# **Balancing Safety and Adoption: A System Dynamics Approach to Regulatory Trade-Offs in Private Autonomous Vehicle Adoption**

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# ABSTRACT

**Balancing Safety and Adoption: A System Dynamics Approach to Regulatory Trade-Offs in Private Autonomous Vehicle Adoption**

S M Samiul Bashir Shihab

The adoption of private autonomous vehicles (AVs) is shaped by a complex interplay of regulatory, technological, and societal factors. This study uses a system dynamics (SD) approach to explore the trade-offs between regulatory safety stringency and AV adoption in urban settings. The model simulates how compliance costs, accident rates, public trust, government incentives, and infrastructure readiness evolve over 30 years. Key feedback loops include public confidence shaped by accidents and media, adaptive regulatory responses to safety trends, dynamic subsidy allocation, and a GHG emission index tracking environmental impact. Infrastructure readiness is modeled based on budget constraints and rising AV demand. Scenario analysis shows that stricter regulations improve safety and public trust but increase costs and suppress adoption. In contrast, higher subsidies and early infrastructure investment boost adoption and reduce emissions, though potentially at the expense of regulatory impact. Results support balanced, time-sensitive policies for sustainable AV integration.



**Keywords:** System Dynamics, AV Adoption, Regulatory Safety Stringency, Scenario Analysis.

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# List of Acronyms

**AVs:** Autonomous Vehicles

**SDVs:** Self-Driving Vehicles

**AFVs:** Alternative Fuel Vehicles

**SD:** System Dynamics

**CLD:** Causal Loop Diagram

**SFD:** Stock and Flow Diagrams

**Infra:** Infrastructure

**NHTSA:** National Highway Traffic Safety Administration

**GHG:** Greenhouse Gas

**Dmnl:** Dimensionless

# Chapter 1

# Introduction

## 1.1 Motivation and Background

The Autonomous Vehicle (AV) concept dates back to 1925 when a radio-controlled car was showcased as a prototype by the "Linrrican Wonder" [1] has always attracted interest throughout the years. Starting from developing radio communication system among the vehicles in the 1920s [2] to electromagnetic guidance development between the period of the 1930s and 1940s, or facilitating the testing of smart highways during the 1950s and 1960s with the installation of magnets in vehicles, exhibits humans' ever-growing interest in the topic of self-driving vehicles (SDVs) [3]. Finally in 1980, there was a breakthrough in the aspiration of AVs when Mercedes-Benz invented the first autonomous vehicle in the world, partnering with the Bundeswehr University in Munich [4]. This invention not only gave people a certain ray of hope but also paved the way for thinking about the adaptation of legislation. Since then, numerous manufacturing and technological companies have launched their individual projects to develop AVs and each passing day we are getting closer to a fully autonomous future.

Over the past few decades, there has been a significant boost over to meet the hurdles of achieving fully autonomous vehicles (Avs), thanks to the drastic advancement in computers, software and sensors. Already, many tech companies and car manufacturers have come out partnering with each other to get past the oncoming obstacles in the way of a highly promising AV reality. Google started their own self-driving car project named "Waymo" back in 2009 intending to achieve fully autonomous cars by 2020 [5] and they are currently operating more than 100,000 paid trips weekly with their Robotaxis as reported in August 2024 [6]. Similarly, Uber and Volvo announced their partnership and declared the development of their third version of AV with the aim of road-testing them as early as possible [7]. Intending to supply AVs by 2016, Apple initiated the "Project Titan" AV project in 2014. Nevertheless, several problems, including leadership conflicts, affected the project, and it was anticipated that the Apple automobile would be available for purchase between 2023 and 2025 [8]. Furthermore, a lot of new businesses were founded to create AVs. Zoox was established in 2014 to provide electric and driverless automobiles; by 2018, its valuation had risen to $3.2 billion [9]. Many cities also permitted the testing and use of AVs on public roads. For example, 29 US states permitted the testing of autonomous vehicles on their highways in 2018 [10] [11]. The main goal of these pilot projects and trials is to comprehend SDV technology and how the public views it. Still there are several challenges, including legal frameworks, public opinion, moral dilemmas, and technological advancements, could prevent the adoption of AVs.

Almost all of the giant tech companies, along with the well-known automobile companies, have already started addressing both the existing and potential barriers towards the future of AVs because of the market's enormous potential [12]. Due to the intense global interest, nowadays the term 'Autonomous Vehicle' has become a catchphrase. These days, hardly a day passes without a new issue, discussion, or story involving self-driving cars (SDVs). However, as of right now, no nation has implemented an AV fleet on a wide scale. The arrival of autonomous vehicles (AVs) has been predicted by academics, automakers, and government agencies in very different ways. Many experts predict that fully automated vehicles (AVs1, level 5) would go on sale between 2025 and 2045, with very erratic market penetration rates that could range from 7% to 61% in 2050 [13]. Whereas some predicted that fully autonomous vehicles (AVs) would become available in the 2020s with low market penetration, but it will reach full saturation by the 2050s [14]. Additionally, the European Technology Platform [15] states that this technology won't be accessible until decades beyond 2030. The public and the automotive industry are often more upbeat: the former has frequently stated that autonomous fleets will be operational by the early 2020s, while the latter believes that most cars will be fully autonomous by 2030 [16].

The global autonomous vehicle (AV) market is undergone a rapid growth in recent years, driven by advancements in artificial intelligence, sensor fusion, connectivity, and growing consumer interest in intelligent mobility solutions. In 2025, the AV market is projected to reach a valuation of approximately USD 273.75 billion, and this figure is expected to grow exponentially to over USD 4,450 billion by 2034[17], reflecting a remarkable compound annual growth rate (CAGR) of 36.3%. This growth is fueled by increasing investments from major automotive manufacturers, supportive government policies, and heightened emphasis on road safety and traffic efficiency. On the production side, autonomous vehicle unit sales are forecast to grow significantly, with global sales projected to reach over 125,660 units by 2030[18][19][20][21]. Figures 1 and 2 illustrate the projected AV sales and market size in the upcoming years respectively. These projections underscore the urgency for policymakers and urban planners to understand and manage the regulatory and infrastructural implications of widespread AV adoption.

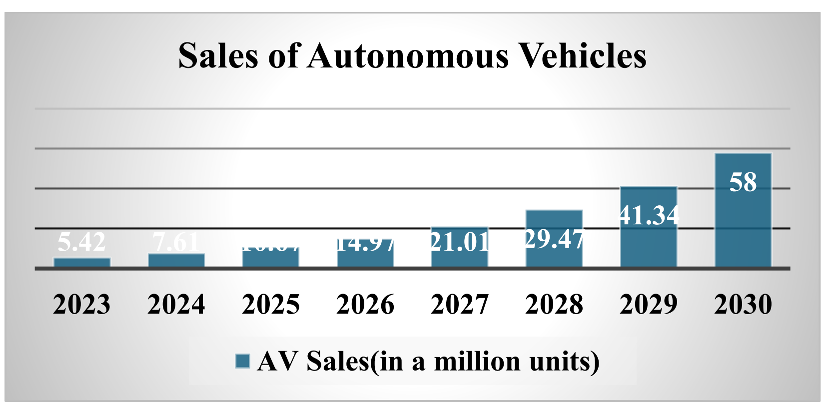


Figure 1: Yearly projected sales of AVs (2023-2030)

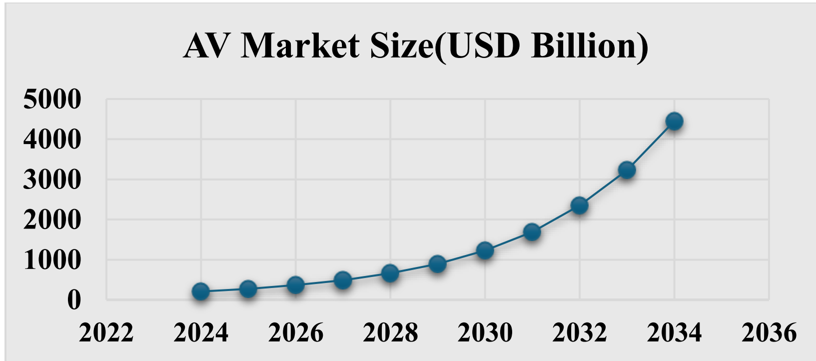


Figure 2: AV market size projection (2024-2034)

Even though SDVs have been the subject of a lot of discussion, it is still important to keep an eye out for any potential problems this new technology may bring. Because of the extreme unpredictability of the shift to autonomous vehicles, laws and regulations are not yet prepared for this change, and public authorities are hesitant to accept this challenge [22][23]. The concerned authorities should revamp the urban planning and policies to address this issue in the near and medium future [24]. Still, there's currently a "watch and wait" mentality. Planners are frequently informed about the advancements in technology and the possible effects of AVs [25][26]. Additionally, they typically lack the knowledge necessary to account for the uncertainty surrounding the spread and effects of AV in their planning decisions [27][28]. It is high time public administrations take the lead instead of following the technological developments of AV. They should be proactive in thinking about the plausible implications and planning the necessary policies so that we are well prepared for the near future when AVs will be on the road on the mass level. If we are late in acting and put our faith unconditionally in the hands of technology personnel and car manufacturers, we will be more likely to endanger the livability of our urban spaces [29][30]. It will only challenge the sustainability of the AV prospect and cause further delays in the fully autonomous future.

The rise of autonomous vehicles (AVs) marks a transformative shift in personal mobility, with the potential to reshape urban transport systems, reduce road accidents, and contribute to environmental sustainability. As a disruptive innovation, AVs are projected to bring substantial changes to the way individuals travel, own, and interact with vehicles. Private AVs offer the promise of increased convenience, accessibility, and efficiency for users, while potentially easing congestion and lowering emissions when properly integrated into the transportation network. However, as mentioned earlier, despite significant advancements in AV technology and the growing interest among manufacturers and consumers, widespread adoption of private AVs remains limited and uncertain.

A central factor influencing AV adoption is the evolving landscape of safety regulations. Policymakers are tasked with the dual responsibility of protecting public safety and fostering innovation. Safety regulations are necessary to ensure the reliability and security of AV systems, especially as they become responsible for critical driving tasks. However, stringent safety standards can increase development and compliance costs, slow down innovation cycles, and introduce uncertainty for manufacturers and consumers alike. This creates a critical policy tension: how can we safeguard the public without stifling a technology that promises to make transport safer in the long run? This dilemma presents a classic example of a regulatory trade-off, where short-term safety concerns must be balanced against the long-term benefits of technological innovation. While stricter regulations may reduce the risks of early AV deployment, they can simultaneously act as barriers to adoption, delay market penetration, and reduce the incentives for private investment in AV development. On the other hand, lenient policies could expose users to unproven technologies and potential hazards, risking public trust and leading to regulatory backlash. This push and pull between caution and progress defines the core problem this thesis seeks to explore.

## 1.2 Problem Statement

The adoption of private Autonomous Vehicles (AVs) can revolutionize urban transportation by improving safety, reducing emissions, and enhancing mobility. However, stringent safety regulations imposed by governments can significantly impact the rate of AV adoption. While strict regulations enhance public confidence and ensure safety, they can also lead to increased compliance costs, delayed technological advancements, and reduced affordability of AVs, ultimately slowing down market growth.

Existing research focuses heavily on the technological and economic factors influencing AV adoption. However, little attention has been given to the trade-offs between regulatory stringency and AV adoption rates in a holistic, feedback-driven manner. There is also a limited understanding of the dynamic interactions between regulatory policies, public perception, and AV market expansion. A key challenge for policymakers is to balance safety stringency with incentivizing private AV ownership to accelerate market penetration without compromising public trust in AV safety. Thus, there is a need for a system dynamics approach to model these complex relationships and determine optimal regulatory strategies that maximize both safety and AV adoption.

This study aims to develop a system dynamics model to analyze the impact of regulatory policies on the adoption of private AVs. The model will consider key factors such as:

- Regulatory Stringency Level and its effect on compliance costs and public confidence in AV safety
- The influence of financial incentives, market demand, and technology advancements on AV affordability and adoption
- The dynamic feedback loops between public perception, media influence, and safety concerns

By conducting scenario-based simulations, this research seeks to identify optimal policy interventions that promote AV adoption while maintaining high safety standards.

For a better understanding of our objective, the following are the questions we are trying to address through this project:

1. How do different levels of regulatory stringency impact AV adoption rates over time?
2. What is the trade-off between increasing safety regulations and reducing AV market expansion?
3. Which policy interventions (e.g., subsidies, technology investment, public awareness) are most effective in balancing safety and adoption?

To address these questions, the study adopts a system dynamics modeling approach implemented in VenSim. SD is particularly well-suited for this research due to its ability to model complex systems characterized by feedback, delays, and nonlinearities. Unlike traditional forecasting methods, SD enables the simulation of policy scenarios under uncertainty and supports the exploration of unintended consequences. The model developed in this thesis captures the interactions between safety regulations, manufacturer innovation, consumer perception, and AV adoption rates over time. This research will provide valuable insights for policymakers, regulators, and industry stakeholders by offering a quantitative decision-support model for designing AV-related regulations. The findings will help identify policies that can simultaneously enhance AV safety, foster public trust, and accelerate market penetration, leading to more efficient, sustainable, and safer transportation systems.

### 1.3 Thesis Outline

This thesis is structured as follows:

- Chapter 2 presents a brief overview of the fundamentals of autonomous vehicle technology, a comprehensive literature review on system dynamics in transportation, AV adoption models, regulatory frameworks, and previous modeling efforts.
- Chapter 3 outlines the methodology, including the modeling process, variable selection, and scenario design.
- Chapter 4 presents the results of scenario simulations and policy experiments.
- Chapter 5 discusses the findings, their implications for policy and theory, and the limitations of the study.

- Chapter 6 concludes with a summary of insights and recommendations for future research and policymaking.

This thesis examines the regulatory trade-offs in AV adoption through a system dynamics lens, aiming to contribute valuable insights for designing effective and adaptive transport policies in an era of technological disruption.

# Chapter 2

# Literature Review

## 2.1 Definition and Technology of AVs

An autonomous vehicle (also known as self driving car or driverless car) is a car which can travel between two predefined destinations without human intervention. A driverless car uses the combination of sensors, cameras, radar along with advanced robotic technologies to be able to navigate between destinations without a human operator, even on the unfamiliar roads and surroundings [31]. Artificial intelligence technologies underpin the operational frameworks of autonomous vehicle systems. Engineers and researchers engaged in the development of self-driving automobiles leverage extensive datasets derived from image recognition algorithms, in conjunction with advanced machine learning methodologies and neural network architectures, to construct systems capable of independent vehicular navigation. Neural networks discern patterns within the dataset, which is subsequently utilized by machine learning algorithms. This dataset is derived from an array of sensors, encompassing radar, lidar, an optical remote sensing technology that quantifies distances, and cameras. These sensors amass information that the neural network employs to acquire the capability to recognize traffic signals, arboreal entities, curbs, pedestrians, traffic signage, and various components of a specified driving milieu.

The autonomous vehicle constructs a comprehensive representation of its surroundings to comprehend its relative environment and initiates its trajectory planning. It must ascertain the most secure and expedient pathways to its intended destination while adhering to traffic regulations and employing mechanisms for obstacle evasion. Additionally, a concept known as geofencing, which facilitates the navigation of vehicles equipped with autonomous capabilities within established parameters, is also utilized. Geofencing in automotive contexts pertains to the employment of Global Positioning System (GPS) technology or alternative location-based methodologies to delineate virtual perimeters the surrounding designated geographical zones. These demarcations can activate automated responses or notifications upon a vehicle's ingress or egress from the specified locale. In the realm of automotive applications, geofencing is frequently utilized for fleet management, vehicle monitoring, and enhancing driver safety.

