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Research Article

An Urban Readiness Index for Connected and Autonomous Vehicles: Evidence from Populated U.S. Cities

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Abstract

Autonomous vehicles are transitioning from experimental deployments toward broader real-world applications. This progress could also pave the way for Connected and Autonomous Vehicles (CAVs), which remain in relatively early stages of maturity, with implementations largely confined to pilot programs and controlled environments. These development raise a critical question regarding the extent to which cities are prepared – institutionally, infrastructurally, and operationally – for this technology. This study develops a comprehensive index to assess urban readiness for the CAV technology, thereby establishing a systematic foundation for comparative readiness analysis. The proposed index captures multiple dimensions of readiness, including cyber infrastructure, regulatory and policy conditions, and hard infrastructure. A total of 29 indicators are identified and aggregated into a composite readiness measure using two alternative scoring schemes: a simple binary scheme and a compound scheme that allows for graded performance across selected indicators. The framework is applied to 98 most populated cities in the contiguous United States. The resulting rankings identify both relatively more prepared and less prepared cities and reveal substantial heterogeneity in readiness levels across urban areas. Overall, the findings indicate that most cities currently exhibit limited preparedness for CAVs. Larger cities tend to achieve higher readiness scores; however, the results also suggest that smaller cities could rapidly improve their relative readiness through targeted infrastructure investments. The study further discusses urban planning implications and offers insights that may inform readiness assessments in other contexts, while also examining the robustness of the results and considering alternative indicator weighting schemes.

1 Introduction

Automated driving is no longer a concept but a reality, propelled by significant contributions from leading entities. Car manufacturers have made substantial improvements to the technology supporting the Autonomous Vehicles (AVs) over the past decade. Most manufacturers have incorporated features of the first and second levels of automation (e.g., parking assist, adaptive cruise control, collision avoidance systems, lane departure warnings, and onboard navigation). Parallel to manufacturers, transportation network companies have been aggressively testing AVs to push for the faster arrival of higher levels of automation. In November 2017, for example, Uber announced its plan to purchase 24,000 autonomous SUVs in the race for driverless mobility on demand (Gibbs, 2017). In addition, the academic community has made significant contributions to better understand the travel environment in the presence of automated driving technology, helping to ensure its safe large-scale implementation. These developments could also pave the way for Connected and Autonomous Vehicles (CAVs), which nevertheless remain in the early stages of maturity, with deployments largely confined to pilot studies and controlled testbeds.

With the arrival of CAVs, transportation systems are expected to undergo substantial changes. While some studies suggest that large-scale deployment – particularly of shared CAVs – could improve system efficiency and move traffic conditions closer to a *system-optimal* state, a larger body of evidence indicates that CAV adoption may increase vehicle kilometers traveled due to induced demand, empty repositioning trips, and changes in travel behavior (Bahamonde-Birke et al., 2018; Fielbaum & Pud  ne, 2024; Sun et al., 2024; Garus et al., 2024). As a result, average vehicle-related emissions are more likely to increase, at least in the absence of strong policy interventions.

While Level 3 semi-autonomous cars are already present in parking garages, the question that remains is to what extent cities are ready to welcome autonomous technology. In the US, in particular, states have proactively undertaken legislative measures to address the challenges that may arise with the arrival of CAVs. As of February 18, 2020, 34 states as well as the District of Columbia have enacted legislation related to CAVs, with Nevada pioneering such legal frameworks in 2011. In addition, governors in 11 states have issued executive orders related to CAVs (NCSL, 2020). Such legislation, however, may not be sufficient to support the large-scale implementation of CAVs, as the infrastructure elements accommodating and policies encouraging the technology may not yet be in place. To assess the *readiness of cities* to accommodate CAVs, there is a need to develop an index (or indicator) that aggregates all aspects of readiness into a single score (or value). Such an index could help decision-makers and city planners better understand where their cities are positioned with respect to CAV readiness compared to other cities. In addition, it could be informative in appraising the effectiveness of various infrastructure investments aimed at elevating readiness. To the best of the authors' knowledge, a CAV readiness index enabling such analysis is currently absent from the literature.

While examples of autonomous vehicle (AV) deployment are increasingly visible, it is important to distinguish between AV adoption and the broader concept of CAVs. The gap between AV and CAV deployment is substantial and extends beyond vehicle automation alone. CAVs encompass AV capabilities but additionally require connectivity, interoperability, and information exchange across vehicles, infrastructure, and traffic management systems. In particular, large-scale CAV operation implies that vehicles produced by different manufacturers – potentially originating from different countries and operating under competitive market conditions – are able to communicate in a compatible manner. Importantly, such interoperability does not necessarily require direct cooperation or proprietary information sharing among competing manufacturers. In many practical implementations, information exchange can be achieved through vehicle-to-infrastructure (V2I) and infrastructure-to-vehicle (I2V) channels, whereby standardized messages are transmitted via roadside units and traffic management systems and subsequently received by heterogeneous vehicle fleets. Comparable information-sharing mechanisms already operate at scale in contemporary mobility systems, in which vehicles from different manufacturers transmit real-time traffic and operational data to centralized platforms that aggregate and redistribute information using standardized communication protocols. While such systems do not constitute

CAV deployment, they illustrate the feasibility of large-scale, cross-manufacturer information exchange mediated through infrastructure rather than direct vehicle-to-vehicle coordination (Milakis et al., 2017).

This study contributes to the literature by establishing a groundwork for CAV readiness analysis. The proposed readiness framework is intended to assess preparedness for the highest levels of vehicle automation, namely SAE Levels 4 and 5, as lower levels generally do not require substantial policy, regulatory, or infrastructure adaptations, and most cities are already capable of supporting them. We develop a holistic readiness index that facilitates the ranking of cities (or larger geographic regions) based on CAV readiness and evaluates individual readiness as well. The index encompasses cyber and hard infrastructure elements, pro-CAV policies, and other factors proxying the potential for accommodating CAVs. We develop two scoring schemes, in the first of which each element of readiness is represented by a dichotomous variable. The second scheme is a compound scoring structure that assigns an integer score between 0 and 5 to a number of variables. Here, a city's performance relative to the average value of a variable determines the city's score for that variable. We employ the proposed indexes to assess the CAV readiness of the 98 most populated cities in the contiguous US, each having a population of 220,000 or more. We choose to focus on populated cities – rather than towns and rural areas – as urban areas with high populations are more likely to exhibit higher CAV market penetration. We rank the cities using the two scoring schemes and discuss the results. We further investigate how infrastructure investment could impact the scores as well as the ordering of cities. Policy implications and insights that may be of interest to other cities and countries are also discussed.

The remainder of this paper is organized as follows. The relevant literature is reviewed in Section 2, based on which the research gap is highlighted. Section 3 discusses various infrastructure elements and policies that can facilitate the use of CAVs, followed by our data collection efforts and the methodology for developing the readiness index in Section 4. Section 5 presents city scores under different scoring schemes and discusses the results. This section further puts forward the urban planning implications of this study as well as broader insights. Section 6 concludes the paper with the study's major findings, a discussion of limitations, and directions for future research.

2 Literature Review

The transportation literature has witnessed a surge in interest in various aspects of the operation, planning, and impacts of CAVs. In what follows, we review some recent contributions across the broad spectrum of CAV research. We then shift our focus to CAV infrastructure research and highlight the associated research gap.

In the area of congestion and traffic operations, numerous studies have addressed challenges arising from the coexistence of CAVs and conventional vehicles. Some studies have attempted to leverage the advanced features of CAVs to design innovative traffic management systems. For example, Martin-Gasulla and Elefteriadou (2021) designed a traffic management system for single-lane roundabouts by enabling coordination among CAVs to minimize average control delay. Guo et al. (2020) examined traffic flow in mixed environments of CAVs and regular vehicles at on-ramp merge and off-ramp diverge sections. Studies by Le Vine et al. (2019), Maciejewski and Bischoff (2018), Le Vine and Polak (2016), and van den Berg et al. (2016) are among the notable contributions this research area.

Since the inception of automated driving, safety and regulatory considerations have been central to research efforts. Overall, previous studies can be categorized into three groups: (i) estimating safety benefits of CAV adoption at different market penetration levels (e.g., Fagnant and Kockelman (2015) and Yang and Fisher (2021)); (ii) techniques and technologies aimed at improving the safety of CAV occupants as well as other motorists and pedestrians (e.g., Alonso et al. (2011), Liu and Khatkhat (2016), Azizi Soldouz et al. (2020), Deb et al. (2019), and Rahman et al. (2021)); and (iii) legal and regulatory challenges associated with CAV deployment (e.g., Gurney (2013) and van Wees (2021)).

Focusing on environmental impacts, researchers have sought to quantify energy savings and emission reductions resulting from the implementation of automated driving technologies. For example, Tsugawa et al. (2011) conducted driving experiments and simulations of truck platoons on expressways and found that CO₂ emissions could be reduced by up to 4.8% when trucks operate with 4 m gaps. Brown et al. (2014) estimated that the impact of CAVs on energy use could range from a 90% reduction to a 150% increase, depending on which effects materialize. A similar discussion was offered by Wadud et al. (2016). Notably, shared autonomous vehicles (SAVs) have been shown to reduce emissions even when their vehicle miles traveled are twice those of the privately owned vehicles they replace. A review of recent studies in this area is provided by Kopelias et al. (2020).

Various dimensions of travel behavior in the presence of CAVs constitute a significantly studied area within transportation research. An extensive portion of this literature revolves around capturing individuals' behavioral characteristics and perceptions of CAVs (e.g., Acheampong et al. (2021), Nair and Bhat (2021), Wang et al. (2020), Penmetsa et al. (2019), Lu et al. (2017), and Hohenberger et al. (2016)). Furthermore, there exist several studies that attempt to estimate the aggregate-level effects of CAVs on travel demand (Hasnat et al., 2021; Truong et al., 2017). Future research is likely to focus on estimating demand for Connected and Autonomous Vehicles (CAVs) using observed, real-time vehicular data. The feasibility of such applications, however, depends on achieving a sufficient level of adoption. Nevertheless, the existing literature on this topic is extensive (e.g., Shafahi and Talebian (2015) and Rao et al. (2018)). In addition, CAV adoption also has a place under the umbrella of travel behavior research (e.g., Lavasani et al. (2016), Talebian and Mishra (2018), and Shabanpour et al. (2018)).

CAV-related problems in the freight transportation area remain relatively uncharted compared to other research domains. The literature is primarily focused on the planning and operations of platoons of trucks (Kunze et al., 2009; Kunze et al., 2011; Muratori et al., 2017; Noruzoliaee et al., 2021), with only very few studies looking at perceptions of autonomous trucks (Anderhofstadt & Spinler, 2020; Kishore Bhoopalam et al., 2023) and adoption of autonomous trucks (Simpson et al., 2019; Simpson & Mishra, 2021; Simpson et al., 2022; Talebian & Mishra, 2022). Another underexplored area pertains to the infrastructure requirements for safe and efficient operations of CAVs, where most of the previous studies have concentrated on the design of proper technologies (e.g., Khayatian et al. (2018), Coutinho and Boukerche (2019), Li and Liu (2020), and Tchuente et al. (2021)).

