existing set of clearly defined transportation equity standards that can be employed to assess new innovations during development. By ensuring the incorporation of equity perspectives for related policies, and identifying equity methods and metrics for use in technological development and evaluation of emerging transportation technologies, we can take significant steps toward mitigating negative effects and balancing uneven benefits in an early stage.

The USDOT Equity Action Plan (EAP) highlights four primary drivers of opportunity within transportation: wealth creation, power of community, interventions, and expanding access. These categories reflect the reality of transportation as a complex system-of-systems which interacts with almost every element of life: employment and education, health and nutrition, social and community life, justice and policing, and of course, mobility. This complicates the creation of any single set of metrics to determine whether or not a service, project, plan or policy is "equitable," as the needs, limitations, and uses for transportation for any given community are extraordinarily diverse. This is true not just across groups, but within them—for example, the accessibility requirements for a blind person with a service animal may differ from a blind person who uses a cane. It is therefore necessary to develop a framework which is flexible enough to be adapted to different types of technology and mobility innovations and future evolutions of the same, inclusive of all travelers and their diversity of need, and can provide guidance for industries and agencies seeking to evaluate, iterate, and implement new technologies.

As the academic literature on transportation equity has grown and equity-related assessments have increased in agency-supported projects and pilots related to emerging transportation technologies, it is crucial to systematically review how equity has been considered and evaluated in the planning or operations of mobility and safety innovations, especially for AI-based transportation solutions.

AI has been involved in almost all aspects of modern life, and the application of AI heralds advantages including lower cost, higher efficiency and fewer risks, but can also exacerbate pre-existing inequities due to the immature understanding of technology. Particularly since it can be deployed in tasks related to safety (e.g., wrong-way driving detection), it is essential to assess its equity issues. Equity problems stemming from AI in the transportation domain have not been well studied; however, it is possible to extrapolate from other domains' experience in AI equity to equip the agencies, industry and academic researchers with essential knowledge of potential equity issues that will arise with the emergence of AI systems in the transportation field. It is worth noting that although fairness has a slightly different definition than equity, it is a more common term used across the AI domain to express equity concerns, as equity is defined as the quality of being fair and impartial. Therefore, in this study we treated fairness as a part of the broader definition of equity.

Real-world examples of AI equity issues in transportation domain - Automated vehicle safety
Automated vehicle aims to operate in a manner equivalent to a human driver and make its own decisions during driving. The US National Highway Traffic Safety Administration (NHTSA) released a checklist that requires semi-autonomous and driverless vehicles to make conscious and intentional ethical judgments and decisions, and the algorithm for solving these situations must be disclosed to the USDOT through the NHTSA *(40)*. However, how to ensure equity, especially social equity (e.g., detecting different race pedestrians equally accurate), in training data and in design of the AI decision-making algorithm responding to safety risk situations, are not addressed directly. The potential consequences can be severe (e.g., lead to an actual crash).

Real-world examples of AI equity issues in non-transportation domains
Numerous AI applications have been developed, such as applications for face and voice recognition, automated speech recognition (ASR) and so on. But these applications often fall short; famously, a photo application developed by Google in 2015 with an automated labeling function was found to make a severe mistake in labeling African American people as "gorillas" *(41)*. Shankar et al. *(42)* reviewed and analyzed two major open-sourced image galleries and found that these images "appear to exhibit an observable Americentric and Eurocentric representation bias". A novel attack method *(43)* assessed gender and racial bias in the speech recognition system and found that the American-English-Male chatter noise attack success rate is greater than Nigerian-Female and Korean-Female noise by 112% and 121% on Google Home Mini smart speaker.

It is worth noting that although these biases were found in AI systems outside the transportation domain, it is these same AI technologies which are applied in transportation systems for such tasks as pedestrian detection and speech recognition for train operators' voices. Practitioners in transportation should therefore be aware of these potential biases and plan to include an equity assessment when using AI-based transportation solutions.

Data-, model-, and systemic bias in AI
Equity issues identified based on existing literature in various AI models and their applications can be generally summarized into three major categories: bias in data, bias in model, and systemic bias. We inherited these first two bias categories introduced in *(44)*. The new systemic bias category has been identified from the literature review in this study.

Bias in data can be learned by models, in turn represented, transmitted, and amplified in model outcomes. In addition, some models can generate biased performance even using unbiased data owing to design features as designers may transmit their own conscious and subconscious biases. Systemic bias is related to macroscopic conditions such as existing and historical social biases and is significantly impacted by the fact that the most advanced AI technologies are in the hands of giant technology companies. The three categories have mutual effects on each other, which means that all these biases in a real-world AI system should be considered and analyzed accordingly. Figure 3 lists the types of bias in AI systems that can result in inequity.