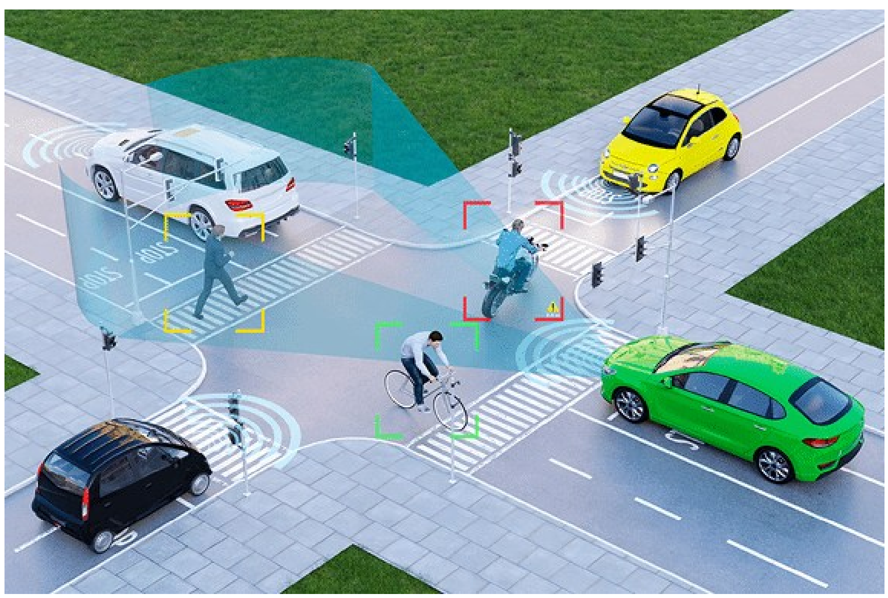

Figure 3: Autonomous Vehicle using a collection of sensors to detect nearby cars and objects

## 2.2 Level of Autonomy

The USA National Highway Traffic Safety Administration (NHTSA) and the Federal Highway Research Institute (BASt) define five levels of automation for AVs; however, the Society of Automobile Engineers (SAE) defines six different levels of automation, but, depart from their differences in definitions all of these organization divide the levels based on the abilities of implemented technologies and human interaction in the control of the vehicle [32][33][34]. The National Highway Traffic Safety Administration (NHTSA) outlines six levels of driving automation, ranging from fully manual operation to complete autonomous functionality. These levels provide a standardized classification of the extent to which a vehicle can perform driving tasks independently of human input.

- **Level 0: No Automation** – At this level, the human driver is responsible for the full control of the vehicle, including steering, acceleration, braking, and monitoring the driving environment. While some driver support systems may exist (e.g., warnings, safety signals or momentary intervention in exceptional cases), there is no sustained vehicle control automation.
- **Level 1: Driver Assistance** – This level introduces limited automation through a single system, such as adaptive cruise control or lane keeping assistance. However, these systems operate independently but not simultaneously. The driver must remain fully engaged and retain overall responsibility for driving and vehicle control.
- **Level 2: Partial Automation** – Vehicles at this level can simultaneously control both steering and acceleration/braking under certain conditions.

Although these systems handle multiple functions as mentioned above, human oversight is still required at this level, and the driver must remain attentive and ready to take control at any particular moment.

- **Level 3: Conditional Automation** – At this level, the vehicle can manage all aspects of the driving task in specific and predefined scenarios (such as highway driving). While the system monitors the environment and drives autonomously within those conditions, the driver must remain available to take control upon request.
- **Level 4: High Automation** – Vehicles equipped with Level 4 automation can operate autonomously without human intervention within certain operational design domains (ODDs), such as urban ride-hailing zones or geofenced areas. Driver's intervention is optional in these contexts, although the system may not function under all driving conditions.
- **Level 5: Full Automation** – At this highest level of autonomy, the vehicle itself is capable of fully autonomous driving in all environments and under all conditions without any driver's input or oversight. No human attention, intervention, or even presence is required at any point during operation.

This classification system is crucial in understanding the evolving regulatory, technological, and behavioral landscape of autonomous vehicles. As autonomous technology progresses toward higher levels of automation, policy frameworks, safety standards, and adoption dynamics must adapt accordingly[33].

## 2.3 AVs in Practice

The autonomous vehicle (AV) industry has transitioned from conceptual innovation to active real-world deployment across multiple regions. Major automotive manufacturers, technology firms, and mobility service providers have launched pilot projects, commercial operations, and research initiatives aimed at advancing AV capabilities and capturing market share in what is poised to become one of the most transformative mobility technologies of the 21st century. These global efforts reflect a diverse spectrum of applications, from passenger transport and ride-hailing to freight logistics and last-mile delivery, offering rich insights into current progress and future expectations. As a part of the ongoing trend, there have been different autonomous vehicle projects worldwide, and this development is not limited to any particular country or continent. In the following part, we will discuss the various AV projects that have been undertaken around the world. We will focus on the development of those projects, their success stories, followed by the failure cases along with the possible causes and challenges they are facing.

- **North America: Gradual but Strategic Deployment**

  In the United States, Tesla remains a front-runner in AV development, with its Full Self-Driving (FSD) software continuously evolving through over-the-air updates and public testing. Tesla's FSD Beta has now been rolled out to over 400,000 users, with CEO Elon Musk announcing the company's plans to launch robotaxis in Austin, Texas, starting June 2025 [35]. The initial fleet of 10 vehicles will operate in a geo-fenced environment with teleoperator support, gradually scaling to 1,000 vehicles. Although the system is not yet fully autonomous (Level 5), Tesla's approach to collecting vast volumes of real-world driving data offers an advantage in training its machine learning algorithms. Despite ongoing concerns about regulatory compliance and system safety, Tesla's steady expansion reflects the growing maturity of AV technologies in consumer markets.

Waymo, a subsidiary of Alphabet, continues to lead in commercializing robotaxi services in urban areas. The company has been operating driverless vehicles in Phoenix and has recently expanded to San Francisco and Los Angeles. With millions of autonomous miles driven and active partnerships with Uber and other mobility platforms, Waymo's cautious, safety-first approach has earned regulatory trust and public acceptance. Uber's integration of AVs (Waymo and others) into its ride-hailing network signifies a new era of hybrid mobility models combining human drivers and autonomous fleets [36].

Aurora Innovation, focusing on autonomous trucking, is another key player in North America. Aurora's pilot programs with logistics giants such as FedEx and Uber Freight have demonstrated consistent performance in highway settings, with the company aiming for full commercial deployment of driverless freight corridors by 2026 [37][38]. The business case for AVs in logistics, particularly for long-haul trucking, is compelling due to cost savings, extended operating hours, and a growing labor shortage in the trucking sector.

- **Asia: Rapid Technological Scaling in China**

  In China, Baidu has taken the lead in deploying large-scale AV fleets through its Apollo Go robotaxi platform. Baidu has surpassed 9 million cumulative autonomous rides, operating across more than 10 cities, including Beijing, Wuhan, and Chongqing [39]. Backed by supportive local governments and advanced 5G connectivity, Baidu's model emphasizes safety, efficiency, and integration with smart city infrastructure. With the increasing development over the last few years, Baidu is now well-positioned to test its robotaxis in Europe[40]. The Chinese government's favorable regulatory environment and strategic investments in AI and V2X (vehicle-to-everything) technologies have positioned the country as a global leader in AV scalability. Analysts project China's robotaxi market will reach $47 billion by 2035, with Baidu, AutoX, Pony.ai, and Didi Chuxing among the key stakeholders.

  AutoX, backed by Alibaba, has launched fully driverless services in Shenzhen and is focusing on removing safety operators to test true Level 4 autonomy [41]. While the vehicles still face limitations in adverse weather and complex traffic conditions, the pace of innovation and deployment in China has outstripped that of most Western nations.

- **Europe and Middle East: Cautious Expansion with Strong Regulations**

  In Europe, AV testing is more conservative due to stringent safety regulations and privacy laws. Companies such as Navya (France), Oxbotica (UK), and EasyMile have focused on autonomous shuttles and logistics vehicles in controlled environments like campuses and industrial zones. These deployments emphasize operational safety and regulatory compliance, often as part of public-private partnerships. The EU-funded projects under the Horizon 2020 [42] program continue to support AV pilots across the continent, aiming to harmonize standards and data protocols.

The Middle East has emerged as a new frontier, particularly the United Arab Emirates. Dubai's Road and Transport Authority [43] is targeting 25% of all trips to be smart and driverless by 2030. The city has partnered with Cruise (backed by General Motors) to deploy AV taxis, making Dubai the first city outside the U.S. to launch commercial robotaxis. The controlled urban environment and government-driven initiatives make the Middle East a promising region for early adoption of AV.

These global projects offer a spectrum of lessons. Technologically, AVs have demonstrated strong performance in specific use-cases such as geo-fenced urban mobility, highway trucking, and campus shuttles where environmental complexity can be controlled. However, challenges remain, particularly in scaling mixed-traffic urban environments with unpredictable human behavior, poor weather, and infrastructure variability. Public trust and regulatory approval continue to act as both enablers and constraints.

So far, the most successful AV implementations have come from companies that adopt a multi-layered safety approach, combining high-resolution mapping with redundant sensing, and maintaining tight operational domains. While Level 5 autonomy remains elusive, Level 4 autonomy (high automation within defined conditions) is becoming commercially viable.

Looking ahead, the AV market is expected to grow exponentially. According to Grand View Research [44], the global autonomous vehicle market size is projected to reach USD 13,632.4 billion by 2030, growing at a CAGR of 32.3%. Meanwhile, McKinsey & Company emphasizes that AVs will become an essential part of a broader ecosystem that includes electric vehicles, shared mobility, and smart city infrastructure [45]. The continued convergence of artificial intelligence, edge computing, and vehicle-to-everything (V2X) communication will be critical in unlocking full autonomy.

Moreover, long-term growth will depend on balancing technological innovation with policy frameworks that address safety, liability, equity, and urban planning. As such, AVs are not just transportation technology but a cornerstone in reimagining urban mobility systems worldwide.

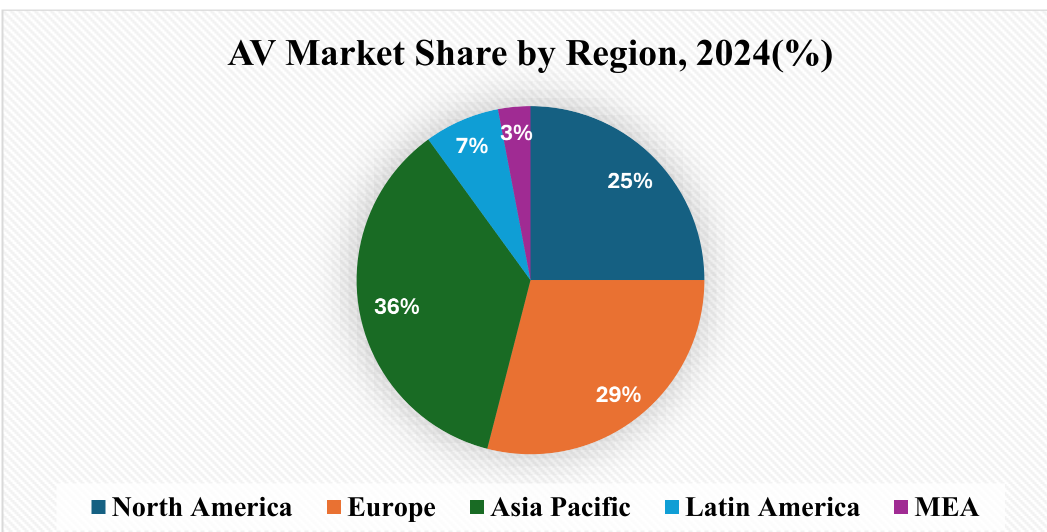


Figure 4: AV market Share by region (2024)

### 2.4 Failure cases in Autonomous Vehicle Projects

Despite significant advancements in autonomous vehicle technology, several high-profile failures have underscored the challenges in deploying AVs safely and effectively. These incidents highlight technical limitations, regulatory oversights, and the complexities of real-world environments. Below, we examine key cases involving Cruise, Zoox, Tesla, and Uber.

- **Cruise: Pedestrian Dragging Incident and Operational Suspension**

  In October 2023, a Cruise robotaxi in San Francisco was involved in a severe incident where it dragged a pedestrian approximately 20 feet after a collision. The pedestrian had initially been struck by another vehicle and was then run over and dragged by the Cruise AV, which failed to detect her presence beneath the vehicle. Investigations revealed that the AV's perception system lost track of the pedestrian and did not recognize the dragging, leading to critical injuries for the victim[46].

  The consequences of this incident were significant:

  - **Regulatory Action**: The California Department of Motor Vehicles suspended Cruise's permit to operate autonomous vehicles, citing safety concerns.
  - **Operational Halt**: Cruise voluntarily paused its driverless operations nationwide, affecting services in multiple states[47].

- **Company Restructuring**: General Motors, Cruise's parent company, decided to scale back its investment, leading to layoffs and a shift in focus away from fully autonomous vehicles[48].

- **Zoox: Repeated Software Recalls Following Collisions**

  Zoox, Amazon's autonomous vehicle subsidiary, faced two software recalls in May 2025 after separate incidents involving its robotaxis[49]. In one case, a Zoox vehicle was struck by an electric scooter while yielding at an intersection in San Francisco. Although the scooter rider sustained only minor injuries, the incident prompted a recall of 270 vehicles to address issues in the AV's perception tracking system.

  These events highlighted:

  - **Technical Shortcomings**: The AVs had difficulty accurately interpreting the movements of nearby objects, increasing the risk of collisions.
  - **Regulatory Scrutiny**: The National Highway Traffic Safety Administration (NHTSA) acknowledged the recalls and advised caution around such vehicles.
  - **Public Trust Concerns**: Repeated incidents raised questions about the readiness of Zoox's technology for widespread deployment.

- **Tesla: Autopilot and Full Self-Driving System Crashes**

  Tesla's Autopilot and Full Self-Driving (FSD) systems have been linked to numerous crashes, some fatal. A notable incident occurred in April 2024, when a Tesla Model S operating on FSD struck and killed a motorcyclist in

Washington State. The driver admitted to being distracted and relying on the vehicle's autonomous capabilities[50].

Key issues identified include:

- **Driver Overreliance**: Tesla's systems were found to inadequately ensure driver engagement, leading to complacency and delayed reactions[51].
- **Sensor Limitations**: Unlike other AV developers, Tesla relies solely on cameras without LiDAR or radar, potentially compromising performance in low-visibility conditions.
- **Regulatory Investigations**: NHTSA has opened multiple probes into Tesla's systems, citing concerns over safety and system design[52].

- **Uber: First Pedestrian Fatality Involving an AV**

In March 2018, an Uber self-driving test vehicle struck and killed pedestrian Elaine Herzberg in Tempe, Arizona[53]. The vehicle was operating in autonomous mode with a safety driver present, who was later found to be distracted at the time of the crash. Investigations revealed that Uber's AV system failed to correctly classify Herzberg as a pedestrian and did not initiate braking.

Consequences included:

- **Suspension of Testing**: Uber halted its AV testing in Arizona and did not renew its testing permit in California.

- **Legal Actions**: The safety driver was charged with negligent homicide, highlighting the complexities of assigning liability in AV incidents.
- **Industry Impact**: The incident prompted widespread reevaluation of safety protocols and testing procedures across the AV industry.

These cases underscore the multifaceted challenges in deploying autonomous vehicles, from technical limitations and sensor deficiencies to regulatory gaps and human factors. Each incident has contributed to a growing awareness of the need for robust safety measures, transparent reporting, and continuous improvement in AV technologies.

### 2.5 Challenges and Failures in Implementing Autonomous Vehicles

The development and deployment of autonomous vehicles (AVs) has been marked by significant technological advancements and ambitious projects. However, the journey toward fully autonomous transportation has encountered numerous challenges, leading to setbacks and failures in various initiatives. Understanding these challenges and analyzing recent failures provide critical insights into the complexities of AV implementation.

- **Technical and Environmental Challenges**
  - **Perception and Decision-Making Capabilities:** While AVs have achieved substantial progress in navigating controlled environments, their performance in complex and dynamic real-world scenarios remains limited. Urban environments, in particular, present numerous edge cases such as

jaywalking pedestrians, erratic cyclists, poorly marked lanes, and construction zones. These situations often confound AV algorithms due to insufficient training data or unpredictable variations, which can compromise safety and operational efficiency. Recent AV crashes have been partly attributed to failures in perception systems and inappropriate responses to ambiguous situations[54]. These shortcomings highlight the difficulty of training autonomous systems to handle infinite permutations of road scenarios in real-time.

- **Sensor Limitations and Adverse Weather Conditions:** AVs typically rely on a fusion of cameras, LiDAR (Light Detection and Ranging), radar, and ultrasonic sensors to perceive their environment. However, each sensor has limitations. For instance:
    - LiDAR struggles with fog, heavy rain, or snow due to light scattering.
    - Cameras can be blinded by direct sunlight or become useless in the dark without adequate illumination.
    - Radar lacks the resolution to distinguish between closely spaced objects.

  Combining data from these sensors (sensor fusion) to create a coherent understanding of the environment is a non-trivial task and remains prone to errors and inconsistencies [55].

- **Regulatory and Legal Hurdles**

The regulatory landscape for AVs is still evolving, with varying standards and requirements across different jurisdictions. Despite various pilot programs, there is no globally standardized framework for certifying the safety of autonomous systems. Many jurisdictions still lack comprehensive policies covering aspects such as:

  - ➢ Testing and operational safety standards.
  - ➢ Insurance and liability in the event of AV accidents.
  - ➢ Data ownership and cyber regulations.
  - ➢ Cross-border AV operations.