Measuring the readiness of cities for CAVs is located at the intersection of three areas: infrastructure requirements, safety and regulations, and travel behavior. To the best of our knowledge, an index that could help quantify readiness to embrace CAVs is missing from the literature. Nonetheless, three pertinent studies in the area of smart urbanization are worth reviewing. First, PwC (2017) developed a smart city readiness index that consists of eleven sub-indexes, including smart housing and utilities, digitalization of culture and tourism, and driverless transport. Some sub-indexes have more than one component. The sub-index for driverless transport has two components, summed with equal weights: unmanned ground and aerial vehicles. PwC also ranked 10 major cities around the world. Overall, this study considers a very limited number of factors contributing to CAV readiness. Second, Debnath et al. (2014) presented a framework for benchmarking smart transport cities. Sixty-six indicators of smartness are identified. The indicators are then combined into a single smartness index, and 26 large cities around the world are compared. This study, however, is not focused on CAVs and does not cover readiness. Third, Zali et al. (2022) explored the key drivers of autonomous vehicle (AV) adoption in developing countries, focusing on Iran. Using a structural analysis method, it draws on primary qualitative data collected through a two-round fuzzy Delphi process combined with a snowballing technique, involving 25 experts. This approach, typical of futurist research, identified 11 critical factors from an initial set of 54 that influence AV adoption in this context.

Readiness measures are integral across various research domains, offering valuable insights into preparedness levels for different phenomena. In the area of health sciences, Rice and Tamburlin

(2004) presented a measure of organ donation readiness. The authors collected information about nine items concerning organ donation, which were then merged into a single readiness index. In the technology adoption domain, Parasuraman (2000) developed a 36-item Technology Readiness Index (TRI) to quantify people's eagerness to use new technologies to accomplish their work- and life-related objectives. The 36 items were clustered into four categories and loading factors were applied to capture the relative importance of items. Parasuraman and Colby (2015) updated Parasuraman's original 36-item index to a 16-item index. These TRIs have been widely used by researchers in various fields. For example, Victorino et al. (2009) discussed the need for a readiness index that can assist private equity investors in exiting investments. Jaafar et al. (2007) used Parasuraman's 36-factor TRI to evaluate the readiness of construction firms in Malaysia to employ information technology measures. Kirkman et al. (2002) proposed an index that assesses countries' capacity to utilize potential opportunities for information and communication technologies.

Continuing on the applications of readiness indices in other domains, Bilici et al. (2024) examined how the dimensions of the consumer Technological Readiness Index (optimism, innovativeness, discomfort, insecurity) and their anthropomorphic perceptions of autonomous cars influence their attitudes towards usage. Additionally, they explored how these attitudes affect intentions to use autonomous cars in the future. The research findings suggested that brands introducing autonomous cars should focus on enhancing the dimensions of optimism, innovativeness, and anthropomorphism, while also addressing and mitigating factors contributing to consumer discomfort and insecurity. In the governance area, the readiness index has been employed to measure countries' propensity to use e-government, including the communication and information technologies needed to provide services to citizens and coordinate intra-government functions. For example, Kirkman et al. (2002) developed an index for readiness to implement e-voting. In the transportation domain, Zayed (2016) put forward an index quantifying the readiness of cities for cycling. The author first considered 12 variables having the potential to impact cycling. Principal component analysis was conducted to identify the subset of effective variables, and five variables were then selected as the main variables explaining cycling readiness.

3 CAV Readiness Elements

The first step in developing the CAV readiness index is to identify the factors and variables affecting readiness. This section outlines the essential policies, infrastructure components (both hard and cyber elements), and considerations pivotal to fostering an environment conducive to CAV integration. A comprehensive set of 29 variables has been delineated, organized into seven distinct categories. These variables are concisely presented in Table 1 for ease of reference and understanding.

Table 1. Summary of variables used to evaluate CAV readiness

Category	Variable
Hard infra.	Var. 1- High-quality road signage and marking
	Var. 2- CAV-compatible parking facilities
	Var. 3- Sensor-equipped cones and beacons
	Var. 4- CAV-only pick-up and drop-off areas
	Var. 5- CAV-compatible tolling facilities
Road cyber infra.	Var. 6- Roadside information communication
	Var. 7- High-resolution maps of the road network

Category	Variable
Vehicle cyber infra.	Var. 8- Infrastructure-based pedestrian detection devices
	Var. 9- Traffic control center
	Var. 10- Vehicle to vehicle communication devices
	Var. 11- Infrastructure to vehicle communication devices
	Var. 12- Autonomous DRT services
Permits and privileges	Var. 13- Driving regulations
	Var. 14- Testing regulations
	Var. 15- Parking privileges
	Var. 16- HOV lane permission
	Var. 17- Autonomous truck permits
	Var. 18- Tolling privileges
Tax reg.	Var. 19- Tax incentives or reduced fees for consumers
	Var. 20- Tax incentives or reduced fees for organizations
	Var. 21- Auto tax rate
Practices promoting smart city development	Var. 22- Preventing misuse of safe harbors
	Var. 23- Maintenance of existing signs and markings
	Var. 24- Guidelines for lowering inconsistency in design and use of signage
	Var. 25- Research on CAV requirements
	Var. 26- Smart City initiatives
City attributes	Var. 27- Land use pattern
	Var. 28- Re-evaluation of bridge structures
	Var. 29- Adverse weather conditions

3.1 Category 1: Hard Infrastructure Requirements

Variable 1- High-quality road signage and marking: The percentage of roads classified as being in good condition, serving as a proxy for high-quality road signage and marking due to limitations in direct data availability

Rationale: Demand-driven and shared mobility services are emerging in urban areas, and the designation of CAV-compatible areas is a necessity (Földes & Csiszár, 2018; Zarkeshev & Csiszár, 2019). Road signage and markings will remain in place as long as there is a mix of CAVs and conventional vehicles. Thus, special attention should be given to signage and markings to accommodate the needs of both vehicle types. Existing advanced driver assistance systems rely on image-processing techniques to detect road signage and markings and therefore require clear and well-maintained signage and markings to perform navigation (Van Brummelen et al., 2018). The current state of road signage should be reviewed to minimize inconsistencies and ensure that signs meet applicable requirements and standards. In cases of substantial inconsistencies or areas (or roads) with low-quality markings, the designation of CAV-compatible areas may be required (Transport Systems Catapult, 2017). By identifying the areas in which automated features operate effectively, travelers will have a clearer view of the benefits of CAVs. This investment is paramount for enhancing the driving performance of cities (Török et al., 2017).

Variable 2- Relative availability of CAV-compatible parking spaces: Measured as the ratio of total CAV-compatible off-street parking capacity to aggregate parking demand, estimated as city population multiplied by the car ownership rate.

Rationale: A CAV will be able to drop off passengers, find a parking spot, and park safely. This capability can be viewed as an “autonomous valet parking” service and presents opportunities for

both users and infrastructure managers. From the users' perspective, the stress, time, and additional fuel costs associated with "cruising for parking" are reduced or even eliminated. From the providers' perspective, opportunities arise from increased parking capacity, as CAVs can block each other and allow coordinated vehicle movements when needed. The capacity of a CAV-compatible parking facility can be up to 2.5 times that of a conventional one (Millard-Ball, 2019). To capture the relative availability of CAV-compatible parking spaces, total CAV-compatible off-street parking capacity is divided by aggregate parking demand. The total number of vehicles in the city—obtained by multiplying city population by the car ownership rate—is used in the denominator, as direct figures on aggregate parking demand are typically unavailable.

Variable 3- Sensor-equipped cones and beacons: Whether the city has acquired any sensor-equipped cones and beacons.

Rationale: While humans can directly sense roads and signs and decide on details such as speed, lane choice, and distance from other vehicles, CAVs rely on detailed road network maps and data received from sensors. Unlike humans, who can correctly sense and analyze a new environment and (re)act accordingly, CAVs may have difficulties interpreting new data and, consequently, navigating unfamiliar conditions. One important activity that can alter road layout and signage is roadwork, including both planned and emergency activities. Sensor-equipped worksite cones and beacons are needed to transmit critical worksite-related information to vehicles approaching roadwork areas (Roaddefender, 2025). Unless CAVs are able to perfectly interpret environmental and traffic conditions in roadwork areas and safely navigate through them, such communication systems appear to be imperative.

Variable 4- CAV-only pick-up and drop-off areas: Whether the city has developed any CAV-only pick-up and drop-off areas in crowded locations.

Rationale: Autonomous demand-responsive transit (DRT) services eliminate the need for a human driver and improve fleet utilization and economic productivity. Autonomous DRT may be used by individual users or shared among multiple user groups. Personal rapid transit (PRT) systems and private vehicles operating as automated taxis are other DRT options that can be considered in a smart city context. Physical infrastructure is required to ensure the safe and efficient operation of autonomous DRT services. Specifically, pick-up and drop-off operations in congested areas cannot be ad hoc and require appropriately designed infrastructure (Medium, 2019; Kittelson & Associates, 2018). In less congested areas, however, vehicles may be able to pick up or drop off passengers at a wider range of locations.

Variable 5- CAV-compatible tolling facilities: Whether the city has toll roads equipped with contactless electronic toll collection systems.

Rationale: To ensure driverless vehicles can conveniently use toll roads, electronic toll collection through transponders and/or plate recognition should be implemented.

3.2 Category 2: Road Cyber Infrastructure Requirements

Variable 6- Roadside information communication: Whether the city has deployed Road Side Units (RSUs) and other devices, such as cameras, that are connected to the infrastructure network using optical fibers or wireless technology to collect data from roads.¹

Rationale: Connected Road Work Warning (CRWW) systems are required to inform CAVs about the location of roadside workers, worksite layout, time of operation, and speed restrictions near the site. Such data can be transmitted to vehicles in real-time by the worksite manager. A CRWW system consists of the roadside information communication devices mentioned above.

¹ A roadside unit provides very low latency data from roadside infrastructure to vehicles' On-board Units (OBUs).

Variable 7- High-resolution maps of the road network: Whether high-resolution maps are available for the city.

Rationale: An alternative to direct sensing of the pavement is to use high-resolution, three-dimensional digital maps of the road infrastructure. A Light Detection and Ranging (LiDAR) scanner can be used to map road signs, buildings, and trees (Ford 2016; Van Brummelen et al., 2018).

Variable 8- Infrastructure-based pedestrian detection technologies: Whether the city has roadside cameras equipped with cutting-edge pedestrian detection technologies.

Rationale: Pedestrians may act unpredictably and cannot be controlled, directed, or fully anticipated; thus, they are considered a non-compliant component of the transportation system. CAVs will frequently encounter pedestrians at crossings. In appropriate locations, infrastructure-based pedestrian detection can be implemented, and information can be transmitted to CAVs (Rasouli & Tsotsos, 2020). Time-of-flight and infrared cameras are among the technologies that can assist with pedestrian detection.

Variable 9- Traffic control center: Whether the city has a traffic control center to transmit real-time information to travelers, passenger cars, and transit vehicles.

Rationale: A traffic control center equipped with advanced technologies is an essential component for managing a mix of conventional and autonomous vehicles safely and efficiently. Although the current center may not be fully CAV-compatible, experience obtained from collecting and utilizing real-time traffic data can better prepare a city to develop, operate, and maintain the cyber infrastructure required for CAV operations.

3.3 Category 3: Vehicle Cyber Infrastructure Requirements

Variable 10- Vehicle-to-vehicle communication devices: Whether the city has equipped emergency vehicles with V2V communication equipment.

Rationale: Some situations require communication between a CAV and non-passenger vehicles. For example, Connected Emergency Vehicle Warning (CEVW) systems inform CAVs of an approaching emergency vehicle. Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication are needed to transmit information about the location, destination, and travel path of the emergency vehicle to nearby CAVs and to the infrastructure control center to give priority to the emergency vehicle (Mostaed et al., 2017; Petrov, 2017).

Variable 11- Infrastructure-to-vehicle communication devices: Whether the city has deployed I2V devices.

Rationale: One example of I2V communication equipment is DSRC-equipped traffic signals. By using head and body movements, saccadic eye motion, and adjusting aperture and focus, a human driver can recognize a green light even if it is not perfectly clear. CAVs rely on image processing technologies to recognize traffic signals. However, this may fail under imperfect conditions, as windscreen-mounted cameras are fixed and cannot adjust aperture and focus. Alternatively, signal phasing can be sent directly to vehicles through I2V communication (Hoadley, 2016).