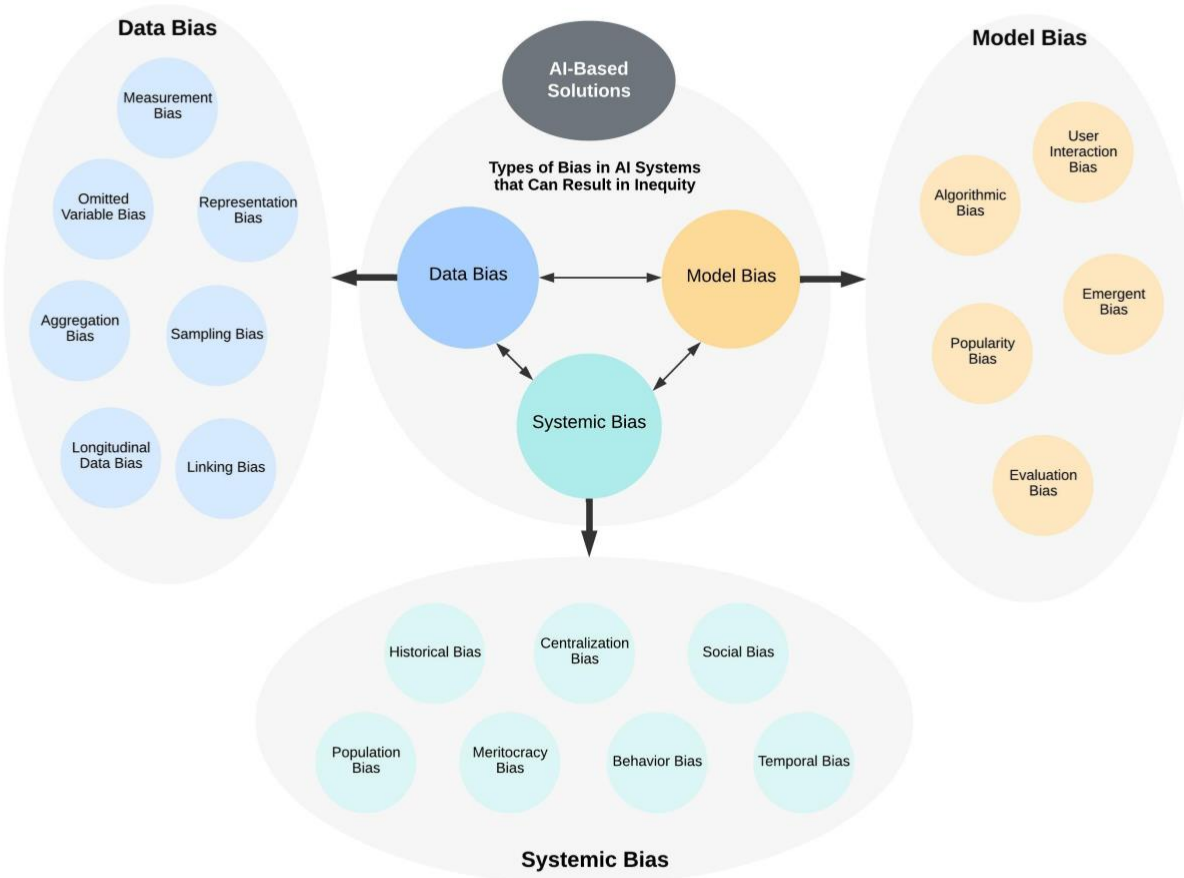

Figure 3 Types of Bias in AI Systems that Can Results in Inequity (adopted and modified based on *(44)* and review of *(45)* in this study)

AI-based transportation solutions categorize equity assessment approaches into three different categories based on processing stages *(46)*:

- *Pre-processing.* Humans generate data via designs for different purposes; thus, bias is inevitable *(46)*. Methods like data documentation can provide information on the dataset generation method, features, motivations, and potential biases *(47)*.
- *In-processing.* In-processing methods can enhance the AI models to remove bias to avoid training inequity *(46)*. Combining common-used fairness metrics as convex constraints into the classification model can be used to guarantee any classification is fair *(48)*. An adversarial learning framework *(47)* can be used to mitigate the unwanted biases from the data.
- *Post-processing.* Post-processing techniques try to access the untouched dataset that was not in the training set to adjust the model *(46)*. A fairness criterion *(48)* can be built to adjust learned predicter to remove unfair results according to the observed outcomes.

Although there is no current standard to directly assess equity in AI-based solutions, we summarized some of the most widely-used measures with the explanations inspired by *(44, 49)* that can be used for potential transportation applications (TABLE 2).

TABLE 2 Equity Measures Used in AI-Based Systems

Name	Type	Objectives	Source

Equalized Odds	Group	The protected and unprotected groups should have equal rates for true positives and false positives.	*(47, 49)*
Equal Opportunity	Group	The equal opportunity definition states that the protected and unprotected groups should have equal true positive rates.	*(47, 49)*
Demographic Parity	Group	The likelihood of a positive outcome should be the same regardless of whether the person is in the protected (e.g., female) group.	*(49, 50)*
Fairness through Awareness	Individual	Any two individuals who are similar with respect to a similarity (inverse distance) metric defined for a particular task should receive a similar outcome.	*(44, 50)*
Fairness through Unawareness	Individual	An algorithm is fair if any protected attributes are not explicitly used in the decision-making process.	*(50)*
Treatment Equality	Group	Treatment equality is achieved when the ratio of false negatives and false positives is the same for both protected group categories.	*(51)*
Test Fairness	Group	For any predicted probability score, people in both protected and unprotected groups must have an equal probability of correctly belonging to the positive class.	*(49)*
Counterfactual Fairness	Individual	A decision is fair towards an individual if it is the same in both the actual world and a counterfactual world where the individual belongs to a different demographic group.	*(50)*
Conditional Statistical Parity	Group	People in both protected and unprotected (female and male) groups should have an equal probability of being assigned to a positive outcome given a set of legitimate factors.	*(49)*

While the AI community has contributed much research in anti-bias, fairness, equality, and equity theoretically and empirically, there are still many gaps that need to be filled, such as the need for a uniform definition and metric, equity vs. efficiency, and domain or specialized field adaptation. For future AI equity assessment in the transportation domain, we suggest the following: 1) enhance the knowledge related to equity in AI systems as the improvement of model equity level necessarily comes from the improvement of model developers' perception of equity, 2) plan data collection carefully and be aware of possible equity issues in the data, 3) select appropriate sensitivity variables, population groups, and performance metrics to assess equity in AI systems, and 4) make algorithms and models more transparent to allow stakeholders to understand the entire decision-making process so them can provide feedback related to equity based on their domain knowledge.

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