This lack of uniformity creates hurdles for AV companies trying to scale operations internationally. Moreover, frequent government interventions such as California's suspension of Cruise's driverless permits in 2023 illustrate how public safety concerns can suddenly stall AV initiatives [56]. Companies face challenges in obtaining approvals for testing and deployment, as well as navigating liability issues in the event of accidents. In the United States, the National Highway Traffic Safety Administration (NHTSA) has initiated investigations into AV-related incidents, highlighting the need for clear regulatory frameworks.

- **Ethical and Social Acceptance Challenges**
  - ➢ **Public Trust and Psychological Barriers:** The acceptance of AVs by the public is crucial for adoption. However, widespread trust remains elusive. According to a 2024 YouGov survey, nearly 37% of respondents in the UK

reported feeling “very unsafe” in driverless vehicles [57]. This fear is exacerbated by media coverage of fatal accidents and software glitches. Building public confidence requires consistent performance, transparency about safety metrics, and proactive communication strategies from AV developers. Misalignment between public perception and technical reality continues to be a significant challenge.

  - **Ethical Decision-Making and Responsibility:** Autonomous systems must make decisions with ethical implications, such as choosing between two harmful outcomes in an unavoidable crash (i.e., the "trolley problem"). There is no global consensus on how AVs should be programmed to handle such dilemmas, making it difficult for manufacturers to adopt a universally acceptable ethical framework[58].

- **Economic and Commercial Viability**
  - **High Development and Operational Costs:** AV development demands massive investment in hardware (sensors, computing units), software (AI and real-time decision systems), and continuous testing. For example, GM’s Cruise reportedly spent over $10 billion before halting most of its operations in 2023 due to mounting costs and regulatory setbacks[59]. Even for well-funded companies, achieving profitability in the AV sector remains uncertain. The transition from prototype to scalable, sustainable business models continues to pose a financial challenge.
  - **Maintenance and Infrastructure Dependencies:** Autonomous systems require consistent updates, recalibrations, and specialized infrastructure

such as 3D-mapped roads, vehicle-to-infrastructure (V2I) communication, and reliable 5G networks. Many regions lack such infrastructure, thereby limiting the practical deployment of AVs outside select urban zones.

- **Cybersecurity and Data Privacy**

With increasing autonomy and connectivity, AVs are becoming vulnerable to cyberattacks. Threat actors could potentially gain unauthorized access to a vehicle's navigation, braking, or control systems, posing grave safety risks. In addition to technical breaches, data privacy concerns arise from the constant collection and transmission of user data, location history, and even passenger conversations[59].

Ensuring robust encryption, secure over-the-air (OTA) updates, and compliance with data protection laws is critical, yet still underdeveloped in many AV systems.

- **Failures in Coordination with Urban Systems**

AVs must operate in harmony with pedestrians, cyclists, manual driven vehicles, and public transport. However, most cities are designed for human drivers, not algorithms. AVs may behave overly cautiously or unpredictably when interacting with humans, leading to traffic flow issues or accidents. Furthermore, lack of coordination between AV companies and local transport authorities has led to friction and public backlash, especially in cities like San Francisco, where robotaxis caused congestion and emergency service delays[60].

- **Operational Failures and Industry Setbacks**

The combination of the challenges listed above has resulted in numerous failures and delays:

- Zoox recalled vehicles after collisions due to tracking system flaws.
- Tesla's FSD remains under federal investigation in the U.S., with numerous fatal crashes reported.
- Waymo has faced sporadic testing bans and backlash despite extensive years of development.
- Uber abandoned its AV program after a pedestrian fatality and sold it to Aurora in 2020.

These cases reflect the high-stakes nature of AV testing and how even small errors can significantly damage public trust and corporate momentum.

As we can conclude from the discussion above, the path to widespread AV deployment is complex and fraught with technical, regulatory, ethical, and social challenges. While ongoing innovations and increasing public-private collaborations offer promise, a long-term commitment to addressing these multifaceted issues is essential. A clearer regulatory landscape, better public communication, advancements in AI safety, and resilient business models will be critical in transitioning from experimental deployments to mainstream adoption.

### 2.6 Existing Work Review

The transportation sector is currently undergoing a profound transformation driven by advances in technology, changing user preferences, environmental challenges, and evolving policy frameworks. Among the most disruptive of these innovations is the emergence of autonomous vehicles (AVs), which promise significant benefits in terms of road safety, operational efficiency, reduced emissions, and improved mobility access. However, the widespread adoption of AVs, especially private AVs, is far from guaranteed and is contingent upon a complex interplay of technological readiness, consumer acceptance, regulatory support, infrastructure development, and economic incentives[61][62].

While AVs are expected to substantially improve safety by reducing human error, this promise comes with its own regulatory challenges. We can set back and ignore these regulatory challenges at our own peril. Policymakers are already being confronted with the trade-off between setting high safety standards to protect the public and encouraging innovation and diffusion of AV technologies[63]. Stricter safety regulations may delay market entry of the fully autonomous vehicles and suppress the private AV ownership rates, whereas more lenient standards may increase risk and public resistance. Understanding how these factors dynamically interact over time is crucial for designing effective and balanced AV policies. To make sense of these dynamic interdependencies, researchers have turned to a variety of modeling techniques. Traditional transportation models, while being useful for forecasting travel demand and evaluating infrastructure investments, might often fall short in capturing feedback loops, delays, behavioral adaptation, and the systemic consequences of policy interventions. As such, system dynamics (SD) modeling has emerged as a promising method for analyzing the uptake of emerging technologies like AVs and evaluating the long-term implications of different policy scenarios[64][65].

The literatures on alternative fuel vehicle (AFV) adoption provide a useful foundation for studying AV uptake, particularly in terms of market diffusion, consumer choice modeling, and policy impact evaluation. Many of the challenges associated with AFVs, such as high upfront costs, uncertain resale value, limited infrastructure, and consumer unfamiliarity, are also relevant in the context of AVs. By exploring how system dynamics has been used to study AFV adoption, valuable insights can be drawn regarding modeling structures, behavioral assumptions, and policy levers applicable to the AV context[66] [67].

This literature review aims to synthesize existing research across few key themes: (1) Policy implications of autonomous vehicles; (2) the application of system dynamics to transportation systems and planning; (3) comparative analysis alternative methodologies used in literature in the AV-adoption context; (4) the exploration of regulatory trade-offs, particularly between safety standards and private AV adoption and (5) research gaps and thesis contribution. Each section highlights relevant models, methodologies, and findings to establish the thesis's conceptual and methodological foundation. This review ultimately bridges prior research and the development of a system dynamics model that investigates the regulatory tension between promoting AV safety and fostering market adoption.

### 2.6.1 Policy Implications of AV

Until now, much of the scholarly research has concentrated on the technological aspects of vehicle automation, such as how these systems perceive the road environment, navigate complex scenarios, and impact traffic flow. Studies have explored how vehicles make decisions, plan routes, and integrate with existing transportation networks, while review articles have primarily focused on the design and operation of automation technologies. [68] [69] [70] [71] [72] [73] [74] [75]

[76]. While these technological advancements are essential, they only address part of the broader implications of autonomous mobility. As AVs are getting inch closer to mainstream adoption, policymakers must grapple with a host of regulatory and societal challenges to ensure a smooth and equitable transition.

One of the key issues involves establishing a regulatory framework to govern the safe operation of AVs on public roads. As highlighted by Anderson [77], this requires addressing critical questions such as liability in accidents involving autonomous vehicles and the privacy implications of the data collected by these systems. These concerns are not just technical but deeply rooted in societal values, raising questions about fairness, accountability, and trust. Without robust policies, the adoption of AVs risks exacerbating existing inequities and introducing new ethical dilemmas.

Recognizing the need to examine the societal and policy-related dimensions of AV adoption, researchers at Delft University of Technology conducted a comprehensive study [78] using a scenario-based approach. Their work went beyond technical evaluations to explore the ripple effects of AV integration on society. Employing the "ripple effect" framework, they categorized the impacts of vehicle automation into three sequential levels. The first ripple focuses on immediate effects, such as changes in traffic patterns, travel costs, and user preferences. The second ripple examines broader implications, including shifts in vehicle ownership models, locational choices, land use, and transportation infrastructure. Finally, the third ripple addresses the far-reaching societal consequences, including energy consumption, air quality, safety, equity, economic impacts, and public health. By reviewing existing literature and identifying gaps, the researchers highlighted areas requiring further investigation and offered a roadmap for future research and policy development. Their findings provide essential insights into how AVs can be integrated into society in a way that balances technological innovation with public good.

To demonstrate the practical application of these insights, a case study [79] conducted in the city of Turin proposed a long-term policy roadmap for managing AV integration. The study employed a collaborative back-casting approach, setting a 30-year vision for the city's mobility system based on the superblock model. This urban planning concept aims to enhance walkability, reduce car dependency, and prioritize public transportation, creating more sustainable and livable cities. Using the Sustainable Urban Mobility Plan (SUMP) as a framework, the roadmap outlined three distinct phases for integrating and regulating AVs:

- 2020–2030: Establish road classifications, introduce 30 km/h superblocks to improve public space quality, test AV technologies, reorganize public transport, reduce on-road parking, and develop AV infrastructure.
- 2030–2040: Deploy AVs equipped with vehicle-to-infrastructure (V2I) systems, integrate autonomous public transport with car-sharing services, and designate restricted traffic zones within superblocks.
- 2040–2050: Fully reconfigure superblocks for shared-vehicle use, eliminate on-road parking in favor of drop-off zones, focus public transport on main routes, and prioritize non-motorized modes of travel.

This phased approach highlights how cities can proactively prepare for AVs while enhancing urban liveability, sustainability, and equity. By integrating AVs within a broader vision of urban development, the Turin case study offers a model for other cities to follow.

While long-term visions like Turin's are critical, it is equally important to address the near-term implications of semi-autonomous vehicles (SDVs). A separate study [80] employed a "policy scenario" methodology to evaluate the potential impacts of SDVs by 2025. This approach examined various plausible futures based on current technological trajectories, engaging stakeholders to uncover overlooked issues. The study identified significant opportunities for SDVs to enhance road safety, reduce traffic accidents, and improve mobility for marginalized groups. However, it also raised concerns about ethical dilemmas in crash algorithms, legal complexities surrounding liability, and the risks of data breaches. Furthermore, social and economic implications, such as changes in urban dynamics, increased vehicle miles traveled (VMT), and job displacement in driving-related sectors, were emphasized. The study provided actionable policy recommendations, including the standardization of safety regulations, the development of robust data governance frameworks, investment in cybersecurity, and the promotion of inclusive mobility solutions using SDVs. These recommendations aim to balance technological progress with societal needs, ensuring a safe and equitable transition to autonomous mobility.

A broader review [81] of AV impacts extended the discussion to encompass various domains, including safety, public behavior, land use, economy, environment, and public health. The review underscored the transformative potential of AVs, such as enhancing mobility, reducing emissions, and reshaping urban spaces. However, it also highlighted significant challenges, such as public acceptance, regulatory gaps, and ethical issues. The importance of shared-use AV models was emphasized, as these could reduce vehicle ownership and parking demands, leading to more efficient urban environments. At the same time, the review cautioned against potential environmental risks, including increased VMT and disruptions to public transit systems. Proactive policies were deemed essential to mitigate these risks, with an emphasis on addressing cybersecurity, data privacy, and equitable access.

Equity, in particular, emerged as a recurring theme in discussions about AV policy. A separate study [82] focused specifically on the equity implications of AVs, analyzing existing policies in the U.S. and identifying trends, gaps, and opportunities. The policies were categorized into three areas: Access & Inclusion (serving low-income individuals, rural residents, and people with disabilities), Multimodal Transportation (improving public transit, shared AVs, and active transportation), and Community Wellbeing (addressing job losses, safety, and sustainability). Shared-use AV models were identified as critical for reducing costs, emissions, and parking demands while improving accessibility. However, significant gaps were noted, such as the lack of policies addressing rural areas, safety concerns in shared AVs, and specific measures targeting marginalized racial groups. The study called for proactive policymaking and collaboration among governments, private sectors, and nonprofits to ensure that AV integration benefits underserved populations. By addressing these gaps, policymakers can promote a fair and sustainable transportation future.

### 2.6.2 System Dynamics and Transportation Planning

Modern transportation systems are becoming increasingly complex due to rapid technological advancements, changing travel behaviors, and growing environmental concerns. Transformative shifts, such as vehicle automation, electric vehicle adoption, increased telework, and multimodal integration, have introduced significant uncertainty into transportation planning. Traditional travel demand models, which often rely on static assumptions and lengthy run times, struggle to accommodate these emerging dynamics and their nonlinear interactions[83]. In response to these limitations, planners and researchers have increasingly turned to strategic modeling tools capable of handling wide scenario spaces and dynamic feedback. Frameworks like VisionEval and the TMIP Exploratory Modeling and Analysis Tool (TMIP-EMAT) exemplify this shift by supporting rapid scenario testing and exploring plausible futures. System dynamics (SD) aligns well with these approaches because it captures complex interdependencies and simulates long-term behavior under uncertainty[84].

System dynamics (SD) offers a powerful lens for understanding the behavior of complex systems by focusing on how structure drives dynamics. While individual causal links within a system may seem simple or intuitive, the resulting system-wide behavior is often nonlinear, delayed, and difficult to predict. SD enables modelers and planners to step back from granular data and construct a high-level representation of the system focusing on the key causal relationships and feedback mechanisms that truly drive change. This makes it a valuable tool for strategic modeling, particularly in domains like transportation where long-term dynamics, behavioral responses, and policy impacts intertwine.

Originally developed by Jay Forrester at MIT in the late 1950s and 1960s [85], system dynamics draws from a rich blend of disciplines, including systems theory, information science, organizational behavior, control theory, cybernetics, and decision-making frameworks. It was first applied in business management but has since expanded to a wide array of fields such as public policy, healthcare, environmental management, urban systems, and the automotive industry [64]. The method typically begins with qualitative causal loop diagrams (CLDs), used to formulate dynamic hypotheses, before moving into quantitative stock-and-flow models that simulate system behavior over time.

According to the Journal of Operations Management [86], several core characteristics that distinguish SD models are given below.

- First, these models emphasize that system behavior stems from structural relationships among components, interacting through the decision rules of agents within the system. Rather than assuming decision-makers act with perfect rationality, SD allows for bounded rationality, heuristics, and even emotion-driven behavior, bringing the approach closer to behavioral realism.
- Another defining feature is that SD models do not presume systems move toward equilibrium. Instead, they simulate how decision-makers respond to

changing conditions at any given moment, allowing equilibrium—if it appears at all—to emerge naturally from the system's structure. This makes SD well-suited for modeling, evolving, path-dependent processes, such as technology adoption or policy resistance.

- A further advantage of SD is its capacity to broaden the model boundary. While mental models often limit analysis to narrow factors, SD encourages inclusion of wider feedback loops and time-lagged effects that may not be immediately visible to stakeholders but could significantly alter long-term outcomes.
- Importantly, SD models are grounded in observable reality. Each element of the model corresponds to a measurable concept, relationship, or component ensuring the model remains testable and traceable.

One landmark example of SD's potential was the System Dynamics National Model Project at MIT, which sought to simulate macroeconomic behavior without imposing conventional theoretical assumptions. Through detailed modeling of interactions between economic actors and sectors, the model was able to replicate phenomena such as inflation, short-term business cycles, long waves of economic activity, and other emergent behaviors. As Dr. Alan Graham, the project's research director, noted, the model demonstrated that such complex macro-outcomes could arise purely from localized decisions made by individual agents, shaped by their motivations and the information available to them, not by top-down economic rules [87]. In this view, system behavior is not assumed but revealed through structure and it captures the essence of what makes SD a distinct and insightful methodology.

One of the earliest and most influential efforts to introduce SD into transportation modeling was made by Abbas and Bell (1994)[88], who highlighted the method's potential for strategic policy analysis and decision support. They identified twelve specific advantages of SD over traditional transport models, emphasizing its ability to model systems with multiple stakeholders and feedback loops operating over varied time scales. This whole-systems perspective is particularly valuable in transport planning, where delayed and indirect effects often drive system behavior. System dynamics enables modelers to move beyond discrete inputs and outputs, instead focusing on how structure drives behavior. Using causal loop diagrams (CLDs), SD helps identify reinforcing and balancing feedback within a system, making it easier to anticipate unintended consequences and policy resistance. This qualitative foundation can be translated into quantitative stock-and-flow models that simulate system responses over time[64].

The usefulness of SD extends beyond analytical rigor. It also plays a role in stakeholder engagement and shared learning. Techniques such as group model building allow diverse actors to co-develop system maps and uncover hidden leverage points, thereby aligning mental models and facilitating consensus[89]. These participatory approaches are particularly relevant in public policy domains like transportation, where decisions often require alignment across sectors and interest groups. Moreover, SD's flexibility and integration of feedback dynamics make it a powerful complement to exploration scenario tools. It can simulate the ripple effects of policy interventions, such as road pricing, fuel taxation, or autonomous vehicle regulations, and reveal how these interventions interact over time. Rather than assuming system equilibrium, SD models highlight the emergence of patterns and behaviors through the interaction of actors governed by bounded rationality and local decision rules[86].