Variable 12- Autonomous DRT services: Whether the city offers any autonomous DRT services.

Rationale: Some DRT services operating on dedicated infrastructure can be computerized to operate without human control. In such cases, a DRT control center should be established. While the development of these services does not directly relate to CAVs, it indicates the city's willingness to adopt smart transportation options. Other services, such as bus rapid transit, trams, and similar transit modes, are also considered under this variable.

3.4 Category 4: Permits and Privileges

Variable 13- Driving regulations: Whether the city has developed legislations allowing the operations of CAVs.

Rationale: CAVs cannot operate in cities unless appropriate legislation permits their use. Therefore, cities without proper legislation in place are less prepared for CAV deployment.

Variable 14- Testing regulations: Whether the city has developed regulations allowing CAV testing.

Rationale: Allowing companies to test CAVs under real-world conditions is a critical first step toward developing a smart transportation system. Cities permitting such tests can reasonably be considered more prepared compared to those that do not.

Variable 15- Parking privileges: Whether the city provides reduced cost, dedicated spaces, or free parking for CAVs.

Rationale: By decreasing the cost and time spent searching for a parking spot, these privileges make the city more attractive to CAV users and potential adopters.

Variable 16- HOV lane permission: Whether the city allows (or plans to allow) single-occupant CAVs to use HOV lanes.

Rationale: Cities may allow CAVs in HOV lanes to incentivize adoption. HOV lanes may gradually become dedicated to CAVs. For example, there is a proposal to allow CAVs in the HOV lane on I-5 from Seattle to Vancouver, considering a gradual conversion to a CAV-only corridor over a 15-year horizon (Sorrel, 2016).

Variable 17- Autonomous truck permits: Whether a city (or the state in which the city is located) has granted permits to autonomous trucks.

Rationale: Granting permits to autonomous trucks may not directly indicate readiness for autonomous cars but reflects that the city or state is more open to this technology compared to those that have not provided similar permits.²

Variable 18- Tolling privilege: Whether the city considers lower toll rates for CAVs.

Rationale: Reduced toll rates lower the recurring cost of CAV use, making them attractive to users.

3.5 Category 5: Tax Regulations

Variable 19- Tax incentives or reduced fees for consumers: Whether the city (or the state in which the city is located) offers any tax credit, rebates, or sales tax exemption, or lower registration fees for consumers purchasing CAVs.

Rationale: CAV prices play an important role in adoption (Talebian & Mishra, 2018; Bansal & Kockelman, 2017), and cities can influence prices by providing incentives. Some US states (e.g., Florida and Colorado) provide incentives such as rebates and state tax credits to buyers of electric vehicles (U.S. Department of Energy, n.d.). States and cities may choose to provide similar incentives to make the city more attractive to potential CAV buyers.

Variable 20- Tax incentives or reduced fees for organizations: Whether the city (or the state in which the city is located) offers lower use and vehicle tax, rebates, or reduced registration fees for the purchase of CAVs by private businesses or governmental agencies.

Rationale: Same as Variable 19.

Variable 21- Auto tax rate: Average automobile tax rate in the city.

Rationale: High tax rates increase the already high initial CAV prices, making the city less favorable for CAV adoption.

² It should be noted that pods can also be platooned. However, due to the clear and significant economic and environmental benefits of truck platooning, this study only considers autonomous truck permits.

3.6 Category 6: Practices Promoting Smart City Development

Variable 22- Preventing misuse of safe harbors: Whether the city has developed provisions to prevent misuse of safe harbors.

Rationale: In some situations, a CAV may require a human driver to regain control of the vehicle. However, this may not always be possible (e.g., the driver may experience a medical issue or fall asleep). When that happens, the CAV needs a safe area to park and wait for further instructions from the driver or control center. On many US highways, continuous hard shoulders can serve as safe harbors. In some states, however, hard shoulders are converted to running lanes for transit vehicles. On other roadways, emergency refuge areas are provided at intervals. There is therefore a need for provisions preventing the misuse of safe harbors.

Variable 23- Maintenance of the existing signs and markings: Whether the city has appropriate maintenance policies in place to maintain signs and markings visible to CAVs.

Rationale: Agencies should have maintenance policies for road markings and signage to ensure CAV operation. Such policies give users confidence that CAVs will remain operational. Note that this variable is not identical to Variable 1: the former primarily measures maintenance, while the latter measures new installations. Lack of regular maintenance can detrimentally affect CAV readiness. While marking maintenance can be costly, CAVs provide a unique opportunity for authorities: CAV sensors can detect problematic markings and report them to agencies, which can then manage maintenance efficiently.

Variable 24- Guidelines for lowering inconsistency in the design and use of signage: Whether the city has developed guidelines mandating organizations and businesses to design and use consistent signage.

Rationale: These guidelines indicate that the city systematically attempts to improve the environment for CAV operation. This is particularly important as many parking facilities are privately owned and may not follow conventional signage and marking standards.

Variable 25- Research on CAV requirements: Whether the city supports or conducts research on CAV requirements.

Rationale: This shows that the city is eager to establish a CAV-friendly environment.

Variable 26- Smart City Initiatives: Whether the city has been among the finalists of the US Department of Transportation (DOT) Smart City Challenge.

Rationale: This indicates that the city has already developed a solid plan to actualize at least some smart transportation initiatives and is likely ready for CAVs.

3.7 Category 7: City Attributes

This category presents additional indicators that may not directly relate to CAVs but implicitly show whether a city is ready to welcome CAVs.

Variable 27- Land use pattern: Whether the city has a dense downtown core and a prevailing land-use structure that allows for outward residential expansion.

Rationale: The relationship between CAV adoption and urban form remains the subject of ongoing debate, with no consensus on whether CAVs will ultimately promote densification, decentralization, or hybrid development patterns (Milakis et al., 2017; Acheampong & Cugurullo, 2019). Heinrichs (2016) outlines several plausible scenarios, one of which – the “hypermobility city” – suggests that reduced perceived travel costs enabled by CAVs could support suburban residential growth while maintaining dense urban cores. Importantly, this study does not assume that this or any other scenario will necessarily materialize. Instead, this variable captures whether a city’s existing spatial structure – specifically, the presence of a dense downtown combined with the availability of peripheral land – could accommodate such a trajectory *should it occur*. This consideration is particularly relevant in the context of US cities, where historical development

patterns often reflect this structure. Accordingly, the variable functions as a proxy for structural capacity and adaptability under uncertainty, rather than as an endorsement or prediction of a specific land-use outcome.

Variable 28- Re-evaluation of the bridge structure: Whether the city has plans to re-evaluate (and possibly reinforce) bridges considering the impacts of truck platooning.

Rationale: Vehicle-to-vehicle communication will enable trucking companies to platoon multiple trucks. This, however, can pose a challenge to bridge structures, as current designs assume heavy vehicles are diluted by light vehicles. The bearable load of bridges should be evaluated against the weight of platooned trucks, and – if necessary – bridges should be reinforced. There is also a need to re-evaluate other aspects of bridges, including collisions on supports, collisions on decks, centrifugal forces on curved decks, and braking forces.

Variable 29- Adverse weather conditions: Average number of rainy or snowy days in a year.

Rationale: CAVs may have difficulty dealing with severe weather conditions, especially snow. On snow-covered roads, CAVs may not sense the pavement perfectly. Salt and ice can block sensors, causing inaccuracies in detection. Heavy rain or snow can also lead to inaccurate data reports by LiDAR sensors. In foggy conditions, vehicles may choose incorrect travel speeds. Furthermore, thunderstorms can negatively impact V2V, V2I, and I2V communications (Sundararajan et al., 2016; Zang et al., 2019). Thus, at least in the early stages of introduction, when vehicles solely rely on direct sensing of the infrastructure, cities with high precipitation or frequent snow may be less ready for CAVs.

4 Data and Methodology

With various elements contributing to CAV readiness in place, we now present the methodology to merge the 29 variables into a single readiness index. Prior to doing so, we describe our data collection effort as data availability, which is a factor that could constrain or even determine the methodology.

4.1 Data

We initially considered the 100 most populated cities in the United States to conduct the readiness analysis. To ensure a more consistent comparison, the cities of Anchorage, Alaska, and Honolulu, Hawaii were excluded so that only cities within the contiguous United States were ranked and analyzed. This resulted in a final list of 98 cities, each with a population of at least 220,000. We note that the baseline year for data collection in this study is 2024. For each variable and each city, official municipal and state-level sources were systematically examined to determine whether the corresponding regulation, policy, or hard/cyber infrastructure component had been formally established or implemented. A value of zero therefore indicates the verified absence of adoption, rather than missing or unavailable data. Given the cutting-edge and disruptive nature of CAV technologies, it is reasonable to expect that cities would publicly announce or formally document the implementation of related infrastructure elements or regulatory measures. Consequently, the likelihood that a city has adopted such measures without any official record is low. Furthermore, as several CAV-related technologies and policy instruments are still emerging, it is not unexpected that a number of cities have not yet implemented certain advanced infrastructure components or policy measures. More specifically, no city in our dataset currently (i) offers purchase incentives for CAVs; (ii) provides parking or tolling privileges for CAVs; (iii) has enacted or is developing regulations allowing CAVs to use HOV lanes; (iv) has enacted or is developing regulations addressing the misuse of safety harbors; (v) has designated CAV-compatible areas; (vi) has enacted or is developing guidelines to eliminate inconsistencies in road signage; (vii) is re-evaluating bridge infrastructure in light of CAV-related impacts; (viii) operates autonomous DRT services; (ix) has enacted or is developing CAV-compatible parking facilities; and (x) has implemented

infrastructure-based pedestrian detection systems. Accordingly, these variables take a value of zero for all cities considered. The values of the remaining variables are determined as follows:

- Variable 1: RI data are obtained from the Bureau of Transportation Statistics (2024). For each state, the percentage of roadway segments with an IRI value below 95 is calculated. According to Bureau of Transportation Statistics (2024), IRI values below 95 indicate good ride quality.
- Variable 3: There is currently no centralized database or authoritative source identifying US cities that have purchased or deployed sensor-equipped cones and/or sensor-enabled beacons specifically for connected and autonomous vehicle (CAV) or smart work-zone applications. These technologies are still emerging and are primarily available through pilot programs or proprietary deployments (Business Wire, 2025). Therefore, city DOTs are individually reviewed to determine whether a city has equipped itself with this type of technology.
- Variable 5: The list of tolled facilities is first obtained from Vinoth (2025). Official city and agency websites were then reviewed to identify cities equipped with electronic toll collection systems.
- Variable 6: Information on Roadside Unit (RSU) deployment was obtained from national connected-vehicle deployment inventories and local documented pilot project reports.
- Variable 7: The US Geological Survey (USGS) is progressively developing high-resolution LiDAR maps covering the entire United States. All cities in the dataset are covered by at least a 1/9 arc-second LiDAR raster; however, only a subset of cities is covered by LiDAR data with a spatial resolution of 1-m pixel size (USGS, 2025). Cities with LiDAR coverage at a resolution of 1 m or better are assumed to exhibit a higher level of readiness.
- Variable 8: Deployment is concentrated in large cities with connected infrastructure or Vision Zero programs; smaller cities generally have no documented pedestrian detection infrastructure (US DOT, 2022).
- Variables 9 and 12: Official city websites are visited to identify cities with a transit or traffic control center and autonomous DRT services.
- Variable 10: Evidence of V2V deployment was drawn from documented connected vehicle pilot programs involving emergency vehicle fleets. These pilots, primarily funded by federal and state transportation agencies, report the use of V2V technology for safety and operational testing in selected cities (Data.gov, 2026).
- Variable 11: Data on I2V deployment were compiled from connected vehicle pilot documentation and state transportation agency reports describing the implementation of SPaT messaging and connected intersections (SMARTER Center, 2025).
- Variables 13 and 17: NCSL's database (NCSL, 2026) is used to determine which states allow driving and testing of autonomous passenger cars and trucks.
- Variable 21: State-level automobile tax rates are obtained from Gareffa (2023) and Tax Foundation (2025).
- Variable 22: Provisions addressing the misuse of safety harbors are rare and are mostly defined at the state level in the US. In most cities, no city-specific regulations exist; therefore, state-level statutes are applied uniformly to all cities within each state. This variable captures regulatory maturity and readiness, reflecting a city's ability to safely implement CAV programs without legal loopholes (Nolte et al., 2025; Congress.gov, 2026).
- Variable 25: Considering the importance of practical research in guiding policy making for CAVs (KPMG, 2018), each city and the corresponding state are individually researched to determine whether they conduct or support research related to CAVs
- Variable 26: The list of US DOT Smart City Challenge finalists is obtained from the US DOT (2016).
- Variables 27: Geographic and political boundaries of cities are visually inspected to assess whether further urban sprawl is possible. We also examine whether cities have implemented specific laws restricting sprawl. For example, Portland has eliminated further

urban expansion through local laws, despite the fact that physical space for expansion still exists.

- Variable 29: Precipitation data are obtained from BestPlaces (2026).

Taken together, the sources listed above reflect CAV-related policy, regulation, and infrastructure provision in the United States. While city-level indicators are employed wherever feasible, some variables necessarily rely on state-level data because the underlying authority, institutional responsibility, or policy framework is exercised uniformly across all cities within a state.

Prior work demonstrates that transportation infrastructure provision, regulatory frameworks, and deployment standards for AV/CAV technologies are strongly shaped by state-level policy and institutional decisions (Brown, 2018; Schepis et al., 2023). Accordingly, while city-level indicators are used wherever feasible, a limited number of variables in this study are measured using state-level data when the underlying policy, regulatory authority, or institutional responsibility is exercised uniformly across all cities within a state. Examples include tax incentives, permitting regimes, and traffic regulations that are determined at the state level and directly constrain or enable city-level action.

In one case – road quality – state-level data were used despite the variable’s conceptual relevance at the city level. This choice was due to the lack of comparable city-level road quality data for some cities in the dataset and was adopted to ensure consistency across observations. Although this approach may mask intra-state variation, it reflects the best available evidence.

In addition, the following information is collected for policy analysis:

1. Total state transportation budgets for 2024 are obtained from the FTA (2026) and divided by state population to calculate per capita transportation budgets.
2. City-level population data for 2024 are obtained from Census.gov (2025).
3. A shapefile showing the geographical boundaries of the 500 most populous US cities is obtained from Data.gov (2025).
4. The shapefile for the National Highway Planning Network (NHPN) is obtained from Bureau of Transportation Statistics (2024). This shapefile is intersected with city geographic boundaries to calculate total roadway mileage within each city. In addition, the mileage of each roadway functional class is computed for each city.

4.2 Methodology

We formally define an *index* as a quantitative measure derived from a series of observed facts to infer the relative positions of objects within a given domain, following Hermans et al. (2008) and Nardo et al. (2008). We further conceptualize a city’s *readiness* for CAVs as its capacity to enable all users to safely, conveniently, efficiently, and cost-effectively operate connected and autonomous vehicles to accomplish activities in both personal and professional contexts, following Jaafar et al. (2007) and Kalamas et al. (2009). Table 2 presents the notations used in this study. Let X_c denote the value of readiness index for city c and x_c^l represent the score of city c on variable v . Assuming an equal weight of 1 for each of the 29 variables, the readiness index for city c is computed as $X_c = \sum_{l \in L} l_c$, where L is the set of all variables.

Table 2. Notations used in the study

Notation	Definition	Avg.	Std. Dev.
X_c	The readiness index for city c		
l_c	The score of city c on variable $l \in L$		
L	The set of all variables		
Q_c	The percentage of roads with good quality condition in city c	μ_Q	σ_Q

Notation	Definition	Avg.	Std. Dev.
P_c	the total capacity of CAV-compatible off-street parking in city c over (city population multiplied by car ownership rate in the city)	μ_P	σ_P
B_c	The number of smart cones and beacons over the total road mileage in city c	μ_B	σ_B
D_c	The number of CAV-only pick-up and drop-off areas over total population in city c	μ_D	σ_D
V_c	The percentage of emergency vehicles in city c that are equipped with V2V and V2I systems	μ_V	σ_V
I_c	Length of roads within city c that are equipped with I2V infrastructure systems over the total mileage of roads in the city	μ_I	σ_I
R_c	Number of infrastructure-based pedestrian detection devices in city c over the total mileage of roads in the city	μ_R	σ_R
W_c	Total precipitation in city c	μ_W	σ_W
T_c	Automobile tax rate in city c	μ_T	σ_T

In this study, we use two separate scoring schemes to assess CAV readiness. In the first scheme, each element is a dichotomous variable that receives a value of 1 if the city has the corresponding feature, and 0 otherwise. For example, if the auto tax rate in a city is greater than the average rate (i.e., $T_c > \mu_T$), the city receives a score of 1 on the corresponding variable (i.e., $T_c = 1$). Similarly, if a city has developed autonomous demand-responsive transit services, it receives a score of 1 on Variable 12. In this scheme, the maximum attainable readiness score is 29. The second scheme, termed compound scoring, assigns an integer score between 0 and 5 for 11 variables that are continuous (i.e., not dichotomous). This is done by considering multiple cutoff points for each variable and assigning higher scores to better practices or conditions that promote CAV usage. In this way, we capture how well a city performs on a specific feature relative to other cities. Here, the maximum readiness score is 73. Table 3 describes how the two scoring schemes are implemented.

Table 3. Methodology for developing CAV readiness score

Variable	Definition in the compound scoring scheme	Definition in the simple scoring scheme
<i>Hard infrastructure</i>		
Variable 1	0 if $Q_c < \mu_Q - 2\sigma_Q$ 1 pt if $\mu_Q - 2\sigma_Q \leq Q_c < \mu_Q - \sigma_Q$ 2 pt if $\mu_Q - \sigma_Q \leq Q_c < \mu_Q$ 3 pt if $\mu_Q \leq Q_c < \mu_Q + \sigma_Q$ 4 pt if $\mu_Q + \sigma_Q \leq Q_c \leq \mu_Q + 2\sigma_Q$ 5 pt if $Q_c > \mu_Q + 2\sigma_Q$	1 pt if $Q_c > \mu_Q$, and 0 otherwise
Variable 2	0 if $P_c < \mu_P - 2\sigma_P$ 1 pt if $\mu_P - 2\sigma_P \leq P_c < \mu_P - \sigma_P$ 2 pt if $\mu_P - \sigma_P \leq P_c < \mu_P$ 3 pt if $\mu_P \leq P_c < \mu_P + \sigma_P$ 4 pt if $\mu_P + \sigma_P \leq P_c \leq \mu_P + 2\sigma_P$ 5 pt if $P_c > \mu_P + 2\sigma_P$	1 pt if $P_c > \mu_P$, and 0 otherwise
Variable 3	0 if $B_c < \mu_B - 2\sigma_B$ 1 pt if $\mu_B - 2\sigma_B \leq B_c < \mu_B - \sigma_B$ 2 pt if $\mu_B - \sigma_B \leq B_c < \mu_B$ 3 pt if $\mu_B \leq B_c < \mu_B + \sigma_B$ 4 pt if $\mu_B + \sigma_B \leq B_c \leq \mu_B + 2\sigma_B$ 5 pt if $B_c > \mu_B + 2\sigma_B$	1 pt if $B_c > \mu_B$, and 0 otherwise
Variable 4	0 if $D_c < \mu_D - 2\sigma_D$	1 pt if $D_c > \mu_D$, and 0 otherwise

Variable	Definition in the compound scoring scheme	Definition in the simple scoring scheme
	1 pt if $\mu_D - 2\sigma_D \leq D_c < \mu_D - \sigma_D$ 2 pt if $\mu_D - \sigma_D \leq D_c < \mu_D$ 3 pt if $\mu_D \leq D_c < \mu_D + \sigma_D$ 4 pt if $\mu_D + \sigma_D \leq D_c \leq \mu_D + 2\sigma_D$ 5 pt if $D_c > \mu_D + 2\sigma_D$	
Variable 5	1 pt if the city has toll roads that allow electronic payment, and 0 otherwise	
<i>Road cyber infrastructure</i>		
Variable 6	1 pt if the city has employed a CRWW system and 0 otherwise	
Variable 7	1 pt if high-resolution maps are available for the city, and 0 otherwise	
Variable 8	0 if $R_c < \mu_R - 2\sigma_R$ 1 pt if $\mu_R - 2\sigma_R \leq R_c < \mu_R - \sigma_R$ 2 pt if $\mu_R - \sigma_R \leq R_c < \mu_R$ 3 pt if $\mu_R \leq R_c < \mu_R + \sigma_R$ 4 pt if $\mu_R + \sigma_R \leq R_c \leq \mu_R + 2\sigma_R$ 5 pt if $R_c > \mu_R + 2\sigma_R$	1 pt if $R_c > \mu_R$, and 0 otherwise
Variable 9	1 pt if the city has a transit control center, and 0 otherwise	
<i>Vehicle cyber infrastructure</i>		
Variable 10	0 if $V_c < \mu_V - 2\sigma_V$ 1 pt if $\mu_V - 2\sigma_V \leq V_c < \mu_V - \sigma_V$ 2 pt if $\mu_V - \sigma_V \leq V_c < \mu_V$ 3 pt if $\mu_V \leq V_c < \mu_V + \sigma_V$ 4 pt if $\mu_V + \sigma_V \leq V_c \leq \mu_V + 2\sigma_V$ 5 pt if $V_c > \mu_V + 2\sigma_V$	1 pt if $V_c > \mu_V$, and 0 otherwise
Variable 11	0 if $I_c < \mu_I - 2\sigma_I$ 1 pt if $\mu_I - 2\sigma_I \leq I_c < \mu_I - \sigma_I$ 2 pt if $\mu_I - \sigma_I \leq I_c < \mu_I$ 3 pt if $\mu_I \leq I_c < \mu_I + \sigma_I$ 4 pt if $\mu_I + \sigma_I \leq I_c \leq \mu_I + 2\sigma_I$ 5 pt if $I_c > \mu_I + 2\sigma_I$	1 pt if $I_c > \mu_I$, and 0 otherwise
Variable 12	1 pt if the city has any autonomous DRT services on dedicated infrastructure, and 0 otherwise	
<i>Permits and privileges</i>		
Variable 13	1 pt if the city allows driving CAVs, and 0 otherwise	
Variable 14	1 pt if the city allows testing CAVs, and 0 otherwise	
Variable 15	1 pt if the city considers parking privileges for CAVs, and 0 otherwise	
Variable 16	1 pt if the city allows CAVs to use HOV lanes, and 0 otherwise	
Variable 17	1 pt if the city allows driving autonomous trucks, and 0 otherwise	
Variable 18	1 pt if the city considers tolling privileges for CAVs, and 0 otherwise	
<i>Tax regulations</i>		
Variable 19	No incentive: 0 \$1-\$2,499 incentive: 1 pt \$2,500-\$4,999 incentive: 2 pts \$5,000-\$7,499 incentive: 4 pts \$7,500-\$9,999 incentive: 4 pts \$10,000+ incentive: 5 pts	\$5,000+ incentive: 1 pts
Variable 20*	Variable between 0 and 5 pts depending on tax incentives and reduced fees considered by the city	0 or 1 depending on tax incentives and reduced fees considered by the city
Variable 21	0 if $T_c > \mu_T + 2\sigma_T$ 1 pt if $\mu_T + \sigma_T \leq T_c \leq \mu_T + 2\sigma_T$ 2 pt if $\mu_T \leq T_c < \mu_T + \sigma_T$ 3 pt if $\mu_T - \sigma_T \leq T_c < \mu_T$ 4 pt if $\mu_T - 2\sigma_T \leq T_c < \mu_T - \sigma_T$ 5 pt if $T_c < \mu_T - 2\sigma_T$	1 if $T_c < \mu_T$, and 0 otherwise
<i>Practices promoting smart city development</i>		
Variable 22	1 pt if the city actively prevents misuse of safety harbors, and 0 otherwise	
Variable 23	1 pt if the city has active programs or documented practices for maintaining roadway signs and pavement markings, and 0 otherwise	