In summary, SD offers a comprehensive and adaptive methodology for transportation planning in an era of rapid change. By enabling planners to visualize, simulate, and evaluate the systemic implications of emerging technologies and policies, system dynamics strengthens the capacity to build more resilient, informed, and forward-looking transportation strategies.

The adoption of alternative fuel vehicles (AFVs) has served as a critical testing ground for understanding the complex interactions among technology, consumer behavior, market forces, and policy instruments, making it an ideal parallel for studying the dynamics of private autonomous vehicle (AV) ownership. System dynamics (SD) has been increasingly employed in this context to explore how feedback mechanisms, time delays, and nonlinear relationships shape the long-term outcomes of interventions aimed at promoting AFVs. The modeling efforts in this space offer valuable methodological and conceptual insights that can be leveraged to structure similar models for AV adoption.

One of the earliest notable applications of SD in this domain is by Stepp [83], who developed a causal loop diagram (CLD) through stakeholder engagement to evaluate the policy implications of supporting high-efficiency vehicles. Their model accounted for consumer preferences, manufacturer responses, vehicle market evolution, and environmental impacts across the vehicle life cycle. Interestingly, while a subsidy for high-efficiency vehicles was shown to reduce emissions by increasing market share, the study also highlighted unintended consequences, such as the rebound effect, wherein increased fuel efficiency leads to lower fuel costs per mile, encouraging greater vehicle miles traveled (VMT). This increased VMT not only partially offsets emission gains but also triggers feedback loops that accelerate vehicle replacement, raising production-related emissions. Moreover, the short-term spike in demand for efficient vehicles can drive up their prices, contradicting the subsidy's original intent. Their findings highlight how policy outcomes depend on the interplay of feedback loops and how CLDs can help surface potential resistance to well-intended policies. They also noted that combining subsidies with measures like carbon taxes, policies that raise the cost per mile, could enhance overall effectiveness.

Expanding these ideas, Struben and Sterman [84] developed a comprehensive SD framework for modeling AFV adoption, incorporating vehicle fleet turnover, consumer choice modeling, and a social-technical diffusion mechanism. Their approach extended traditional Bass diffusion models by including word-of-mouth advertising, and social visibility, allowing the model to simulate both growth and decline in adoption. For instance, without sustained policy support or positive social reinforcement, a promising new technology could fail to reach critical mass, as was observed when compressed natural gas vehicle programs were discontinued in Canada and New Zealand [90]. This highlights how SD models can reveal potential failure paths that might not be captured by more static modeling techniques.

Some authors, though focusing on recycling behavior, offered insights relevant to AFV adoption by outlining model structures that can be applied broadly to technology acceptance and rejection dynamics, for paradigm shifts and evolving public preferences[67]. Building on these foundations, various studies have introduced additional policy dimensions and contextual factors. For example, models have explored the influence of regulatory interventions and manufacturer behavior [91], impacts on government fuel tax revenue [92], and the infrastructure development into diffusion models, especially for natural gas [93] and hydrogen fuel cell vehicles [94], emphasizing the interdependence between vehicle adoption and refueling or recharging network availability. Others have examined the role of strategic niche management [95], policy distributional effects[96], and the diffusion of electric motorcycles in Taiwan [97]. Across many of these studies, a common conclusion emerges subsidies alone often have limited impact on accelerating adoption. Instead, regulatory measures and supporting infrastructure play more decisive roles. Moreover, as emphasized in the literature, the sensitivity of adoption outcomes to social influence, such as peer exposure and marketing etc. can outweigh the effects of technical improvements. The ability of SD models to integrate these "soft" factors and test outcomes under various assumptions makes them uniquely suited for evaluating policy strategies in the face of complexity and uncertainty.

Building on the extensive use of SD in modeling alternative fuel vehicle adoption, recent research has increasingly applied SD to explore the complex, multi-layered impacts of autonomous vehicle (AV) deployment, particularly in relation to behavioral dynamics, infrastructure readiness, and policy design. These efforts reflect a growing recognition that AV adoption, like that of alternate fuel adoption, is not solely driven by technological advancement, but by a web of interdependent factors that unfold over time and interact through feedback-rich structures.

One of the contributions to this field is by Sayyadi and Awasthi (2017)[98], who developed a system dynamics model to evaluate urban transportation policies related to trip sharing and car ownership. Using causal loop diagrams (CLDs) and a stock-and-flow structure, their model quantified how strategic investments in public transit infrastructure and regulatory constraints on car ownership influenced system-level outcomes such as congestion, emissions, and transit usage. The study demonstrated that SD models can effectively simulate multiple policy scenarios, revealing both intended outcomes and systemic side effects. Their work reinforced the value of SD for designing adaptive and region-specific transportation policies by integrating economic, environmental, and behavioral dimensions.

Further advancing this modeling tradition, the Volpe National Transportation Systems Center (2020) applied SD to analyze the emergent behaviors and uncertainties associated with AVs, especially within shared fleet and mobility-on-demand contexts[99]. Faced with limited empirical data for AVs, the researchers constructed two proxy models: one mimicking transportation network company (TNC) dynamics and another reflecting dockless bikeshare operations. These models captured critical feedback loops, such as the interplay between user adoption, service quality, financial sustainability, and congestion effects. While the study centered on shared AV services, the insights regarding technology adoption patterns, generalized travel costs, and mode-switching behaviors are directly transferable to private AV ownership contexts. The authors also emphasized the importance of integrating SD with strategic planning tools such as Robust Decision Making (RDM) to evaluate policy effectiveness under deep uncertainty.

Building on this work, the Volpe Center's 2023 report expanded the scope and realism of SD modeling for AVs by calibrating a quantitative system dynamics model with real-world TNC data from Massachusetts and Chicago[100]. This model simulated a range of automation scenarios, accounting for traveler decision-making, operator behavior, and system performance metrics like fleet size and ridership. A key innovation of this study was its strong emphasis on stakeholder engagement through group model building (GMB) workshops, which brought together urban planners and policymakers from both the U.S. and Europe. These sessions helped map out the feedback structures linking AV adoption to broader goals such as urban livability, equity, and residential patterns. The findings underscored that AV deployment should not be viewed in isolation, but as part of a larger, adaptive urban system where regulatory interventions, land use, and behavioral responses are deeply interconnected.

Complementing these urban mobility-focused studies, another SD-based investigation[101] explored the behavioral and enforcement-related dynamics of AV adoption, particularly during the transitional phase when human-driven vehicles (HVs) and AVs share the road. This study introduced the concept of First-In-First-Out (FIFO) violations, representing cases where human drivers bypass AV safety protocols to gain perceived benefits, thereby compromising traffic order and system safety. By distinguishing between AV installation (vehicles equipped with AV technology) and AV usage (actual engagement of autonomous driving), the model revealed that manual overrides, driven by individual risk-benefit assessments, can significantly dampen the long-term benefits of AV implementation. The study also showed how public sentiment, media framing, and law enforcement funding interact through feedback loops to affect policy outcomes and infrastructure planning. These findings highlight the need for regulatory strategies that address not just technology deployment, but also behavioral dynamics, public perception, and institutional capacity.

Adding a broader modal dimension to the literature, another study employed SD to analyze the interplay between AVs, conventional vehicles (CVs), and public transport (PT) over a 50-year horizon in Victoria, Australia[102]. Using detailed travel data and national surveys, the model explored how trip costs, public transport capacity, and awareness campaigns shape modal shifts and infrastructure demands. Notably, the study found that awareness programs promoting AV benefits were more effective in influencing adoption than traditional road expansion. It also observed that public transport usage stabilized after several decades, suggesting a potential modal equilibrium in the long run. The results emphasized that transitions from CVs to AVs depend not only on technological progress, but also on user confidence, trip utility, and policy responsiveness, underscoring the importance of flexible, adaptive planning approaches.

Taken together, these studies illustrate the expanding role of system dynamics modeling in understanding the challenges and opportunities of AV adoption. From shared mobility and urban policy to manual driving behaviors and multi-modal network interactions, SD offers a unifying framework to evaluate regulatory trade-offs, simulate long-term impacts, and surface unintended consequences. . Its ability to represent both quantitative factors (e.g., price, infrastructure, policy incentives) and qualitative influences (e.g., public perception, behavioral inertia, social influence) makes it an especially suitable tool for informing policy decisions under uncertainty. As these models demonstrate, achieving sustainable and safe AV adoption, particularly in the context of private ownership, requires careful attention to behavioral feedback, policy resistance, infrastructure dynamics, and public perception. These lessons directly inform this thesis's focus on modeling the regulatory trade-offs between safety standards and private AV adoption, providing both the conceptual foundation and methodological precedent for building an SD model that is responsive, realistic, and relevant to future urban mobility challenges.

### 2.6.3 Alternative Methodologies for AV Adoption Studies

- **Agent-Based Modeling (ABM)**

Agent-Based Modeling (ABM) is a widely used computational method for simulating the adoption and diffusion of autonomous vehicles (AVs) by modeling individual agents, such as consumers, vehicles, or policymakers, and their interactions within a defined environment. Unlike aggregate approaches like System Dynamics, ABM captures behavioral heterogeneity and emergent system-level outcomes from micro-level decisions.

Liu[103] employed ABM to examine AV adoption under uncertainty, incorporating individual preferences, learning behavior, and peer influence. Their findings highlighted how social dynamics and policy scenarios can shape adoption trajectories. Similarly, Paddeu [104] modeled the deployment of shared autonomous shuttles, demonstrating how user behavior varies depending on different factors during first-time use. ABM is particularly suited for analyzing spatial and demographic variability. Narayanan[105] used ABM to explore regional AV uptake based on infrastructure, socio-demographics, and local policies, underscoring the model's utility for targeted interventions.

While ABM enables detailed behavioral representation, it can be sensitive to assumptions and requires extensive data and computational resources. Nonetheless, it remains a valuable tool for studying decentralized decisions, behavioral diversity, and localized policy impacts in AV adoption.

- **Technology Diffusion Models (TDM):**

Technology diffusion models have been extensively utilized in forecasting the adoption of emerging innovations, including autonomous vehicles (AVs). These models typically focus on how new technologies penetrate markets over time, capturing adoption dynamics influenced by consumer behavior, innovation maturity, and market conditions. Among these, the Bass Diffusion Model is one of the most prominent. It classifies adopters into two categories: innovators, who adopt early due to interest in new technologies, and imitators, who are influenced by social and market dynamics[106].

In the context of AV adoption, diffusion models have been employed to simulate the integration of connected autonomous vehicles and the impact of the integration in the UK transportation system[107]. For instance, studies have shown that public exposure to AVs, combined with favorable government incentives and declining unit costs, can accelerate adoption rates following the classic S-shaped curve of diffusion [105][108]. More sophisticated variants, such as agent-based diffusion models and multi-generation models, introduce heterogeneity by modeling diverse consumer profiles and preferences[103]. These models can also incorporate geographic, demographic, and behavioral segmentation to reflect real-world adoption patterns better.

However, a key limitation of traditional diffusion approaches is their typically exogenous treatment of policy, safety incidents, and public sentiment, factors that are crucial in the AV context. As such, while diffusion models offer valuable insights into the tempo and trajectory of AV adoption, they often fall short in capturing the endogenous feedback loops present in the sociotechnical system surrounding the deployment of AVs. This limitation highlights the complementary role of System Dynamics (SD) in integrating policy interventions, public trust, and infrastructure dynamics within a unified simulation framework.

- **Discrete Event Simulation (DES):**

Discrete Event Simulation (DES) is a process-oriented modeling approach that represents system behavior as a sequence of discrete events occurring over time. In autonomous vehicle (AV) research, DES is particularly effective for evaluating operational performance, infrastructure interactions, and system efficiency under various deployment scenarios. Bischoff and Maciejewski [109] used DES with MATSim to simulate a fleet of autonomous taxis in Berlin, demonstrating that AVs can reduce the total number of vehicles while maintaining service quality, highlighting their potential to alleviate congestion. Similarly, Levin and Boyles [110] applied DES to study AV interactions with traffic signals and intersections, showing improvements in throughput and reduced delays at higher AV penetration rates.

DES has also been used to assess logistics and car-sharing systems. Boyacı with other authors[111] simulated electric vehicle-based car-sharing services, accounting for demand patterns, vehicle availability, and relocation strategies, offering insights into service feasibility and efficiency. Compared to Agent-Based Modeling (ABM) or System Dynamics (SD), DES excels at simulating operational-level details such as queueing, resource allocation, and scheduling but is less suited for modeling behavioral or policy-driven dynamics unless integrated with other methods.

In summary, DES is a powerful tool for analyzing the functional performance of AV systems, especially in urban transport, traffic control, and fleet logistics, making it a valuable complement to strategic and behavioral modeling approaches.

- **Machine Learning (ML) Approaches:**

Machine Learning (ML) offers a data-driven framework for modeling and forecasting autonomous vehicle (AV) adoption. Unlike rule-based models, ML algorithms learn patterns from large, complex datasets, making them ideal for capturing non-linear and high-dimensional relationships in AV studies. In AV adoption research, supervised learning methods such as regression, decision trees, random forests, and neural networks are commonly used to predict user preferences and forecast ownership trends. For example, Wang[112] applied ensemble methods like gradient boosting and random forests to survey data in China, accurately predicting public acceptance of AVs and identifying key factors like safety perception and income. Their models outperformed traditional logistic regression in both accuracy and variable insight. Daziano[113] integrated deep learning into discrete choice models to better capture non-compensatory behavior in AV decisions. Their hybrid approach improved predictive performance and bridged behavioral modeling with ML's feature learning capabilities.

ML has also been employed for spatiotemporal forecasting. Altche and Fortelle[114] developed a Long Short-Term Memory (LSTM) neural network model to predict vehicle trajectories on highways. The model aimed to enhance the decision-making processes of autonomous vehicles by accurately forecasting the movements of surrounding vehicles, thereby improving safety and efficiency. Despite their predictive power, ML models, especially neural networks, often lack interpretability, posing challenges for policy applications unless paired with explainable AI (XAI) techniques. Moreover, they require high-quality data and careful validation to avoid overfitting.

In summary, ML provides powerful tools for understanding and forecasting AV adoption patterns. When combined with domain expertise or hybrid models, ML can enhance both operational planning and strategic policy development in AV research.

- **Reinforcement Learning (RL) Approaches**

Reinforcement Learning (RL) is a data-driven decision-making method where an agent learns optimal strategies through trial-and-error interactions with its environment to maximize cumulative rewards. In autonomous vehicle (AV) research, RL is applied in two key areas: (1) operational driving control and (2) strategic policymaking and adoption modeling.

For operational use, RL, particularly Deep RL (DRL), has been used to train AVs in tasks like lane-keeping, obstacle avoidance, and traffic negotiation. Kiran[115] provide a comprehensive review of DRL applications in autonomous driving, showing how agents learn from complex, dynamic simulations. At the strategic level, RL has been employed to simulate adaptive policymaking under uncertainty. Other authors modeled government decision-making as an RL agent optimizing AV adoption incentives, safety regulations, and infrastructure investment[116]. Their study showed that adaptive policy learning can outperform static strategies, especially in evolving environments.

RL's strength lies in its adaptability and ability to handle delayed feedback, ideal for modeling long-term effects in AV adoption influenced by public trust, tech evolution, and regulation. However, challenges include defining meaningful reward functions and the computational cost of training, along with interpretability issues. Despite these, RL offers a powerful complement to system dynamics and agent-based models, enabling exploration of complex regulatory trade-offs and multi-agent interactions in AV policy planning.

- **Hybrid Choice Modeling (HCM)**

Hybrid Choice Modeling (HCM) enhances traditional discrete choice models by incorporating latent psychological factors, such as attitudes, perceptions, and social norms, into utility-based decision frameworks. This makes HCM particularly suited for analyzing autonomous vehicle (AV) adoption, where choices are shaped by both observable attributes (e.g., price, travel time) and unobservable constructs (e.g., trust, safety concerns). HCM uses structural equation modeling to link latent variables, derived from attitudinal indicators (e.g., survey responses), to individual choices. This approach provides deeper behavioral insight than standard models.

Bansal, Kockelman, and Singh [117]used HCM to assess AV adoption in Texas, showing that trust in technology, safety perception, and interest in innovation significantly influenced willingness to adopt. Becker and Axhausen[118] found that psychological barriers like risk aversion and tech skepticism were critical in shaping AV uptake across demographic groups. HCM also aids policy analysis. Krueger, Rashidi, and Rose[119] simulated how incentives such as reduced parking fees or HOV access interact with consumer attitudes. Their results indicated that combining financial incentives with trust-building efforts (e.g., safety certifications) can greatly enhance adoption rates.