Variable	Definition in the compound scoring scheme	Definition in the simple scoring scheme
Variable 24	1 pt if the city has established guidelines or standards aimed at reducing inconsistency in the design and use of roadway signage, and 0 otherwise	
Variable 25	1 pt if the city supported (or plans to support) research on CAV requirements, and 0 otherwise	
Variable 26	1 pt if the city has been among finalists of US DOT Smart City Challenge, and 0 otherwise	
<i>City attributes</i>		
Variable 27	1 pt if the city allows further urban sprawl, and 0 otherwise	
Variable 28	1 pt if the city is revaluating (or is considering to re-evaluate) the bridges, and 0 otherwise	
Variable 29	0 if $W_c > \mu_W + 2\sigma_W$ 1 pt if $\mu_W + \sigma_W \leq W_c \leq \mu_W + 2\sigma_W$ 2 pt if $\mu_W \leq W_c < \mu_W + \sigma_W$ 3 pt if $\mu_W - \sigma_W \leq W_c < \mu_W$ 4 pt if $\mu_W - 2\sigma_W \leq W_c < \mu_W - \sigma_W$ 5 pt if $W_c < \mu_W - 2\sigma_W$	1 if $W_c < \mu_W$, and 0 otherwise
*Tax incentives and reduced fees for organizations are typically more complex than those for consumers; so, segmentation of benefits requires precise information on how the benefits are determined by cities. Therefore, we suffice to present the general rule for distributing the points.		

5 Results and Discussions

In this section, we employ the simple and compound scoring schemes discussed in Section 4 to rank US populated cities. We first present and discuss the results. Next, we elaborate on how infrastructure investment could improve the readiness index and provide policy recommendations. We continue by highlighting urban planning implications and offering insights that may be of interest to other cities around the globe. The section concludes with a robustness analysis and an investigation of how category weights could impact the ranking results.

5.1 Readiness Results

The CAV readiness scores obtained from the simple and compound scoring schemes are presented in Tables 3 and 4 and Figures 1 and 2. As noted, the maximum scores in the simple and compound scoring schemes are 29 and 73, respectively. Based on the results in Tables 3 and 4, the highest-ranked cities under the simple scoring scheme achieve a relatively limited share of the total attainable score, indicating that even leading US cities are only moderately prepared for widespread CAV deployment. In the compound scoring scheme, this gap becomes more pronounced, as the top-performing cities capture a slightly higher – but still constrained – portion of the total available points. Atlanta ranks first in the compound scheme, while New York City, Philadelphia, Columbus, and Minneapolis consistently appear among the most prepared cities across both scoring approaches. Denver, Portland, Oakland, Boston, and Orlando also maintain strong positions in both schemes, suggesting a balanced performance across infrastructure, policy, and complementary indicators. In contrast, New Orleans, Wichita, Fort Wayne, and Toledo are consistently ranked among the least ready cities, regardless of the scoring methodology. A comparison between the two schemes reveals that score dispersion is larger under the compound approach, indicating that weighting and aggregation amplify differences in multidimensional readiness factors. Spatially, cities located on the East and West Coasts, along with selected Midwestern metropolitan areas such as Minneapolis and Columbus, tend to outperform cities in the Southwest and parts of the South, highlighting persistent regional disparities in CAV readiness across the United States.

Table 4. CAV readiness index for 98 cities across the Contiguous US using the simple scoring method

Rank	City	Score	Rank	City	Score	Rank	City	Score
1	New York City, NY	18	5	Madison, WI	14		Tulsa, OK	11
	Atlanta, GA	18		San Bernadino, CA	14		Bakersfield, CA	11
	Minneapolis, MN	18		Chicago, IL	13		Aurora, CO	11
2	Philadelphia, PA	17		Austin, TX	13		Lexington, KY	11
	Columbus, OH	17		Sacramento, CA	13		Cincinnati, OH	11
	Orlando, FL	17		Stockton, CA	13	8	Henderson, NV	11
	San Jose, CA	16	6	Chandler, AZ	13		Jersey City, NJ	11
	Boston, MA	16		Reno, NV	13		Laredo, TX	11
	Portland, OR	16		Garland, TX	13		Buffalo, NY	11
3	Oakland, CA	16		Jacksonville, FL	12		Winston-Salem, NC	11
	Cleveland, OH	16		Oklahoma City, OK	12		Gilbert, AZ	11
	Tampa, FL	16		Kansas City, MO	12		Baton Rouge, LA	11
	Saint Paul, MN	16		Raleigh, NC	12		Indianapolis, IN	10
	San Jose, CA	16		Arlington, TX	12		Fort Worth, TX	10
	Boston, MA	16		Corpus Christi, TX	12		Nashville, TN	10
	Houston, TX	15		St. Louis, MO	12		Memphis, TN	10
	Dallas, TX	15	7	Greensboro, NC	12	9	Milwaukee, WI	10
	Seattle, WA	15		Plano, TX	12		Albuquerque, NM	10
	Denver, CO	15		Durham, NC	12		Fresno, CA	10
	Detroit, MI	15		St. Petersburg, FL	12		Mesa, AZ	10
	Las Vegas, NV	15		Scottsdale, AZ	12		Omaha, NE	10
4	Baltimore, MD	15		Glendale, AZ	12		Wichita, KS	10
	Anaheim, CA	15		North Las Vegas, NV	12		Newark, NJ	10
	Santa Ana, CA	15		Irving, TX	12		Lincoln, NE	10
	Pittsburgh, PA	15		Hialeah, FL	12		Toledo, OH	10
	Chula Vista, CA	15		Boise, ID	12		Lubbock, TX	10
	Fremont, CA	15		Phoenix, AZ	11		Louisville, KY	9
	Los Angeles, CA	14		San Antonio, TX	11		New Orleans, LA	9
	San Diego, CA	14		Charlotte, NC	11	10	Fort Wayne, IN	9
5	San Francisco, CA	14	8	El Paso, TX	11		Norfolk, VA	9
	Washington D.C.	14		Tucson, AZ	11		Chesapeake, VA	9
	Long Beach, CA	14		Colorado Springs, CO	11		Richmond, VA	9
	Miami, FL	14		Virginia Beach, VA	11			
	Riverside, CA	14						

Note: Maximum value of readiness index by the simple scoring method is 29.

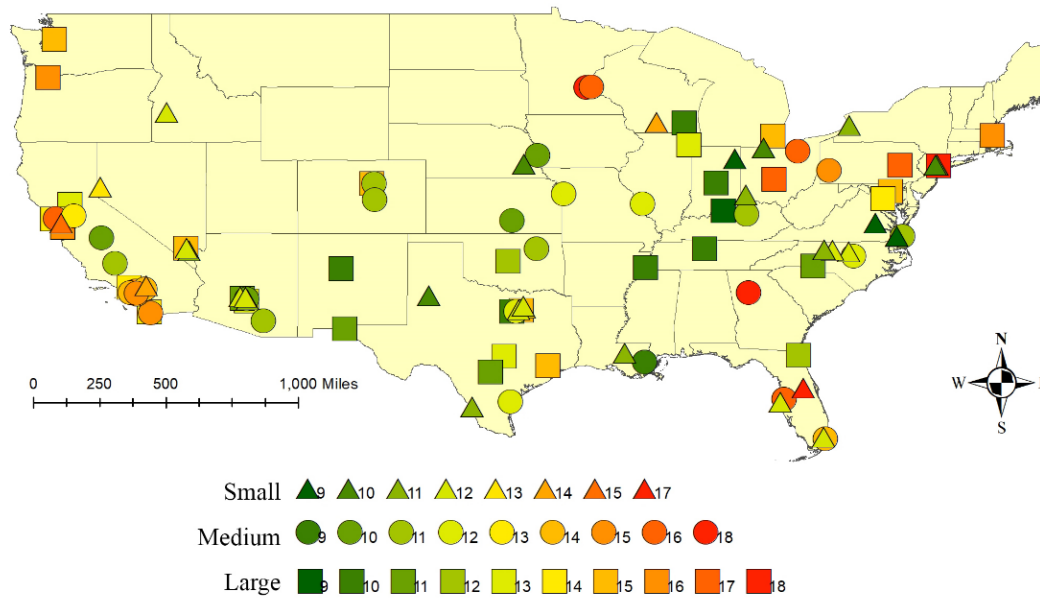


Figure 1. Graphical representation of CAV readiness index, obtained by the simple scoring method

Table 5. CAV readiness index for 98 cities across the Contiguous US using the compound scoring method

Rank	City	Score	Rank	City	Score	Rank	City	Score
1	Atlanta, GA	28		Chicago, IL	21		Albuquerque, NM	18
2	New York City, NY	27		Austin, TX	21		Mesa, AZ	18
	Philadelphia, PA	26	8	Greensboro, NC	21		Virginia Beach, VA	18
3	Columbus, OH	26		Durham, NC	21		Corpus Christi, TX	18
	Minneapolis, MN	26		Chandler, AZ	21		Lexington, KY	18
4	Boston, MA	25		Phoenix, AZ	20		Cincinnati, OH	18
	Orlando, FL	25		Jacksonville, FL	20	11	Henderson, NV	18
	Denver, CO	24		Charlotte, NC	20		Plano, TX	18
5	Portland, OR	24		El Paso, TX	20		Jersey City, NJ	18
	Oakland, CA	24		Sacramento, CA	20		St. Petersburg, FL	18
	Dallas, TX	23	9	Kansas City, MO	20		Reno, NV	18
	San Jose, CA	23		Raleigh, NC	20		Irving, TX	18
	San Francisco, CA	23		Stockton, CA	20		Baton Rouge, LA	18
	Detroit, MI	23		Madison, WI	20		Nashville, TN	17
	Las Vegas, NV	23		Scottsdale, AZ	20		Louisville, KY	17
6	Miami, FL	23		Winston-Salem, NC	20		Milwaukee, WI	17
	Tampa, FL	23		Boise, ID	20		Fresno, CA	17
	Anaheim, CA	23		Washington D.C.	19		Omaha, NE	17
	Santa Ana, CA	23		Oklahoma City, OK	19	12	Arlington, TX	17
	Saint Paul, MN	23		Tucson, AZ	19		Lincoln, NE	17
	Chula Vista, CA	23		Colorado Springs, CO	19		Lubbock, TX	17
	Fremont, CA	23		Tulsa, OK	19		Norfolk, VA	17
	Los Angeles, CA	22	10	Bakersfield, CA	19		Chesapeake, VA	17
	Houston, TX	22		Aurora, CO	19		Richmond, VA	17
	San Diego, CA	22		St. Louis, MO	19		Fort Worth, TX	16
7	Seattle, WA	22		Buffalo, NY	19		Memphis, TN	16
	Baltimore, MD	22		Glendale, AZ	19	13	Newark, NJ	16
	Long Beach, CA	22		North Las Vegas, NV	19		Toledo, OH	16
	Cleveland, OH	22		Gilbert, AZ	19		Fort Wayne, IN	16

Rank	City	Score	Rank	City	Score	Rank	City	Score
	Riverside, CA	22		Hialeah, FL	19		Laredo, TX	16
	Pittsburgh, PA	22		Garland, TX	19	14	Wichita, KS	15
	Irvine, CA	22	11	San Antonio, TX	18	15	New Orleans, LA	14
	San Bernadino, CA	22		Indianapolis, IN	18			

Note: Maximum value of readiness index by the compound scoring method is 73.