While HCM offers strong behavioral realism, it requires large-scale survey data, careful latent variable specification, and computationally intensive estimation. Still, its ability to capture the "why" behind consumer choices makes it a valuable complement to system-level tools like system dynamics and agent-based modeling, especially for demand-side analysis of AV adoption.

- **Multinomial Logistic Regression (MNL)**

Multinomial Logistic Regression (MNL) is a widely used statistical method in travel behavior research for modeling choices among multiple discrete alternatives. In the context of autonomous vehicle (AV) adoption, MNL helps quantify how socioeconomic, attitudinal, and trip-related factors influence the likelihood of choosing AVs over other transport options. MNL estimates the probability of selecting an option based on a linear combination of explanatory variables, such as age, income, travel cost, or AV attributes. It relies on the independence of irrelevant alternatives (IIA) assumption, which simplifies analysis but may be limiting when alternatives are closely related.

Bansal and Kockelman[120] applied MNL to model AV adoption under various pricing and deployment scenarios, finding that younger, more educated, and tech-savvy individuals were more likely to adopt AVs. Haboucha, Ishaq, and Shiftan[121] used MNL to explore preferences among private AVs, shared AVs, and conventional vehicles, revealing significant effects from income, environmental concern, and commuting patterns. MNL is also frequently paired with stated preference (SP) surveys. For instance, Winter, Cats, and Martens[122] used MNL in the Netherlands to analyze public responses to hypothetical AV service designs, assess the impact of different parking strategies, showing that trust and perceived reliability were strong predictors of AV acceptance.

While the IIA assumption is a key limitation, it can be addressed through extensions like nested or mixed logit models. Despite this, MNL remains a popular and interpretable tool, particularly useful for early-stage AV adoption modeling, demand forecasting, and policy evaluation when behavioral complexity is moderate and data availability is limited.

- **Active Inference and Cognitive Modeling**

Active Inference and Cognitive Modeling are emerging approaches from neuroscience and cognitive science that aim to simulate human-like decision-making under uncertainty. These frameworks are increasingly applied in autonomous vehicle (AV) research to model complex behavioral processes like trust formation, adaptation, and user interaction; elements often simplified in traditional models.

  - **Active Inference Framework:** Rooted in theoretical neuroscience [123], Active Inference posits that agents act to minimize expected "free energy", a proxy for prediction error between expected and observed outcomes. In AV adoption contexts, this approach models how individuals update beliefs about AV safety, reliability, or utility, and how these beliefs guide adoption behavior over time. Schwartenbeck[124] demonstrated that Active Inference can model adaptive trust, explaining how consistent experiences (e.g., safe AV rides) reinforce confidence, while negative incidents (e.g., crashes) lead to skepticism. This makes it particularly relevant for simulating the dynamics of public trust and acceptance of AVs.

- **Cognitive Modeling in AV Research:** Cognitive models simulate internal psychological processes such as attention, memory, and decision-making. Frameworks like ACT-R and SOAR have been used to analyze AV-human interaction. For example, Calvert[125] modeled human responses during Level 3 AV handovers, identifying how alert systems can reduce reaction times and cognitive load. Körber[126] also used cognitive modeling to assess how media exposure and prior experience influence AV risk perception.

These models offer a deeper behavioral representation than statistical models, capturing emotional states, individual differences, and learning over time. Some of the applications of this methodology in AV Studies are**:**

- **Trust Calibration**: Simulating how repeated AV experiences shape user trust.
- **Policy Evaluation**: Testing the impact of transparency campaigns or safety demonstrations.
- **Interface Design**: Assessing mental workload during AV-human transitions.

Active Inference and cognitive models provide high behavioral realism, especially for modeling trust, adaptation, and decision-making under uncertainty. They are especially useful when analyzing heterogeneous user responses and interface design impacts. However, these models are data-intensive, computationally demanding, and require interdisciplinary expertise. Despite their complexity, they offer valuable tools for complementing system-level approaches by focusing on the human element in AV adoption and interaction.

Table 1: Comparative Analysis of Modeling Approach

| **Comparative Analysis of Modeling Approaches for AV Adoption** | | | |
|---|---|---|---|
| **Methodology** | **Strengths** | **Limitations** | **Application to AV Adoption** |
| **SD** | Captures feedback loops and time delays- | Less granular than micro-level methods | System-wide policy analysis |
| **ABM** | Models individual behaviors and interactions | Computationally intensive | Useful for simulating individual decision-making processes |
| **TDM** | Captures aggregate adoption trends | Limited feedback and policy endogeneity | Forecasting long-term market penetration |

| | | | |
|---|---|---|---|
| **DES** | High-resolution, event-driven simulation | Lacks a feedback structure | Operational modeling |
| **ML** | High predictive accuracy | limited causal insights | Forecasting, sentiment analysis |
| **RL** | Adaptive learning | Data-intensive, low-interpretability | Agent-level control tasks |
| **HCM** | Behavioral realism | Static, limited in feedback | User preference studies |
| **MNL** | Easy to estimate and interpret | IIA assumption, static nature | Initial adoption modeling |
| **Active Interface & Cognitive Modeling** | Models human decision-making processes- Incorporates uncertainty and learning | Theoretically complex- Limited empirical applications | Promising for exploring human-AV interactions and trust dynamics |

For our study, we chose the System-Dynamics (SD) approach because of its holistic approach provides a strategic overview, making it an appropriate choice for your study on regulatory trade-offs in AV adoption. While other methods offer valuable perspectives, they often focus on micro-level behaviors or require extensive data, which may not be feasible in the context of emerging technologies like AVs. Systems Dynamics is particularly well-suited for modeling AV adoption due to its ability to:

1. **Captured Feedback Mechanisms**: SD excels at representing feedback loops, such as how increased AV adoption can influence public perception, which in turn affects future adoption rates.

2. **Model Policy Impacts Over Time**: SD allows for the simulation of policy interventions and their long-term effects on AV adoption, enabling the assessment of strategies like subsidies or regulatory changes.

3. **Handle System Complexity**: By focusing on system-level behaviors and interactions, SD provides insights into the broader dynamics of AV adoption, including technological advancements, infrastructure development, and societal acceptance.

4. **Facilitate Stakeholder Engagement**: The visual nature of SD models, through tools like causal loop diagrams, aids in communicating complex system behaviors to stakeholders, fostering collaborative decision-making.

In summary, while alternative methods such as ABM, DES, ML, RL, HCM, and MNL offer valuable tools for analyzing specific facets of AV systems, System Dynamics provides a uniquely powerful framework for simulating the long-term, feedback-driven, and policy-sensitive nature of AV adoption. The SD model developed in this study enables the exploration of regulatory trade-offs, public trust dynamics, and infrastructure readiness over time, making it well-suited for the research objectives.

### 2.6.4 Exploration of regulatory Trade-off for AV adoption

As autonomous vehicles (AVs) transition from prototypes to a viable market reality, understanding the dynamics of their adoption becomes a critical area of interest for transportation planners, policymakers, and technology developers. The deployment of AVs is shaped by a web of interacting factors such as technological, economic, regulatory, infrastructural, and societal, that evolve and exert reinforcing or balancing influences on one another. This intricate complexity renders AV adoption an ideal candidate for system dynamics (SD) modeling, particularly in contexts where policy trade-offs such as those between stringent safety regulations and market diffusion must be evaluated.

A key insight from existing literature is that AV adoption is not driven by a singular factor but by a constellation of variables working across multiple domains. For example, technological readiness, measured through the advancement of perception systems, real-time decision-making algorithms, and fail-safe redundancies, is often cited as a prerequisite for large-scale AV deployment [14]. Similarly, economic factors such as declining costs of sensors, computing units, and battery technologies can facilitate diffusion, especially when bundled with ownership models such as leasing or subscription services [62].

On the regulatory front, government action plays a dual role. On one hand, supportive policies, such as AV testing frameworks, AV-compatible road infrastructure, tax incentives, and relaxed parking or lane usage rules, can significantly accelerate adoption [63]. On the other hand, strict safety regulations, driven by legitimate concerns about liability, cybersecurity, and ethical decision-making in edge cases, can slow down AV deployment. These constraints, while crucial from a public safety perspective, can result in longer development timelines, delayed approvals, and higher compliance costs, particularly for smaller market players. This regulatory dichotomy forms the heart of the trade-off addressed in this thesis.

System dynamics modeling provides a valuable framework for exploring this policy dilemma by representing how adoption rates evolve under varying regulatory intensities and feedback mechanisms. For instance, increased safety regulations may improve public trust and reduce crash rates, both of which are positive contributors to adoption in the long run. However, if these regulations significantly delay vehicle launches or raise costs, they could weaken early adoption momentum and stifle industry investment [127]. A delay in adoption may also postpone learning curve benefits and infrastructure development, creating a balancing feedback loop that counteracts growth. Conversely, relaxed safety standards might expedite short-term deployment but lead to public backlash in the event of high-profile accidents, triggering negative perception loops that could stall adoption altogether [128].

From a behavioral perspective, consumer trust and perceived safety are pivotal adoption drivers. Studies have shown that media coverage, peer influence, and direct exposure to AVs can dramatically shape public perception, either reinforcing confidence or amplifying skepticism [129]. These variables are inherently dynamic, and their effects accumulate over time, making them particularly well-suited for inclusion in an SD framework that can simulate gradual shifts in public opinion and tipping points.

Several researchers have begun to explore AV adoption using SD models. For instance, Milakis[78] proposed a conceptual framework outlining potential feedback loops in AV adoption, identifying important interactions such as reduced car ownership through shared AVs and induced travel demand due to convenience. Others [102] went further by developing a quantitative SD model to simulate AV adoption, factoring in variables such as cost reductions, accident rates, fuel economy, and consumer willingness to pay. Their work demonstrated that policy incentives (e.g., tax rebates and infrastructure support) were effective primarily in the early stages, while consumer awareness and trust were the key drivers in the later stages of diffusion.

However, the unique regulatory dynamics of AVs, particularly the trade-off between promoting innovation and ensuring safety, remain underexplored in SD literature. This thesis addresses this gap by building a system dynamics model that simulates how different safety policy regimes impact AV adoption over time. The model explicitly considers feedback-rich relationships between regulatory strictness, public perception, cost structures, and overall vehicle uptake. In doing so, it aims to uncover policy leverage points that strike a balance between accelerating adoption and safeguarding public interest.

Importantly, the model adopts a broad boundary perspective, consistent with SD best practices[130], incorporating not only vehicle and infrastructure systems but also sociopolitical dynamics, such as shifts in media narrative, advocacy group influence, and legislative cycles. This allows the simulation of emergent behaviors like policy resistance or sudden acceleration of adoption due to breakthrough events or tipping points in public sentiment.

In sum, while AVs present a transformative opportunity for sustainable and safe mobility, the path to their adoption is shaped by a complex interplay of endogenous feedback loops and policy decisions. System dynamics modeling offers a structured approach to understanding these interactions, enabling decision-makers to simulate future trajectories under varying regulatory scenarios. By capturing these dynamics, this thesis contributes to a growing body of work that not only explains AV diffusion patterns but also supports evidence-informed policymaking that aligns innovation with safety imperatives.

## 2.7 Research Gaps and Thesis Contributions

The growing body of literature on transportation modeling has seen a significant rise in the use of system dynamics (SD) to understand and simulate the adoption of emerging mobility technologies. These include alternative fuel vehicles (AFVs), electric vehicles (EVs), and more recently, autonomous vehicles (AVs). Prior studies have shown that SD is particularly effective in capturing feedback-rich, nonlinear interactions in transportation systems, especially in the face of policy uncertainty and behavioral shifts [131][67][92]. While substantial efforts have been made to use SD in modeling technology diffusion and the influence of financial incentives, infrastructure co-evolution, or consumer behavior, one specific area remains relatively underexplored which is the regulatory trade-offs between safety policies and AV adoption rates.

Existing AV adoption models, including those using agent-based modeling, discrete choice frameworks, and SD approaches, have primarily focused on technical performance, market dynamics, and infrastructure requirements [62][132][97]. Although these models contribute valuable insights, they tend to either oversimplify the regulatory environment or treat safety-related policies as static exogenous inputs, rather than as dynamic factors that evolve in response to technology maturity, social perception, and political feedback.

Furthermore, while studies like those of Stepp [83] and Walther [91] have illustrated the unintended consequences of incentive-based policies using causal loop diagrams, the intersection of stringent safety regulations and public AV adoption behavior has not been given adequate attention in dynamic modeling frameworks. Questions such as "How might high safety standards slow down AV uptake?" or "Could overly lenient regulations backfire in the long run by reducing public trust?" are critical to shaping balanced policy interventions but have not yet been thoroughly explored through SD simulations.

Another research gap lies in how public perception of AV safety, often shaped by media narratives, early adopter experiences, and accident reports, dynamically feeds back into policy formation and adoption rates. While some studies have begun to model public trust [129][133], this factor is rarely integrated into feedback-based models that simulate long-term system behavior. The delay between regulatory changes, shifts in public acceptance, and their cumulative impact on AV market penetration remains a missing link in much of the existing literature.

This thesis seeks to address these gaps by developing a system dynamics model that specifically focuses on the policy trade-off between AV safety standards and private AV adoption. It builds on the foundation of previous SD studies in transportation but adds a novel contribution by:

- Explicitly modeling safety regulations and public safety perception as interacting, endogenous variables.
- Simulating how regulatory stringency, trust dynamics, and market feedback loops affect AV adoption over time;
- Exploring policy scenarios that reveal potential nonlinearities, delays, and unintended consequences of over- or under-regulating AV safety standards.

The proposed model aims to support policymakers in designing more adaptive, feedback-informed regulatory strategies that balance safety goals with innovation and adoption objectives. By integrating system-wide interactions, behavioral elements, and institutional responses into a coherent dynamic framework, this thesis offers a valuable tool for strategic planning in the era of autonomous mobility.

# Chapter 3

# Methodology

## 3.1 Research Methodology Overview

This chapter outlines the methodological approach used to investigate the trade-offs between safety regulations and the adoption of private autonomous vehicles (AVs). The primary objective of this study is to develop a system dynamics (SD) model that captures the feedback mechanisms, delays, and policy effects influencing AV adoption in response to evolving safety standards. This approach enables a comprehensive understanding of the interplay between regulatory decisions and adoption behavior, facilitating policy experimentation in a simulated environment.

System dynamics is particularly well-suited for this research due to its ability to model complex socio-technical systems where human behavior, technology diffusion, and institutional factors interact over time. Being very dynamic and uncertain in nature, AV adoption is mainly shaped by technological readiness, public perception, policy incentives, and regulatory stringency. SD approach offers an ideal framework to represent these elements endogenously within a coherent system structure.

The research methodology consists of five major phases:

1. **Problem Definition and Scope Delimitation** – Framing the problem as a policy trade-off between the pursuit of high safety standards and the goal of

increasing private AV ownership, while identifying key endogenous variables and boundaries of the system.

2. **Conceptual Modeling** – Developing causal loop diagrams (CLDs) to visualize the hypothesized feedback mechanisms that influence the AV adoption ecosystem.

3. **Stock and Flow Model Development** – Translating the conceptual model into a formal quantitative model using Vensim, defining stocks, flows, auxiliary variables, and equations.

4. **Model Validation and Behavior Testing** – Conducting structural and behavioral validation, as well as sensitivity testing, to ensure model credibility and internal consistency.

5. **Policy Simulation and Scenario Analysis** – Running simulations under various policy scenarios (e.g., high safety standards, balanced regulation, relaxed standards) to evaluate adoption outcomes and assess trade-offs.

The methodological emphasis lies in systematically linking safety regulations with AV market dynamics, not only through direct cause and effect but also by tracing the indirect loops of influence, such as public perception, infrastructure readiness, policy synergy, and economic feedback. This approach allows for capturing both the reinforcing and balancing dynamics that emerge from complex interactions among stakeholders, technologies, and institutional settings.

The model prioritizes interpretability and structure over precise numerical accuracy to inform long-term policy decisions. Therefore, parameter estimation is grounded in theoretical insights, expert judgment, and literature-backed assumptions instead of relying heavily on real-world data. This makes the model more adaptable to diverse contexts and enables exploratory scenario analysis, which is critical in the face of uncertainty surrounding future AV development and policy landscapes[134]

## 3.2 Conceptual Modeling

### 3.2.1 Introduction to Causal Loop Diagram

The development of the conceptual model marks a critical phase in translating the real-world problem into a formal system structure. Causal loop diagram (CLD) is a foundational tool for conceptual modeling in system dynamics approach. It helps us visualize important elements of the system and conceptualize their relation. Elements of a system may be caused by former element(s) or can give rise to subsequent element(s). It also helps understand major issue(s) through the number of feedback loops.

As outlined by some authors[135] in a project of US transportation system, CLDs are constructed using a limited set of components: variables, parameters, and causal links. Each variable or parameter represents a measurable concept or factor within the system, while causal links denote directional relationships between them. Arrows are used to indicate the direction of causality, pointing from the independent (causing) variable to the dependent (affected) variable.

Every causal link in a CLD carries a polarity, either positive (+) or negative (−), which describes the nature of the causal relationship. A positive link implies that an increase in the independent variable will result in an increase (or a smaller-than-expected decrease) in the dependent variable, and vice versa. Conversely, a negative link suggests that an increase in the independent variable will lead to a decrease (or a smaller-than-expected increase) in the dependent variable. It is essential to understand that polarity does not guarantee absolute increases or decreases but rather reflects a direction of influence relative to a baseline scenario.

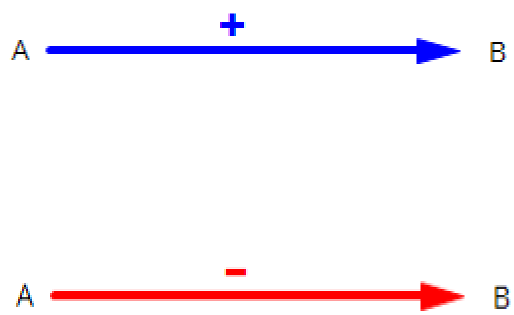


Figure 5: Causal links with positive (left) and negative (right) polarities

CLDs may also include time delays, often represented by hash marks across causal arrows. Delayed effects are common in real-world systems and can significantly influence the dynamics of behavior over time, sometimes masking true cause-and-effect relationships in a system. Recognizing and indicating these delays is crucial in capturing the temporal complexity inherent in systems such as autonomous vehicle (AV) adoption, where regulatory policies, technological maturation, and public perception evolve at different paces.

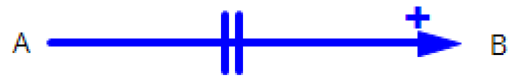


Figure 6: Casual link with delay mark

When these causal connections form closed chains that loop back to the original variable, feedback loops emerge. These loops are the primary mechanisms through which systems exhibit dynamic behavior. CLDs typically distinguish between two fundamental types of feedback loops: reinforcing loops (R) and balancing loops (B). Reinforcing loops amplify changes and can lead to exponential growth or collapse, as seen in positive technology adoption feedback. In contrast, balancing loops resist change, often stabilizing the system around an equilibrium point. However, in systems with significant delays or nonlinearities, balancing loops may also produce oscillatory behavior.

Labeling feedback loops is a common practice to aid interpretation. Each loop is usually named based on the process or dynamic behavior it represents (e.g., "Innovation Reinforcement Loop" or "Regulatory Resistance Loop"), along with its polarity type. This helps identify dominant feedback structures and how they interact to drive system-wide behavior. In practice, most systems contain multiple interacting loops, and their combined effects can lead to complex, sometimes counterintuitive, system behavior.

An example of a CLD on the 'AV Adoption' (partially taken from our designed model for this project) is shown in Figure 7. It is to noting that this is a typical adoption model for any kind of autonomous vehicle (electric or other fuel-based). And a balance should be drawn between the social exposure dynamics, which results from more adoption, and necessary infrastructure constraints to enhance user experience to ultimately keep up the adoption rate.

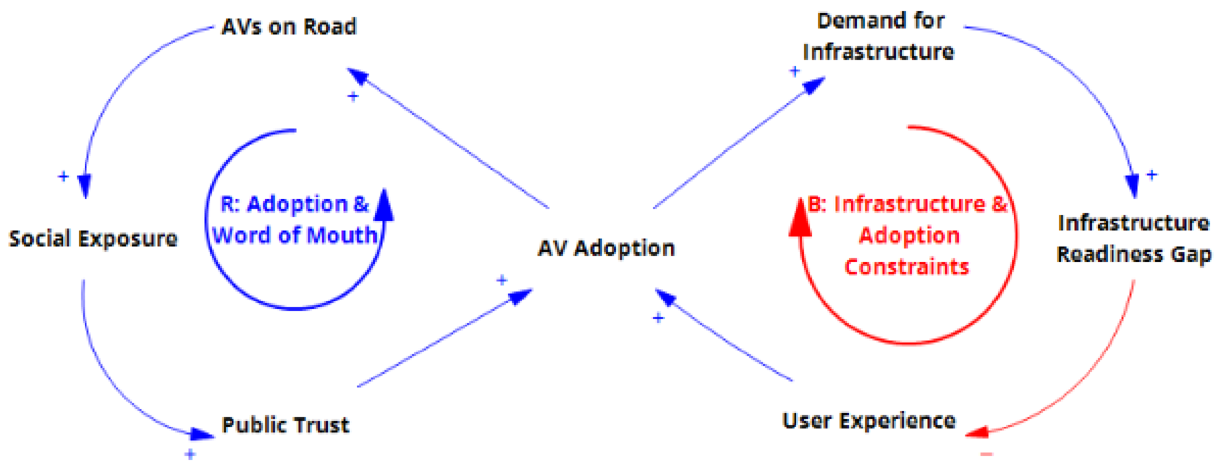


Figure 7: An example CLD of 'AV Adoption', demonstrating the counter-effect of social exposure and infrastructure constraints on the autonomous vehicle adoption

As can be seen from Figure 7, there are two loops in this diagram. The first one is the reinforcing loop, which is denoted by 'R: Adoption & Word of Mouth'. This feedback loop describes how the social exposure dynamics can impact the AV Adoption. All else equal, more AV adoption leads to more AVs on the road, which will ultimately lead to more public or social exposure of the AV. With more exposure on the road, public trust will also increase by seeing other users on the road. This rising trust will lead to higher adoption of AVs, thus closing the loop in a reinforcing manner.

The second loop, denoted by ‘B: Infrastructure and Adoption Constraints’, is a balancing loop demonstrating the impact of necessary infrastructure on the AV adoption mechanism. More adoption will create a demand for infrastructure. Given that we are still not fully ready infrastructure-wise, there will be a clear readiness gap in the market. And this will force a compromise in the user experience for the AV owners. If the user experience is not satisfactory, ultimately, the adoption rate will drop significantly.

In summary, building a qualitative and conceptual model is a crucial step for designing a system dynamics model. This step involves all the stakeholders to put their perspectives into the model. So, the conceptual model actually demonstrates a basic understanding of the problem being addressed and helps us to design an efficient system dynamics-based solution for the problem. The feedback-dynamic loops allow us to get a holistic overview of different actors in the system and detect any unexpected system behaviors as the interactions are developed between the variables. Thus, conceptual modelling through CLDs bears a significant value while designing an SD model [135].

### 3.2.2 Casual Loop Diagram for our ‘Policy Trade-off Model’

In the context of this research, exploring regulatory trade-offs between safety standards and the adoption of private autonomous vehicles (AVs), a causal loop diagram (CLD) was developed as the foundational tool for understanding and visualizing the system’s feedback dynamics. Figure 8 presents the proposed causal loop diagram for understanding the sustainable AV adoption mechanism from a safety perspective. This diagram was developed by brainstorming among a few academic experts in the autonomous vehicle policy planning area. This CLD captures both reinforcing and balancing mechanisms that influence the adoption rate of private AVs in response to policy shifts, technological development, and public perception.

The conceptualization began by identifying the key variables that influence the adoption of AV based on a synthesis of literature, expert consultation, and the defined research objectives. These include AV adoption rate, Safety regulation stringency, Public trust in safety, Policy advocacy, AV purchase cost, and Govt. Incentive, Infrastructure development, Public awareness, and User experience etc. Each of these variables interacts within a complex web of cause-and-effect relationships, leading to both direct and indirect influences across the system.

As we can see from Figure 8, the CLD consists of a total of 7 feedback loops: 4 of which are positive or reinforcing loops (denoted by R1, R2, R3 and R4) and the rest of the loops are negative or balancing loops (denoted by B1, B2, and B3). In the diagram, the 'blue' color demonstrates the positive or reinforcing effect, whereas the 'red' color translates the negative or balanced effect.

The first reinforcing loop (R1) demonstrates how the social exposure dynamics can impact private AV Adoption. All else equal, more AV adoption leads to more AVs on the road, which will ultimately lead to more public or social exposure of the AV. With increased exposure on the road, public trust will also rise as users see others on the road. This rising trust will lead to higher adoption of AVs, thus closing the loop in a reinforcing manner.

The reinforcing loop 2 (R2) describes the feedback dynamics between the GHG emissions and adoption rates. If the adoption rate is higher, then obviously there will be more AVs on the roads. And as we are here talking about only electrical AVs, so more AVs will reduce the GHG emissions in the environment and thus there will be a higher chance of favorable policy advocacy for the AVs. This will result in a higher percentage of govt. incentives as the government will be more interested in patronizing AV adoption. Higher incentives will also pave the way for higher adoption, thus closing the loop.

Reinforcing loop 3 (R3) explains the dynamics between the AV adoption and the regulatory stringency. More adoption of AVs means there will be more data for training the autonomous system which will lead to higher technological maturity ultimately. And the technological maturity will make the driving system more friendly and safer, causing much less AV related accidents. With less accidents occurring on the roads, the regulatory stringency regarding autonomous vehicles will loosen up more. If the regulatory stringency is less, then there will also be less cost to comply with the regulations and ultimately the purchase cost of AV will drop to facilitate more adoption.

The last reinforcing loop (R4) starts like the previous loop, where higher adoption leads to a smaller number of AV-related accidents due to better technological maturity. If there are less accidents on the road, there will be less concern regarding AV safety, which will increase the public's trust in AV safety. When the trust is higher, there will be less regulatory pressure, making a stronger case for policy advocacy in favor of autonomous vehicles. So, the government will be allocating a higher incentive ratio, resulting in higher adoption rates to close the loop.

Among the three balancing loops, the first one (B1) demonstrates the impact of necessary infrastructure on the AV adoption mechanism. More adoption will create a demand for infrastructure. Given that we are still not fully ready infrastructure-wise, there will be a clear readiness gap in the market. And this will force a compromise in the user experience for the AV owners. If the user experience is not satisfactory, ultimately, the adoption rate will drop significantly.

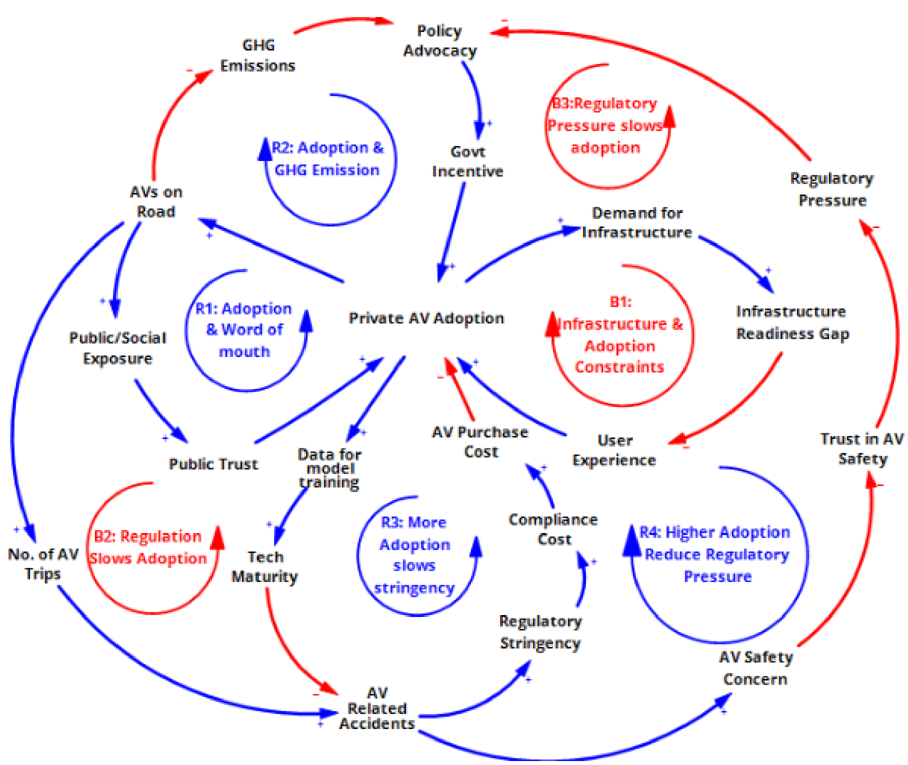


Figure 8: Causal loop diagram for understanding the main factors in the regulatory trade-off model for Private AV adoption.

The next balancing loop (B2) starts with a larger number of AVs resulting from higher adoption rates. More AVs lead to a higher number of total trips covered by AVs, ultimately leading to a higher number of accidents caused by AVs. If there are more accidents, then the regulatory stringency will be higher, obliging the government to implement stricter rules and regulations regarding AVs. Then, there will be higher compliance costs accordingly, and ultimately, this will increase the purchase cost of AVs for users. Higher costs will naturally slow down the private AV adoption rates.

The last balancing loop (B3) is about the relationship between the adoption rate and the regulatory pressure from the users. As before, more adoption leads to more AVs to more AV trips. When there are more AV trips, naturally, there will be more AV-related accidents, which will raise concerns related to AV safety and will eventually reduce the public's trust in AV safety. If the trust in AV safety is compromised, there will be higher regulatory pressure on the authority which will work against the policy advocacy for AV adoption. Ultimately, the govt. will reduce the incentive percentage by translating into lower adoption rates.

The feedback loops are more like the cause-and-effect diagram. For example, higher adoption causes more AVs to operate on the roads, which results in more social exposure for AVs. So one actor gets affected by the change in the other and thus translates the effect to other actors. Variables acting in more than one feedback loop are usually more influential in the system and demand more attention towards them. In our CLD, the most important variable is the 'Private AV Adoption', which is involved in a total of 7 feedback loops. The details of the 7 loops are presented below:

(1) Loop 1 with 4 participants:

Private AV Adoption → Demand for Infrastructure → Infrastructure Readiness Gap → User Experience → Private AV Adoption

(2) Loop 2 with 4 participants:

Private AV Adoption → AVs on Road→ Public/Social Exposure → Public Trust→ Private AV Adoption

(3) Loop 3 with 5 participants:

Private AV Adoption → AVs on Road → GHG Emissions → Policy Advocacy → Govt Incentive → Private AV Adoption

(4) Loop 4 with 7 participants:

Private AV Adoption → Data for model training → Tech Maturity → AV Related Accidents → Regulatory Stringency → Compliance Cost → AV Purchase Cost →Private AV Adoption

(5) Loop 5 with 7 participants:

Private AV Adoption → AVs on Road → No. of AV Trips → AV Related Accidents → Regulatory Stringency → Compliance Cost → AV Purchase Cost →Private AV Adoption

(6) Loop 6 with 9 participants:

Private AV Adoption → Data for model training → Tech Maturity → AV Related Accidents → AV Safety Concern → Trust in AV Safety → Regulatory Pressure → Policy Advocacy → Govt Incentive → Private AV Adoption

(7) Loop 7 with 9 participants:

Private AV Adoption → AVs on Road → No. of AV Trips → AV Related Accidents → AV Safety Concern → Trust in AV Safety → Regulatory Pressure → Policy Advocacy → Govt Incentive → Private AV Adoption.

Like these, other influential variables are 'AVs on the Road' and 'AV related Accidents', both are involved in 4 loops respectively. As our project is about AV adoption from a safety policy perspective, it's understandable that these two variables play a vital role in the system. Then, two other significant variables are the 'Govt incentives' and 'Policy Advocacy', which are present in 3 feedback loops of our model. Variables like 'Tech Maturity', 'Regulatory Stringency', 'Compliance Cost', 'AV Purchase Cost', 'Regulatory Pressure', 'Trust in AV Safety', and 'AV Safety Concern' are similarly important in our system, with each of them being involved in two feedback loops respectively.

### 3.3 Stock and Flow Model Development

Following the construction of the conceptual model using Causal Loop Diagrams (CLDs), the next step in the system dynamics modeling process involves the formulation of a quantitative stock-flow structure. While CLDs help in identifying feedback mechanisms and the underlying causal logic of the system, stock-flow diagrams serve as a more detailed and formal representation that enables simulation and analysis of system behavior over time.

In system dynamics, stocks represent accumulations or state variables that describe the current condition of the system at any point in time, such as the total number of private autonomous vehicles (AVs) adopted. Flows, on the other hand, represent the rates of change in these stocks, such as the rate of AV adoption or the regulation tightening rate. Stocks are affected by inflows and outflows, and they integrate this over time, thus capturing the system's memory and inertia.