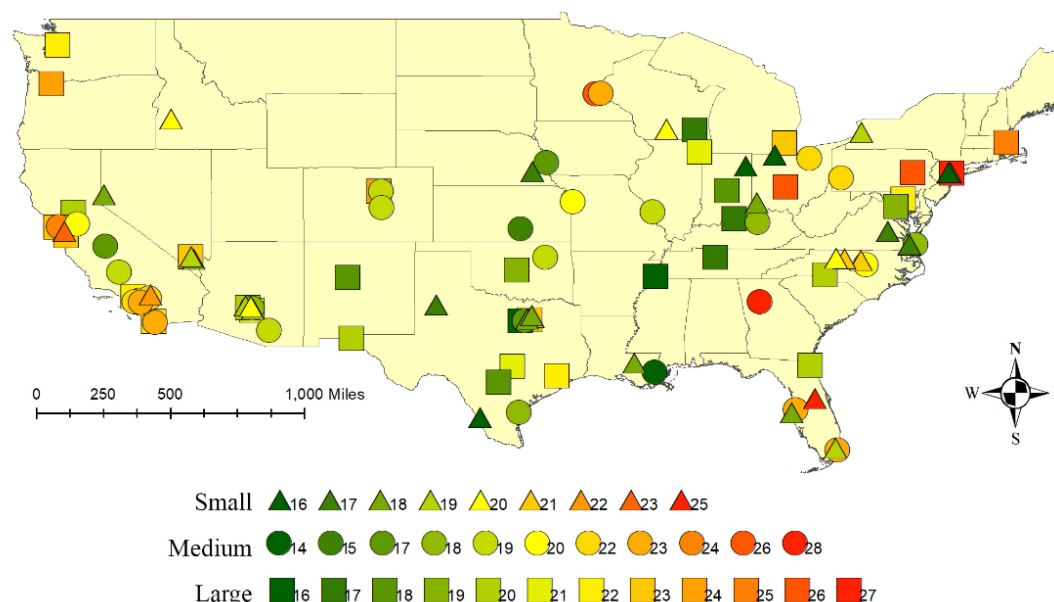


Figure 2. Graphical representation of CAV readiness index, obtained by the compound scoring method

In order to investigate the association between readiness score and city size, we first use the Two-Step Clustering method to group the cities into three categories based on population. For each cluster, we then sort the cities based on readiness scores (Table 6) and rank them. By comparing Table 6 with Tables 4 and 5, we find that large cities are generally readier to welcome CAVs compared to small- and medium-sized cities. This is not surprising, as larger cities typically have more facilities and take the initiative in implementing radical innovations, new strategies, and policies. Among medium-sized cities, Riverside, Colorado Springs, and Aurora are the leading cities, while North Las Vegas, Plano and Fremont are readier than other small cities.

5.2 Policy Discussions

This section discusses how the readiness index can be improved. We first elaborate on how each of the seven categories influencing CAV readiness could be enhanced. We then shift our focus to investment in cyber infrastructure and examine the extent to which allocating a portion of a city's transportation budget could increase the city's readiness for CAVs. The methodology for this analysis is described first, followed by the presentation of data collection efforts, results, and discussion.

Table 6. CAV readiness ranking of cities based on size

Large			Medium			Small		
City	Scoring scheme		City	Scoring scheme		City	Scoring scheme	
	Simpl	Compound		Simpl	Compound		Simpl	Compound
Albuquerque	9	10	Anaheim	9	10	Baton Rouge	9	10
Austin	6	7	Arlington	6	7	Boise	6	7

Baltimore	4	6	Atlanta	4	6	Buffalo	4	6
Boston	3	3	Aurora	3	3	Chesapeake	3	3
Chandler	6	7	Bakersfield	6	7	Cincinnati	6	7
Charlotte	8	8	Chula Vista	8	8	Durham	8	8
Chicago	6	7	Cleveland	6	7	Fort Wayne	6	7
Columbus	2	2	Colorado Springs	2	2	Fremont	2	2
Dallas	4	5	Corpus Christi	4	5	Garland	4	5
Denver	4	4	Fresno	4	4	Gilbert	4	4
Detroit	4	5	Irvine	4	5	Glendale	4	5
El Paso	8	8	Kansas City	8	8	Greensboro	8	8
Fort Worth	9	12	Lexington	9	12	Henderson	9	12
Houston	4	6	Long Beach	4	6	Hialeah	4	6
Indianapolis	9	10	Mesa	9	10	Irving	9	10
Jacksonville	7	8	Miami	7	8	Jersey City	7	8
Las Vegas	4	5	Minneapolis	4	5	Laredo	4	5
Los Angeles	5	6	New Orleans	5	6	Lincoln	5	6
Louisville	10	11	Oakland	10	11	Lubbock	10	11
Memphis	9	12	Omaha	9	12	Madison	9	12
Milwaukee	9	11	Pittsburgh	9	11	Newark	9	11
Nashville	9	11	Raleigh	9	11	Norfolk	9	11
New York City	1	1	Riverside	1	1	North Las Vegas	1	1
Oklahoma City	7	9	Saint Paul	7	9	Orlando	7	9
Philadelphia	2	2	Santa Ana	2	2	Plano	2	2
Phoenix	8	8	St. Louis	8	8	Reno	8	8
Portland	3	4	Stockton	3	4	Richmond	3	4
Sacramento	6	8	Tampa	6	8	San Bernadino	6	8
San Antonio	8	10	Tucson	8	10	Scottsdale	8	10
San Diego	5	6	Tulsa	5	6	St. Petersburg	5	6
San Francisco	5	5	Virginia Beach	5	5	Toledo	5	5
San Jose	3	5	Wichita	3	5	Winston-Salem	3	5
Seattle	4	6						
Washington								
D.C.	5	9						

Recall that we group elements contributing to CAV readiness into seven categories. Considering the similar nature of Categories 2 and 3, we merge them in this discussion and recognize them as the cyber infrastructure category. Also, Categories 4–6 have a similar nature and can therefore be discussed under the umbrella of policy and regulation. Improving the first category, i.e., hard infrastructure, usually requires capital investment, which can significantly differ by place because cities and states have different tax rates and regulations, and the cost of human resources is substantially higher in some locations. Cyber infrastructure elements, on the other hand, can be added or improved relatively quickly and at a reasonable cost. Furthermore, these costs may not vary significantly by place of implementation, as technology is the main determinant of an element's cost. These factors make investment in cyber infrastructure an ideal option for cities seeking cost-effective, high-return, and quickly implementable solutions. Such solutions are particularly favorable during economic downturns (Bhattarai et al., 2020). Policy- and regulation-related variables, on the other hand, can typically be altered at no or low cost. It should be acknowledged, however, that making such changes may take time because some may be subject to prolonged debate among policymakers and lawmakers, and others may require studies to determine effectiveness and possible side effects. Since the additional indicators do not directly relate to readiness – and largely cannot be changed by external intervention – we assume their contributions to readiness are fixed.

We investigate the impact of infrastructure investment in a straightforward manner. First, we determine the budget that each city allocates to cyber infrastructure, assumed to be a percentage of the total transportation budget. We plausibly assume that cities are interested in deploying smart

technologies along urban principal and minor arterials (i.e., functional classes 14 and 16 in the NHPN data), with principal arterials given higher priority. The cost of installing cyber infrastructure is approximated in dollars per lane-mile. We then compute the unit cost of implementing cyber infrastructure (in dollars per mile) by assuming specific numbers of lanes on principal and minor arterials. Using this cost and the allocated budget, we calculate the total mileage of principal arterials that can be equipped with smart technologies accommodating CAVs. If the budget allows, cities then invest in implementing these technologies along minor arterials. The ratio of smart road mileage to total road mileage is subsequently calculated. For each city, this ratio is used as a proxy for the combined contribution of Variables 6, 8, and 11. Readiness indices are then recalculated, and cities are re-ranked.

Several pieces of information are required to conduct the above analysis. First, we estimate the transportation budget allocated to each city. We approximate the per capita transportation budget for each city using the corresponding state value and then multiply it by the city population. We assume that each city dedicates 5% of its total transportation budget to the implementation of smart cyber/soft infrastructure. The next required input is the deployment cost of each cyber infrastructure element. Such disaggregated information is largely unavailable, mainly because infrastructure technologies that accommodate CAVs are still immature. However, Smith et al. (2009), Kandarpa et al. (2009), and the US DOT (2024b) estimate that the cost of integrating cyber infrastructure elements with the roadway network is approximately \$0.25 million per lane-mile. Updating this estimate to 2024 dollars using a 5% annual inflation rate yields an approximate cost of \$0.4 million per lane-mile. This estimate includes technologies such as coordinated traffic signal fiber systems, integrated electronic signage, sensors, connected vehicle dedicated short-range communication (DSRC), and smart electric grids. Assuming four lanes for urban principal arterials (two lanes in each direction), the cost of developing a smart corridor is approximately \$1.6 million per mile. Similarly, assuming two lanes for urban minor arterials (one lane in each direction), the cost of implementing smart technologies is \$0.8 million per mile. Using these cost estimates, the annual smart transportation budgets of cities, and the total mileage of urban principal and minor arterials, we calculate the total mileage of urban arterials that can be equipped with CAV-compatible technologies.

Table 7 illustrates the ranking of cities when infrastructure investment is made. Boston, New York City, Chula Vista, Minneapolis, Oakland, Santa Ana, and Fremont are the leading city with the simple scoring scheme. With the compound scoring method, however, New York City, Boston, and Washington D.C. are the readiest cities. Also, New Orleans remains the least-ready city in both scoring schemes. Graphical representations of the CAV readiness index in Figures 3 and 4 indicate that the cities on the west and east coasts are still readier than those in other regions.