To develop the stock-flow model for analyzing the regulatory trade-offs in private AV adoption, the key causal loops identified earlier, the reinforcing loops and the balancing loops, are operationalized through mathematical relationships between stocks and flows. Each feedback loop contributes to the dynamic hypotheses that guide model formulation. For instance:

- The stock of Private AVs in use is influenced by the Adoption Rate, which in turn is affected by Public Confidence in Safety, AV Purchase Cost, Govt. Incentive/Subsidy.
- The 'Public Confidence in Safety', a crucial endogenous factor, evolves as a function of safety perception improvement rate and safety concern rate.
- Regulatory Stringency Level is modeled as a policy-driven variable and is a function of the regulation tightening rate and regulation relaxation rate. This stock is potentially endogenized through a Policy Feedback Success

variable that depends on the perceived effectiveness of regulations in reducing accidents and improving public trust.

Each of these variables is represented quantitatively with initial conditions and equations based on literature-derived assumptions or plausible parameter estimates when empirical data is unavailable. The relationships between variables are typically modeled using nonlinear functions, lookup tables, or decision rules, consistent with practices in policy-oriented SD modeling [130].

The formulation also requires a clear definition of time delays, particularly where behavioral or technological processes do not respond instantaneously. For example, the Market Saturation Effect might not affect the adoption rate instantly, it may take a few years of time to put it into an effect. So, we have introduced the 'Delayed Saturation Effect', which makes sure there is a certain delay in the effect of market saturation on the adoption rate. These delays are explicitly modeled to capture realistic system dynamics and avoid misleading oversimplification of cause-effect timing.

Moreover, attention is given to model boundary adequacy, ensuring that all relevant feedback and external influences like government incentives, media narratives (both positive and negative), and are considered while keeping the model structure manageable and focused on the core research problem. Exogenous inputs like 'Regulatory factor' or 'Base Incentive' are treated as constant or scenario variables where appropriate.

The overall model is constructed and simulated using Vensim, a widely used SD modeling software. Vensim enables both qualitative structure building and quantitative simulation, offering tools for sensitivity analysis, policy testing, and behavior-over-time analysis. Once the stock-flow model is complete, it becomes the foundation for running baseline and policy scenario simulations to test the impact of different levels of safety regulation on AV adoption dynamics.

This rigorous translation from qualitative loops to quantitative structures is critical to ensuring the internal consistency, transparency, and policy relevance of the model. It allows researchers and decision-makers to explore not only the equilibrium outcomes but also the dynamic paths and unintended consequences of regulatory interventions in the emerging AV landscape.

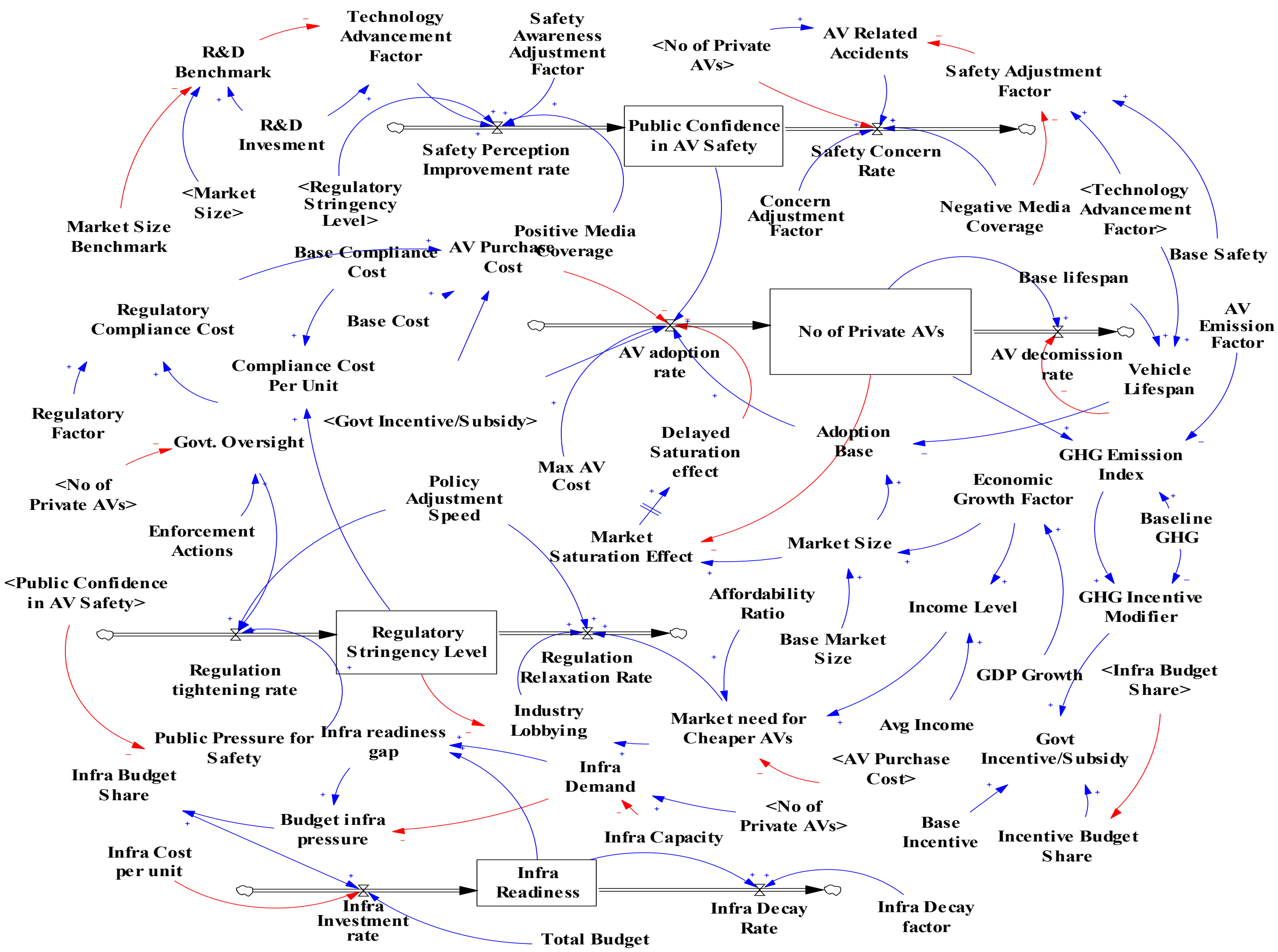


Figure 9: Proposed Stock & Flow model for regulatory trade-off model

Figure 9 consists of four main stock variables, eight flow variables, and fifty-one auxiliary variables in total. The stock variables are in the rectangular box with their corresponding flow rates associated with them and other elements are the normal auxiliary variables, which can be constant, rate, dependent or independent variables. Dependent variables, also known as 'Endogenous variables', are calculated within the system based on their relationship with other system elements. But the independent or constant variables (Exogenous variables) are introduced into the system. These variables can be influenced from outside and taken as a policy impact or statistical dataset. Usually, there might be a series of other factors or variables that can be considered to design such complex systems, but we should identify and focus on the ones which can interpret our objectives more clearly and what we desire to explore in our research. Due to the broadness of the system only the comparatively more significant variables are studies in our proposed model and the other variables are added to illustrate the capability of the working model.

The equations employed in this system dynamics model were designed following a combination of qualitative causal mapping and quantitative stock-flow formulation principles. The core structure of the model was first derived from causal loop diagrams (CLDs), which were developed to capture the dynamic interplay among safety regulation stringency, technological adaptation, public trust, and autonomous vehicle (AV) adoption rates. These CLDs served as the conceptual foundation for identifying feedback loops and interdependencies, which were then translated into mathematical relationships using first-order differential equations. Specifically, each stock variable, such as "Private AV Adoption," "Regulatory Stringency Level," or "Public Confidence in AV Safety", were governed by inflow and outflow equations that determined its rate of change over time. The method for defining these equations followed standard system dynamics practice, as described by Sterman [130], where each flow is a function of its influencing variables and includes time constants or sensitivity parameters to model delays and non-linear effects. Where empirical data was unavailable, parameter values were estimated using expert judgment, literature-based ranges, or were varied during sensitivity testing. The method involved formulating rate equations based on hypothesized causal relationships, defining mathematical functions (e.g., linear, goal-seeking, S-shaped, or delayed responses), and assigning parameter values based on literature or exploratory sensitivity testing. For example, the 'AV Purchase Cost' is influenced by Base Cost, Regulatory Compliance Cost, and Govt. Incentive and is calculated using a goal-gap formulation that adjusts over time as system conditions evolve.

$$AV\ Purchase\ Cost = [(Base\ Cost + Regulatory\ Compliance\ Cost) \times (1 - Govt.\ Incentive)$$

Here, the *Base Cost* is an exogenous constant that can be controlled from outside the system, and its values are derived from empirical data available online. Whereas *Regulatory Compliance Cost* and *Govt. Incentive* are endogenous variables that are changed internally as the system runs.

The mathematical implementation was carried out in Vensim, using its equation editor to define relationships among variables with algebraic and delay functions. In doing so, the model ensures internal consistency, dimensional validity, and the ability to simulate emergent behavior under different regulatory scenarios. This equation-based approach enables the exploration of how different regulatory strategies affect the trajectory of private AV adoption over time, based on logical and transparent model dynamics. A comprehensive list of the equations used in the model, including their descriptions, units and parameter values, and sources, is provided in the table below. The endogenous variables are changed as the system runs, but the values of exogenous variables can be changed from outside. And for our system, the value of maximum exogenous variables is directly derived from different literature and articles (references provided). The rest of them are assumed from the modern urban context of North America or Canada, based on recent scholarly reports. For the assumed values, explanations are given below the table with proper references. This level of transparency supports replication, validation, and future extension of the model for policy analysis and academic research.

Table 2: Equations of the endogenous variables used in the model

| Serial. No. | Variable Name | Equation / Definition | Unit |
|---|---|---|---|
| 1 | Adoption Base | Market Size / Vehicle Lifespan | vehicles/Year |
| 2 | AV adoption rate | Adoption Base * Public Confidence in AV Safety * Govt Incentive * (1 - (AV Purchase Cost / Max AV Cost)) * (1 - Delayed Saturation effect) | vehicles/Year |
| 3 | AV decommission rate | No of Private AVs / Vehicle Lifespan | vehicles/Year |
| 4 | AV Purchase Cost | (Base Cost + Regulatory Compliance Cost) * (1 - Govt Incentive) | Dollar/vehicle |
| 5 | AV Related Accidents | No of Private AVs / Safety Adjustment Factor | vehicles |
| 6 | Budget infra pressure | Infra Readiness Gap / Infra Demand | Dmnl |
| 7 | Compliance Cost Per Unit | Base Compliance Cost * (1 + (Regulatory Stringency Level / 10)) | Dollar/vehicle |

| | | | |
|---|---|---|---|
| 8 | Delayed Saturation effect | DELAY INFORMATION (Market Saturation Effect) | Dmnl |
| 9 | Economic Growth Factor | GDP Growth / 100 | Dmnl |
| 10 | GHG Emission Index | Baseline GHG - (AV Emission Factor * No of Private AVs) | tonnes CO2 |
| 11 | GHG Incentive Modifier | GHG Emission Index / Baseline GHG | Dmnl |
| 12 | Govt Incentive | Base Incentive * GHG Incentive Modifier * Incentive Budget Share | Dmnl |
| 13 | Govt. Oversight | Enforcement Actions / No of Private AVs | Dmnl |
| 14 | Incentive Budget Share | 1 - Infra Budget Share | Dmnl |
| 15 | Income Level | Avg Income * (1 + Economic Growth Factor) | Dollar |
| 16 | Industry Lobbying | Market Need for Cheaper AVs / Regulatory Stringency Level | 1 |
| 17 | Infra Budget Share | Budget infra pressure * 1 | Dmnl |
| 18 | Infra Decay Rate | Infra Readiness * Infra Decay factor | Dmnl/Year |
| 19 | Infra Demand | No of Private AVs / Infra Capacity | Dmnl |
| 20 | Infra Investment Rate | (Infra Budget Share * Total Budget) / Infra Cost per unit | Dmnl/Year |
| 21 | Infra Readiness | INTEG (Infra Investment Rate - Infra Decay Rate) | Dmnl |
| 21 | Infra readiness gap | Infra Demand - Infra Readiness | Dmnl |
| 22 | Market need for Cheaper AVs | 1-(AV Purchase Cost/(Income Level*Affordability Ratio)) | Dmnl |
| 23 | Market Size | Base Market Size*(1+Economic Growth Factor) | vehicles |
| 24 | Market Saturation Effect | 1- (No of Private AVs/Market Size) | Dmnl |
| 25 | No of Private Avs | INTEG (AV adoption rate- AV decommission rate) | Dmnl |
| 26 | Public Confidence in AV Safety | INTEG (Safety Perception Improvement rate -Safety Concern Rate) | Dmnl |

| | | | |
|---|---|---|---|
| 27 | Public Pressure for Safety | 1- Public Confidence in Safety | Dmnl |
| 28 | R&D Benchmark | R&D Investment *(1+(Market Size/Market Size Benchmark)) | Dollar/Year |
| 29 | Regulation Relaxation Rate | Industry Lobbying*Market need for Cheaper AVs *Policy Adjustment Speed | 1/Year |
| 30 | Regulation tightening rate | Govt. Oversight*Public Pressure for Safety *Policy Adjustment Speed | 1/Year |
| 31 | Regulatory Compliance Cost | Compliance Cost Per Unit*Regulatory Factor | Dollar/vehicle |
| 32 | Regulatory Stringency Level | INTEG (Regulation tightening rate-Regulation Relaxation Rate) | Dmnl |
| 33 | Safety Adjustment Factor | Base Safety*(1+Technology Advancement Factor) *(1-Negative Media Coverage) | Dmnl |
| 34 | Safety Concern Rate | (AV Related Accidents/No of Private AVs) *Negative Media Coverage *Concern Adjustment Factor | 1/Year |
| 35 | Safety Perception Improvement Rate | (Regulatory Stringency Level*Technology Advancement Factor *Positive Media Coverage*Safety Awareness Adjustment Factor) | 1/Year |
| 36 | Technology Advancement Factor | R&D Investment / R&D Benchmark | Dmnl |
| 37 | Vehicle Lifespan | Base lifespan*(1+Technology Advancement Factor) | Year |

Table 3: Exogenous variables input metrics

| **Serial. No.** | **Variable Name** | **Input Value** | **Unit** |
|---|---|---|---|
| 1 | Affordability Ratio | 0.2 (0-1 range) | 1/vehicle |
| 2 | AV Emission Factor | 2 [1] | tonnes CO2/vehicles |

| | | | |
|---|---|---|---|
| 3 | Base Compliance Cost | 2000 [107] | Dollar/vehicle |
| 4 | Avg Income | 25000 [136] | Dollar |
| 5 | Base Cost | 30000 [137] | Dollar/vehicle |
| 6 | Base Incentive | 0.1(0-1 range) | Dmnl |
| 7 | Base lifespan | 12 [2] | Year |
| 8 | Base Market Size | 10000[3] | vehicles |
| 9 | Base Safety | 1/1000[4] | Dmnl |
| 10 | Baseline GHG | 100000[5] | tonnes CO2 |
| 11 | Concern Adjustment Factor | 0.05[6] | 1/Year |
| 12 | Enforcement Actions | 0.2 (0-1 range) | vehicles |
| 13 | GDP Growth | 10 [136] | Dmnl |
| 14 | Infra Capacity | 1000 [7] | vehicles |
| 15 | Infra Cost per unit | 1e+06[8] | Dollar |
| 16 | Infra Decay factor | 0.05[9] | 1/Year |
| 17 | Market Size Benchmark | 25000[10] | Vehicles |
| 18 | Max AV Cost | 50000 [138] | Dollar/vehicle |
| 19 | Negative Media Coverage | 0.2(0-1 range) | Dmnl |
| 20 | Policy Adjustment Speed | 0.2(0-1 range) | 1/Year |
| 20 | Positive Media Coverage | 0.6(0-1 range) | Dmnl |
| 21 | R&D Investment | 0.5(0-1 range) | Dollar/Year |
| 22 | Regulatory Factor | 0.5(0.1 range) | Dmnl |
| 23 | Safety Awareness Adjustment Factor | 0.2 (0-1 range) | 1/Year |
| 24 | Total Budget | 1e+08[11] | Dollar/Year |

[1] A commonly cited lifecycle emission for an EV in countries with mixed power grids is ~2 tonnes $CO_2$/year. With higher mileage expected from AVs, especially if used privately but heavily, 2 tonnes/vehicle/year is a conservative but supportable assumption for urban-level system dynamics modeling[139][140][141].

[2] Base lifespan of a fully autonomous vehicle has been estimated between 12-15 years in different literature. Being on the conservative side, we took the 12-year value for our simulation[142].

[3]The Base Market size is taken as a sample of 10000 vehicles of the given city. This is a conservative assumption for the initial installation of the AVs in a city; the simulation can be run based on a higher market size as well by adjusting the necessary variables.

[4] According to NHTSA Fatality and Injury Reports (2022), the rate of fatal crashes is around 1 per 100 million vehicle miles. The rate of injury crashes is around 1 per 100,000 miles. When adjusted for severity and perception, 1 significant incident per 1,000 vehicles/year is a reasonable and conservative benchmark[143][144].