Table 7. CAV readiness indexes with infrastructure investment in place

Large			Medium			Small		
City	Scoring scheme		City	Scoring scheme		City	Scoring scheme	
	Simpled	Compound		Simpled	Compound		Simpled	Compound
Albuquerque	10	24	Anaheim	15	29	Baton Rouge	11	24
Austin	13	27	Arlington	12	23	Boise	12	26
Baltimore	12	25	Atlanta	15	31	Buffalo	14	28
Boston	18	33	Aurora	11	25	Chesapeake	9	23
Chandler	13	27	Bakersfield	11	25	Cincinnati	11	24

Charlotte	11	26	Chula Vista	18	32	Durham	12	27
Chicago	15	32	Cleveland	14	26	Fort Wayne	9	22
Columbus	14	29	Colorado Springs	11	25	Fremont	18	32
Dallas	15	29	Corpus Christi	12	24	Garland	13	25
Denver	12	27	Fresno	13	26	Gilbert	14	28
Detroit	13	27	Irvine	14	28	Glendale	12	25
El Paso	11	26	Kansas City	12	26	Greensboro	12	27
Fort Worth	10	22	Lexington	11	24	Henderson	14	27
Houston	15	28	Long Beach	17	31	Hialeah	15	28
Indianapolis	10	24	Mesa	10	24	Irving	12	24
Jacksonville	12	26	Miami	17	32	Jersey City	14	30
Las Vegas	15	29	Minneapolis	18	32	Laredo	11	22
Los Angeles	16	30	New Orleans	9	20	Lincoln	10	23
Louisville	9	23	Oakland	18	32	Lubbock	10	23
Memphis	10	22	Omaha	10	23	Madison	12	24
Milwaukee	10	23	Pittsburgh	12	25	Newark	13	25
Nashville	10	23	Raleigh	12	26	Norfolk	9	23
New York City	18	39	Riverside	17	31	North Las Vegas	12	25
Oklahoma City	12	25	Saint Paul	16	29	Orlando	14	28
Philadelphia	17	32	Santa Ana	18	32	Plano	12	24
Phoenix	11	26	St. Louis	12	25	Reno	13	24
Portland	15	29	Stockton	13	26	Richmond	9	23
Sacramento	13	26	Tampa	14	27	San Bernardino	14	28
San Antonio	11	24	Tucson	11	25	Scottsdale	12	26
San Diego	17	31	Tulsa	11	25	St. Petersburg	12	24
San Francisco	16	31	Virginia Beach	11	24	Toledo	10	22
San Jose	16	29	Wichita	10	21	Winston-Salem	11	26
Seattle	14	27						
Washington D.C.	16	33						

Let us also investigate the association between ranking and city size. Focusing on the simple scoring scheme, we observe that four out of the seven readiest cities, all with a score of 18, are medium-sized cities (i.e., Miami and Oakland). Turning to the compound scoring method, while the readiest cities – New York City (score: 39), Boston (score: 33), and Washington, D.C. (score: 33) – are large cities, six medium- and small-sized cities (such as Minneapolis and Oakland) score 32, which is close to the performance of large cities when infrastructure investment is made. This indicates that medium-sized cities have the potential to compete with large cities in terms of CAV readiness if appropriate investments are made.

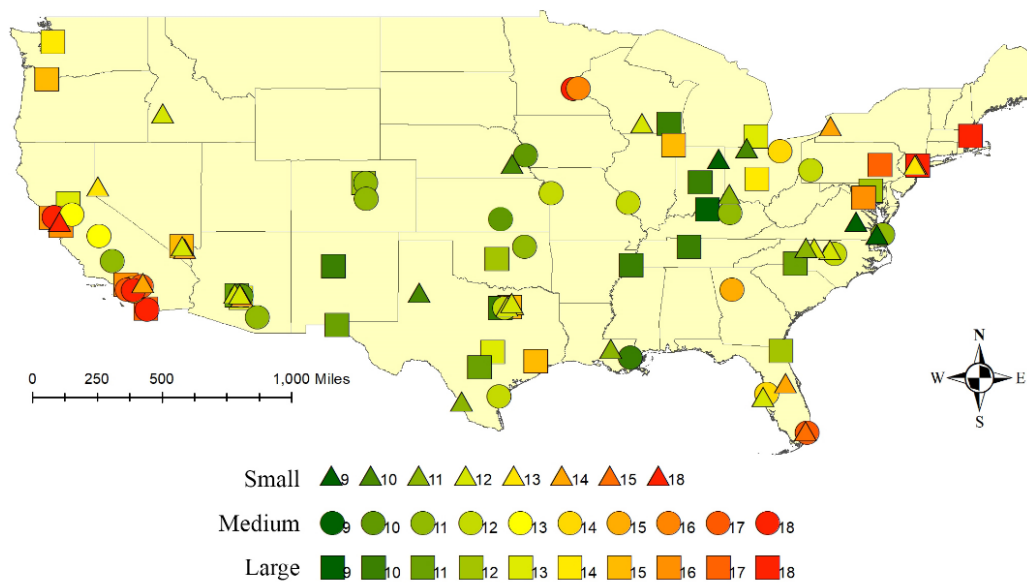


Figure 3. Graphical representation of the CAV readiness index after investment making with the simple scoring scheme

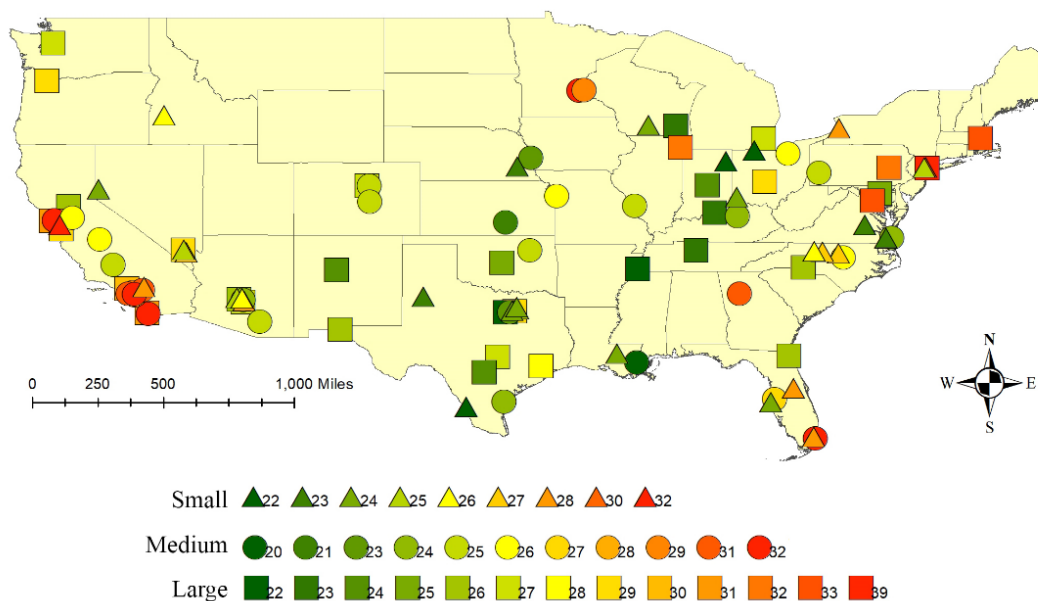


Figure 4. Graphical representation of the CAV readiness index after investment making with the compound scoring scheme

Next, we examine the breakdown of readiness scores (Figure 5). We present results only for the compound scoring scheme, as the breakdown under the simple scoring scheme yields similar insights. The results indicate that the general category of cyber infrastructure – constructed by merging Categories 2 and 3 – contributes more to the overall readiness index of each city than either policy and regulation or hard infrastructure. Across cities, the contribution of the policy and regulation category is consistently the smallest, while city attributes and hard infrastructure contribute relatively equally to overall readiness. Notably, this pattern appears to be largely independent of city size. These findings suggest that most cities are underprepared in terms of pro-CAV regulatory and policy frameworks. Moreover, given the relatively high costs and long implementation horizons associated with physical assets, only limited improvements in hard infrastructure can be expected from marginal investments.

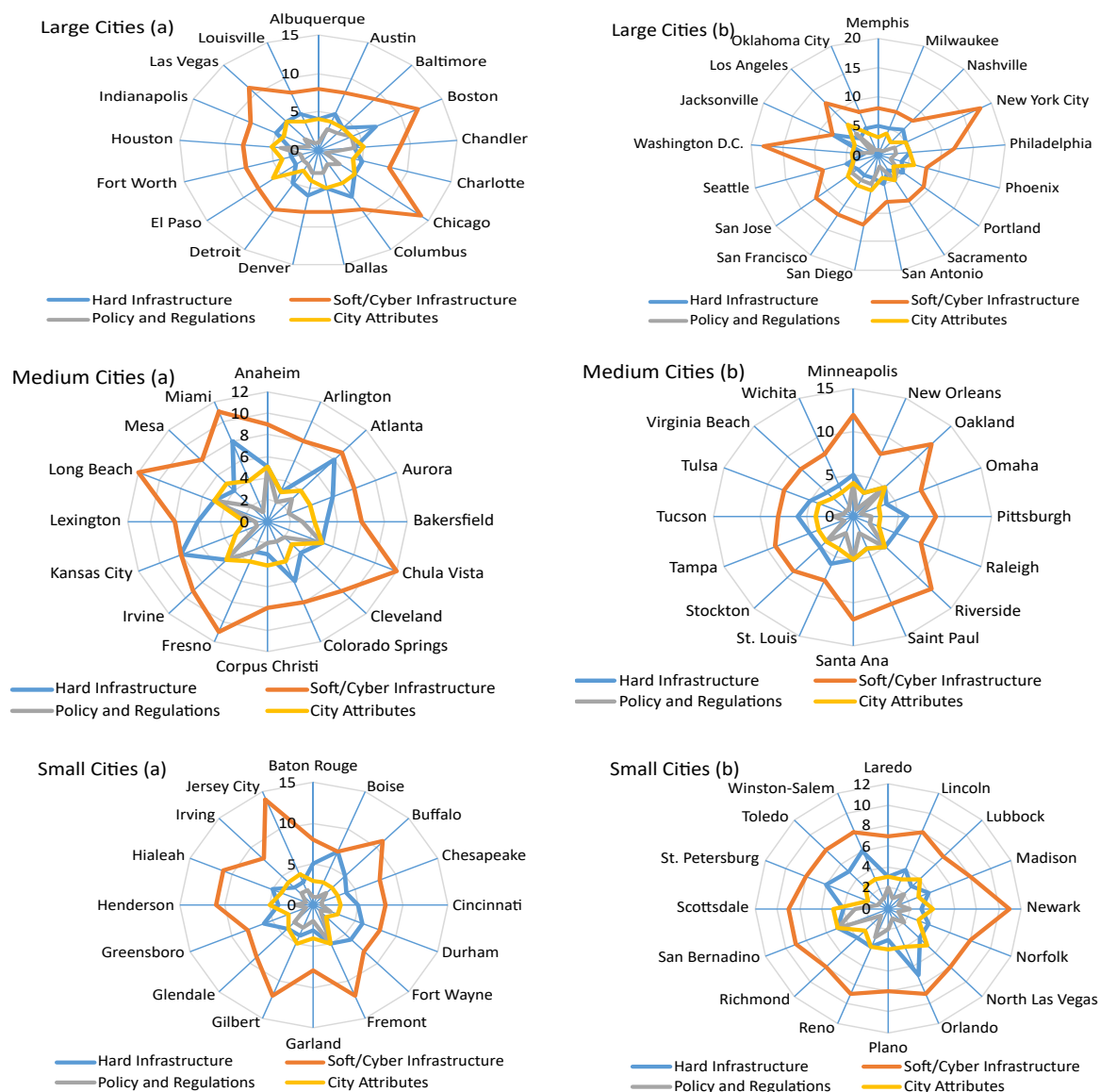


Figure 5. The breakdown of readiness scores in the compound scheme after infrastructure investment

To conclude, we note that, as previous studies have acknowledged (e.g., Cucor et al. (2022)), there is currently no widely accepted framework for assessing city-level readiness for CAV deployment. In this context, the present study makes a foundational contribution by developing a multi-aspect readiness index tailored to large US cities and by formalizing the underlying measurement logic across regulatory, infrastructural, and institutional dimensions. While comprehensive benchmark data are not yet available to support direct empirical validation, the proposed index establishes a replicable baseline that can be refined and empirically tested as CAV deployments expand and standardized datasets emerge.

5.3 Urban Planning Implications and Broader Insights

The CAV readiness index is a proactive measure that cities can consider while embracing technological innovations as part of their investment in transportation, utilities, buildings, digital equity, safety, and public services. This paper aims to provide broader insights and urban planning implications that can help cities around the world become smarter. These insights are summarized as follows:

1. The factors identified in this paper constitute a comprehensive set that can be considered collectively or selectively to guide the adoption of technological innovations. For example, the provision of fiber-optic networks as an internet platform enables seamless data access and dissemination across residents and agencies, facilitating interaction with city infrastructure and global networks. Although fiber-optic networks are presented as an illustrative example, this analogy applies to all factors discussed in the paper.
2. Cities may benefit from adopting both short- and long-term visions for implementing technological innovations while evaluating their progress on an annual basis – a practice commonly observed among US cities. Annual evaluations of implementation plans allow cities to incrementally achieve objectives while efficiently utilizing limited resources.
3. Countries or regions can organize smart city challenge programs to encourage cities to showcase their progress and strategic vision, ultimately recognizing one or more winners annually, as has occurred in the United States (US DOT, 2024a). Publishing the results and best practices of successful cities on accessible platforms fosters knowledge sharing and creates a collaborative environment for collective progress. Providing CAV readiness scores at the regional level can further motivate cities to improve their performance relative to peers.
4. Policymakers can leverage annual CAV readiness index reports to allocate funding toward essential factors identified in this study, either annually or within established budget cycles. While the factors and methodology presented are based on US cities, they can be adapted to other contexts by modifying data sources and approaches in accordance with local data availability and transferability considerations.
5. Short- and long-term planning horizons play a critical role in allocating funds aimed at improving CAV readiness. As illustrated in Figure 6, legislative and policy measures may be implemented at relatively low cost, although some may require extended timeframes. Policy adoption decisions can also be bundled to reduce time and budget constraints. Many cyber infrastructure components can be deployed within reasonable timeframes and are therefore considered quickly implementable solutions.
6. Providing accessible transportation remains a major challenge for small- and medium-sized cities in the United States and globally. As demonstrated in the previous subsection, targeted infrastructure investments in such cities can significantly enhance CAV readiness – potentially surpassing that of larger cities. This creates opportunities for shared autonomous mobility to serve as a more efficient and cost-effective alternative to conventional transit, while advancing equity, a central goal of sustainable transportation. Nevertheless, appropriate regulatory constraints are necessary to prevent uncontrolled urban sprawl.

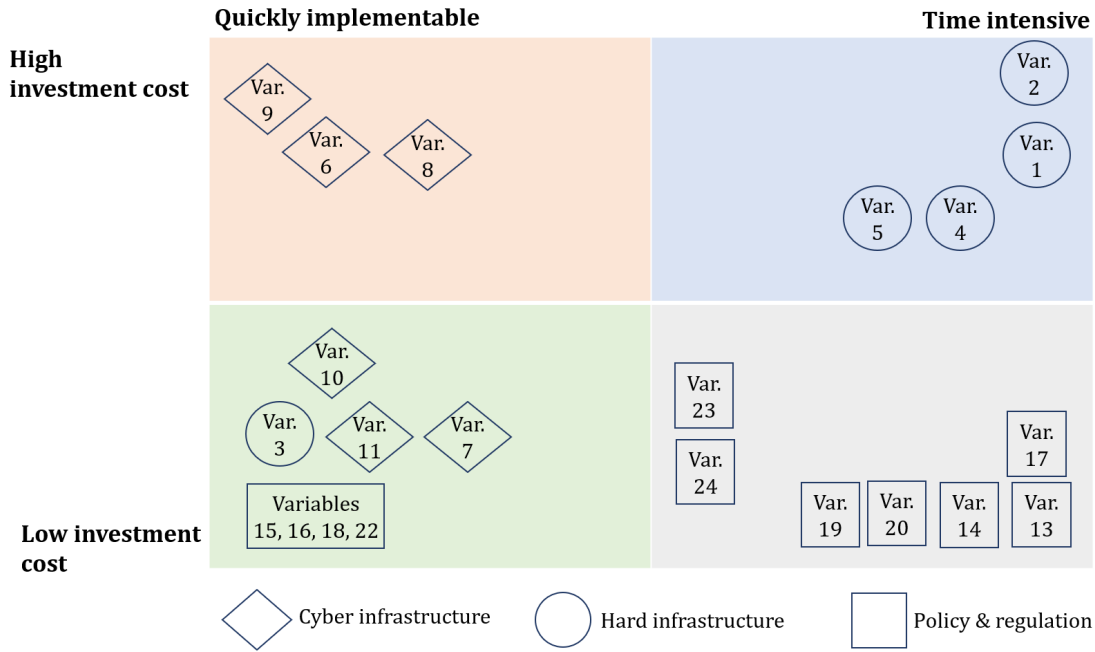


Figure 6. Time-cost trade-off for improving variables forming the readiness index

5.4 Robustness of Results

We conduct a robustness analysis to examine the sensitivity of city readiness rankings to omitted variables. Specifically, a leave-one-out procedure is applied in which each of the 29 readiness variables is excluded sequentially from the index. For each omission k , the readiness score for city c is recomputed as $X_c^{(-k)} = \sum_{l \in L \setminus \{k\}} l_c$. After each exclusion, readiness scores are recalculated and cities are re-ranked accordingly. This procedure produces 29 alternative ranking outcomes. For each iteration, the top five cities are recorded and compared across all omission scenarios. The results based on the simple scoring scheme show that the top-five rankings consistently draw from a small and relatively stable set of seven cities – New York City, Philadelphia, Atlanta, Minneapolis, San Jose, Columbus, and Orlando. When the compound scoring scheme is applied, the top tier further narrows to five cities: New York City, Philadelphia, Atlanta, Minneapolis, and Columbus. Although the exact ordering varies across iterations, inclusion in the top tier is not driven by any single variable. This limited variation indicates that the rankings of the most CAV-ready cities are not overly sensitive to the inclusion or exclusion of individual variables, thereby supporting the robustness of the proposed city readiness index.

5.5 Weighted Scheme

To account for heterogeneity in the relative importance of different dimensions of urban readiness for CAV technology, weighted readiness indexes are developed based on the Analytic Hierarchy Process (AHP). Recall that the 29 variables are first grouped into seven conceptually coherent categories. Rather than eliciting weights at the individual indicator level, AHP is applied exclusively at the category level, with indicators within each category assumed to contribute equally. This design choice substantially reduces respondent burden while maintaining consistency in expert judgments.

Expert preferences were collected through a structured pairwise comparison survey covering all 21 possible category pairs. (Eliciting additional intra-category weights would require 50 more pairwise comparisons, making the survey practically infeasible.) Respondents assessed the relative importance of each category pair using a seven-level ordinal scale. These verbal judgments were subsequently mapped onto the standard numerical AHP scale while preserving their ordinal structure. Individual judgments for each category pair were aggregated across respondents using the geometric mean, yielding a single reciprocal comparison matrix. Category weights were then

derived from the principal right eigenvector of this matrix. Internal consistency of the aggregated judgments was evaluated using the consistency ratio (CR), following standard AHP practice. All computations were carried out using the Python package *ahpy*. The resulting category weights were used to compute weighted readiness indexes under both the simple and compound scoring schemes. Specifically, the weighted index for city c is computed as $X_c = \sum_{l \in L} \alpha_l / c_l$, where α_l is the weight of category l .

The survey invitation was distributed to over 100 individuals, primarily based in the United States and affiliated with academia, state/local Departments of Transportation, or the private sector. In total, 24 complete responses were received. Among respondents, 17 held PhD degrees, five held Master's degrees, and two held Bachelor's degrees. Fifteen respondents were from academia, five from DOTs, and two from private transportation companies. The aggregated judgments exhibited an acceptable level of internal consistency, with a consistency ratio of 0.1085, supporting the reliability of the derived weights. The estimated weights for categories one through seven were 0.337, 0.223, 0.169, 0.098, 0.073, 0.059, and 0.041, respectively.

Because the AHP-derived category weights sum to unity, the weighted composite index is expressed on a reduced numerical scale. City rankings and scores under the weighted simple and compound schemes are reported in Table 8. For brevity, only the top ten readiest cities are presented. A comparison of Table 8 with Table 4 (unweighted simple scoring scheme) shows that eight out of the top ten cities remain the same, although their relative ordering differs. A similar pattern is observed when comparing Table 8 with Table 5, where seven out of the top ten cities are identical but with different rank positions. This suggests that while weighting affects the relative ordering of cities, the identification of top-performing cities is largely preserved.

Table 8. Top 10 readiest cities under weighted simple and weighted compound schemes

Rank	Simple scoring scheme		Compound scoring scheme	
	City	Score	City	Score
1	Atlanta, GA	2.742	Atlanta, GA	4.631
2	Orlando, FL	2.715	Columbus, OH	4.253
3	Columbus, OH	2.701	Orlando, FL	4.195
4	Denver, CO	2.509	Boston, MA	3.920
5	New York City, NY	2.464	Pittsburgh, PA	3.794
6	Minneapolis, MN	2.464	Miami, FL	3.788
7	San Jose, CA	2.440	Denver, CO	3.765
8	Philadelphia, PA	2.423	New York City, NY	3.720
9	Boston, MA	2.368	Philadelphia, PA	3.679
10	Pittsburgh, PA	2.324	Minneapolis, MN	3.679

6 Conclusion

With substantial technological advances achieved by automobile manufacturers, autonomous vehicles are increasingly transitioning from experimental deployments toward broader real-world applications, a trajectory that may also facilitate the evolution of Connected and Autonomous Vehicles (CAVs). Although some legislative efforts have been undertaken, a critical question remains: *are cities ready to embrace this technology?* This paper lays the foundation for research on CAV readiness by proposing a holistic index to evaluate cities' preparedness to accommodate smart driverless vehicles. The index is intended to support decision makers and planners by enabling them to assess current conditions, compare cities, and plan strategically to achieve targeted levels of readiness.

We identify 29 variables that contribute to a city's readiness and discuss the rationale for including each variable. These variables are grouped into seven categories. Two scoring schemes are introduced. Under the simple scoring scheme, each element or policy is represented by a binary variable that takes a value of 1 if the city possesses the corresponding feature and 0 otherwise.

Under the compound scoring scheme, selected variables are assigned integer scores ranging from 0 to 5, with higher values reflecting practices or conditions that more effectively support CAV deployment. Using these schemes, 98 of the most populous cities in the contiguous United States are ranked based on CAV readiness, and the results are analyzed.

Overall, the findings indicate that most cities remain largely unprepared to accommodate CAVs. Atlanta and New York City emerge as the readiest city under both the simple and compound scoring schemes. In contrast, New Orleans receives the lowest readiness scores in both schemes. The results suggest that large cities are currently more prepared than small- and medium-sized cities. However, medium-size cities have the potential to surpass some larger cities in readiness if appropriate infrastructure investments are undertaken. Our robustness analysis indicates that the results are not overly sensitive to the inclusion or exclusion of individual variables.

This study can be extended in a few directions. It represents an initial effort to examine the impact of investment decisions on CAV readiness. Future empirical research could focus on quantifying the effects of individual infrastructure elements and policy measures on readiness outcomes. A logical next step is the development of optimization models to guide decision makers in allocating investments so as to maximize readiness and the benefits of implementing smart transportation technologies. Another promising direction within the smart city domain is last-mile delivery, where technologies such as autonomous delivery robots and drones have emerged (Riahi Samani et al., 2025). Building on the methodology developed in this study, future research may examine the readiness of urban areas for such technologies. Finally, future research could focus on validating the results presented in this study.

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Data Access Statement

The datasets used in this study are publicly available and all data sources are cited and included in the reference list. No new dataset was generated during this study.

Contributor Statement

Ahmadreza Talebian: Conceptualization, Data curation, Formal analysis, Investigation, Supervision, Methodology, Writing – review & editing.

Sabyasachee (Sabya) Mishra: Conceptualization, Supervision, Methodology, Writing – review & editing.

Reza Shahpasand: Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing – review & editing.

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Conflict Of Interest (COI)

There is no conflict of interest.

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