[5] The Baseline GHG value of 100,000 tonnes $CO_2$ approximates the annual greenhouse gas emissions from a conventional private vehicle fleet in a mid-sized urban setting prior to AV adoption. This figure is consistent with emissions estimates from typical ICE vehicles and allows the model to meaningfully capture the impact of AV-related emission reductions. It also serves as a stable reference point for the GHG Incentive Modifier, enabling dynamic policy feedback based on relative emission trends rather than absolute values alone[145][146][143].

[6] Concern Adjustment factor has been taken as an assumption. It’s been assumed that people’s concern is adjusted (positive or negative) after every 5 accidents out of every 100 accidents caused by AVs.

[7] The infrastructure capacity was set at 1,000 vehicles, representing the initial upper limit of AV-supportive infrastructure in the modeled urban setting. This value aligns with the initial AV fleet size, ensuring that infrastructure strain emerges gradually as adoption grows. It enables the model to realistically trigger infrastructure-related budget trade-offs, which influence AV adoption through reduced government incentives. The value is chosen to balance feedback sensitivity and reflect a city transitioning from traditional infrastructure to AV-compatible systems[147][148].

[8] The infrastructure cost per unit assumed at $1,000,000 per AV, reflecting the comprehensive investment required to equip a city with AV-supportive infrastructure per additional vehicle. This includes physical infrastructure, digital communication networks, and urban planning adaptations. The value also functions as a scaling mechanism within the model, ensuring a realistic feedback loop between infrastructure demand, government budget constraints, and the pace of AV adoption.

[9] The infrastructure decay factor was set at 0.05 (1/year) to reflect an assumed annual degradation rate of 5%, capturing both physical wear and technological obsolescence of AV-related infrastructure. This value aligns with typical depreciation rates found in infrastructure asset management literature and ensures realistic modeling of maintenance needs and budgetary pressure over time.

[10] The Market Size Benchmark was set at 25,000 vehicles, representing the anticipated scale of a mature private AV market in a mid-sized city. This value facilitates normalization in scaling functions (e.g., R&D investment

responsiveness) and enables realistic simulation of policy impact and technological development under varying adoption scenarios.

[11] The Total Budget was set to $100 million/year, consistent with public expenditure estimates for AV-related infrastructure and incentive programs in mid-to-large cities. This amount allows simulation of realistic trade-offs between subsidy allocation and infrastructure readiness while maintaining model stability. Budget estimates are aligned with planning benchmarks found in urban transportation reports and smart mobility policy recommendations [149][150].

### 3.4 Scenario Design

The scenarios are designed to be realistic yet exploratory, providing a basis for understanding how different combinations of regulatory and incentive mechanisms shape the adoption trajectory of private AVs.

Table 4: Scenario Description

| **Scenario Description** | |
|---|---|
| **Scenario** | **Description** |
| Baseline | Low incentive and regulatory strictness |
| Scenario 1 | Zero incentive with very strict regulations |
| Scenario 2 | Higher incentives with low regulatory strictness |
| Scenario 3 | Moderate incentives with a balanced stringency level |

Keeping the other exogenous and endogenous variables as it, the scenarios vary from each other based on the input metrics of the variables listed in the following table:

Table 5: Input Metrics of Different Scenarios

| Input Metrics of the Scenarios | | | | |
|---|---|---|---|---|
| **Input Metrics** | **Baseline** | **Scenario 1** | **Scenario 2** | **Scenario 3** |
| Base Incentive (Range 0-1) | 0.1 | 0 | 0.7 | 0.5 |
| Regulatory Factor (Range 0-1) | 0.2 | 0.8 | 0.1 | 0.5 |
| Initial Public Confidence in AV Safety | 0.1 | 0.1 | 0.1 | 0.1 |
| Initial Regulatory Stringency Level | 0.2 | 0.8 | 0.1 | 0.5 |

### 3.5 Model Boundary and Assumptions

Establishing a clear and well-justified model boundary is a foundational step in any system dynamics modeling process. It ensures that the model remains focused, manageable, and aligned with the research objectives while capturing the core feedback mechanisms that govern the system's behavior. The present study explores the dynamic trade-offs between regulatory safety stringency and the adoption of privately owned autonomous vehicles (AVs) in an urban context. To this end, the boundaries and underlying assumptions of the system dynamics model were defined to represent a simplified yet policy-relevant abstraction of the real-world system.

- **Temporal Boundary:**

  The simulation timeframe spans from 2025 to 2055, allowing for the analysis of long-term effects of regulatory and policy interventions on AV adoption patterns. This 30-year horizon aligns with common practice in transportation planning and policy forecasting studies, offering sufficient time to observe S-shaped diffusion behavior, delayed feedback effects, and infrastructure development cycles[151][152].

- **Geographical and Demographic Scope:**

  The model is scoped at the city level in a developed urban setting. It assumes a relatively homogeneous population with respect to socio-economic and technological readiness. Population growth is held constant throughout the simulation to isolate the effects of policy and technological drivers from demographic shifts. This approach mirrors modeling conventions in AV adoption research, where demographic complexity is often abstracted to focus on systemic policy levers[153].

- **Sectoral and Technological Boundary:**

  The model focuses exclusively on the private ownership of autonomous passenger vehicles (Levels 3–5), excluding shared AV fleets, ride-hailing services, and freight automation. This distinction is essential for analyzing regulatory safety impacts on individual ownership decisions, which differ fundamentally in motivation and behavior from shared mobility contexts

[154][155]. The model assumes that the AVs in question are electric vehicles (EVs) by default, consistent with the convergence of electrification and automation trends.

**Core Assumptions:**

The model operates under several structural and behavioral assumptions:

1. **Technology Progression is Linear and Irreversible:**

   Once a higher level of automation is achieved and made commercially available, it remains available and is not withdrawn due to policy changes or market forces. The model assumes smooth technological progression toward higher levels of automation (Level 4 and 5) without setbacks, reflecting trends in AV research and pilot deployments[156].

2. **AV Purchase Decisions Are Driven by Perceived Cost-Benefit:**

   Adoption is modeled as a function of economic incentives, perceived safety, public trust, and regulatory stringency. Behavioral responses are based on aggregated population trends rather than individual-level heterogeneity. This assumption is consistent with diffusion of innovation theory and macro-level SD models[130].

3. **Public Trust Responds to Accidents and Media Framing:**

   Public acceptance of AVs is modeled as a dynamic variable, influenced by accident frequency and media narratives. High-profile incidents reduce trust, which in turn suppresses adoption rates, while sustained safe performance builds confidence over time[157].

4. **Government Response is Endogenous:**

   Government incentives (e.g., subsidies, tax rebates) and regulatory stringency are modeled as endogenous responses to system variables such as AV accidents, GHG emission levels, and AV market penetration. This dynamic policy adjustment mirrors real-world feedback processes in transportation and energy policy [151][130]

These assumptions allow the model to maintain simplicity while still yielding meaningful insights into adoption dynamics and regulatory trade-offs.

**Exclusions from the Model Boundary:**

To maintain model parsimony and focus on strategic policy analysis, several elements are deliberately excluded:

- Individual-level heterogeneity in income, preferences, or risk perception.
- Geopolitical shocks such as wars, pandemics, or energy crises.
- Inter-city or inter-state policy diffusion, assuming regulatory decisions are made at the city level.
- Technical subsystem dynamics such as software development cycles, sensor failures, or AI decision-making algorithms.

These exclusions are consistent with best practices in system dynamics, which emphasize boundary adequacy over boundary completeness, that is, including enough detail to capture the dominant behavior-generating feedback loops while omitting detail that adds complexity without insight [130][158].

### 3.6 Model Validation and Behavior Testing

Model validation is a critical phase in the system dynamics (SD) modeling process, ensuring that the developed model accurately represents the real-world system it is intended to simulate. In the context of this thesis, where the focus lies on the regulatory trade-offs between safety standards and the adoption of private autonomous vehicles (AVs), validation aims to test the model's structural and behavioral integrity and establish its credibility for use in policy analysis.

System dynamics models are often abstract representations of reality, so validation does not always involve direct numerical prediction. Instead, as emphasized by Sterman [130]. Validation in SD is about building confidence that the model is an appropriate tool for gaining insights into system behavior. For this purpose, multiple validation techniques were employed, categorized into structural validation, behavior reproduction tests, and sensitivity analysis.

#### 3.6.1 Structural Validation

Structural validation ensures that the model structure, the causal relationships, equations, and logic faithfully represent the real-world processes and interactions it aims to capture. This includes verifying the conceptual soundness of the causal loop diagrams, as well as the mathematical integrity of the stock-flow formulation.

To support structural validation, several techniques were used:

- **Expert Judgment:** The model structure was reviewed considering existing literature and contemporary research on AV adoption, transportation regulation, and safety standards[159][108]. This helped assess whether the included variables and feedback loops reflected well-understood phenomena.
- **Dimensional Consistency Tests:** Each equation in the model was checked for unit consistency using Vensim's built-in diagnostic tools to ensure mathematical correctness. And after checking, we found all the units of the model are consistent and don't showcase any kind of discrepancy.
- **Extreme Condition Testing:** The model was tested under hypothetical extreme values (e.g., zero public confidence in safety or zero govt. incentive) to verify whether it produced reasonable and interpretable outputs without collapsing or generating unrealistic behavior (shown in Figure 10 and Figure 11).

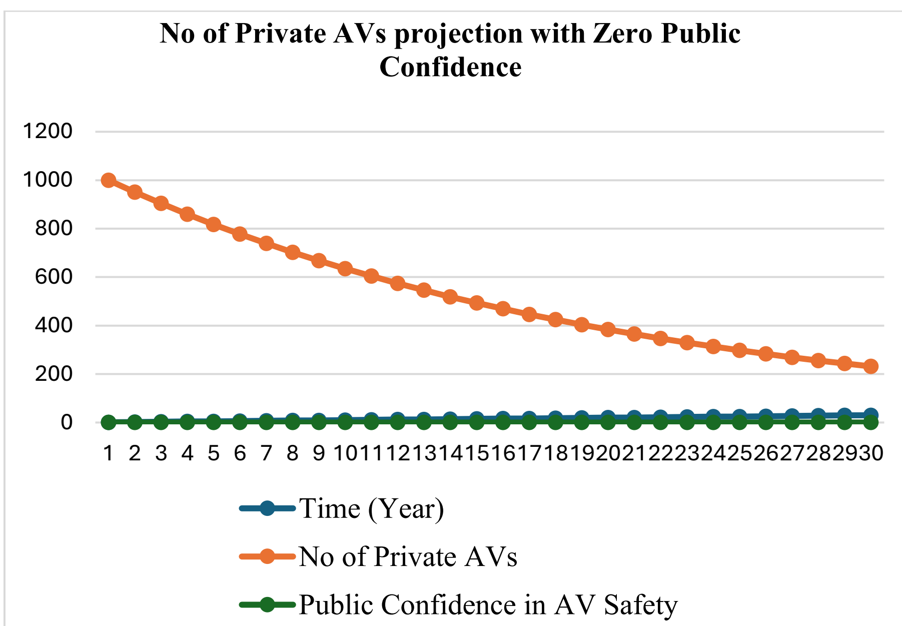


Figure 10: No. of Private AVs projection with zero public confidence in safety over the years

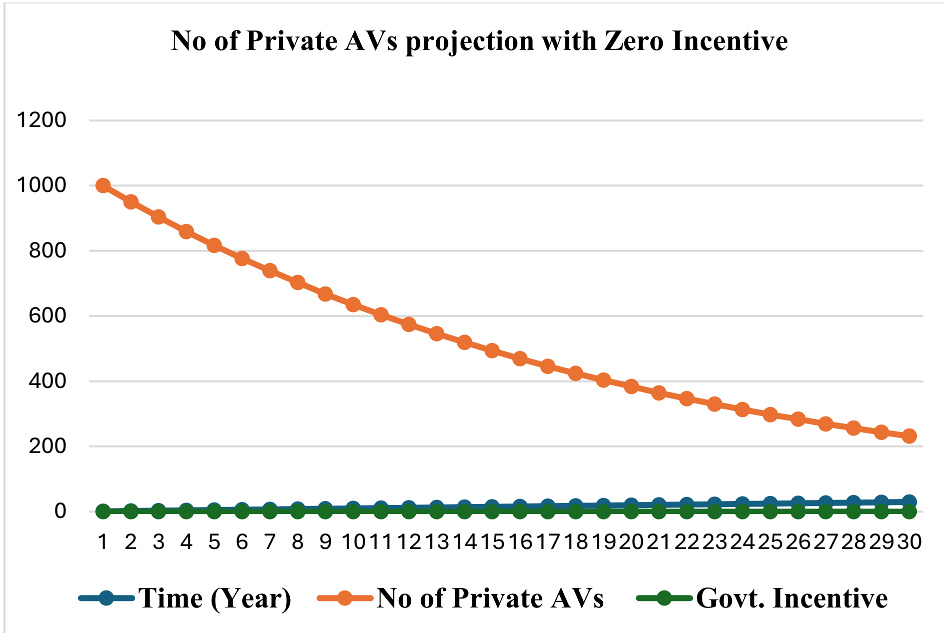


Figure 11: No. of Private AVs projection with zero govt. incentives over the years

### 3.6.2 Behavior Reproduction Tests

Behavior testing focuses on assessing whether the model can reproduce stylized facts or known behavior patterns observed in real or hypothetical AV adoption scenarios. While the adoption of AVs is still in its nascent stages and comprehensive empirical data is limited, the model was assessed on its ability to replicate general trends such as:

- S-shaped adoption curves, typical of technological diffusion processes (Figure 12) [160].

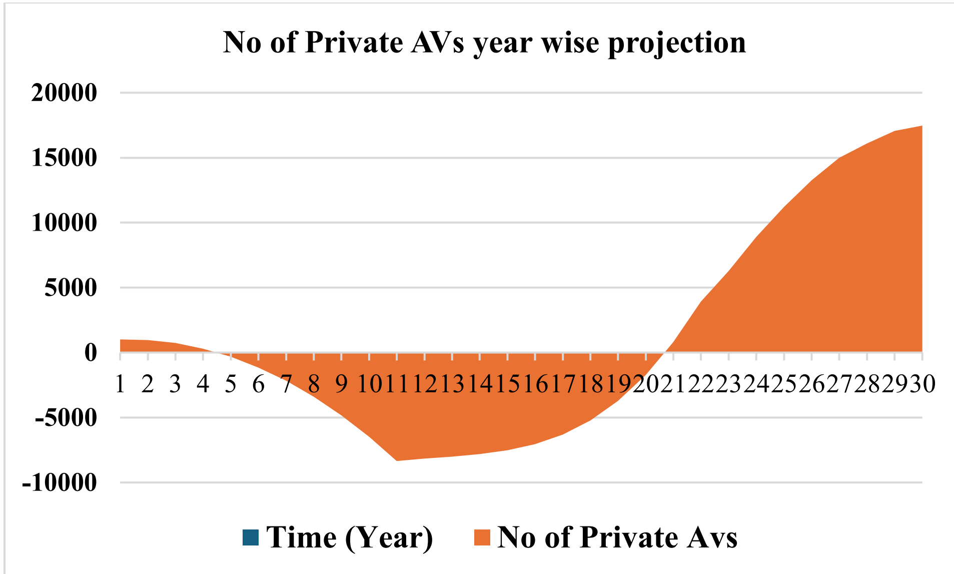


Figure 12: 'S' shaped nature of the projection of 'No. of Private AVs' over the years

- The delayed effect of market saturation on actual AV uptake due to the time required for regulatory adaptation.
- Oscillatory or unintended policy impacts, such as feedback delays in AV adoption following the implementation of regulatory standards to control the high adoption rate.

Simulations were run for baseline and hypothetical policy scenarios, and the resulting behavior was analyzed to ensure alignment with both theoretical expectations and insights from the literature [156][161]. Any anomalous or counterintuitive behaviors were investigated and traced back to potential structural issues or overly simplistic assumptions.

### 3.6.3 Sensitivity Analysis

Given that many parameters in the model are based on assumptions or estimated from qualitative insights due to limited empirical data, sensitivity analysis plays a vital role in understanding how changes in parameter values affect model behavior. The model was subjected to one-way and multi-way sensitivity tests to identify:

- **High-leverage variables**: Parameters to which model outputs are particularly sensitive.
- **Robustness of key policy insights**: To explore whether increased regulatory stringency consistently leads to diminished or delayed AV adoption across different parameter sets.

This analysis helps determine the reliability of policy recommendations derived from the model, by identifying which conclusions are generalizable and which are contingent on specific assumptions. It also serves as a precursor to the policy scenario testing conducted in the next chapter. The full sensitivity analysis report targeting our main stock variable, No of Private AVs, has been attached below:

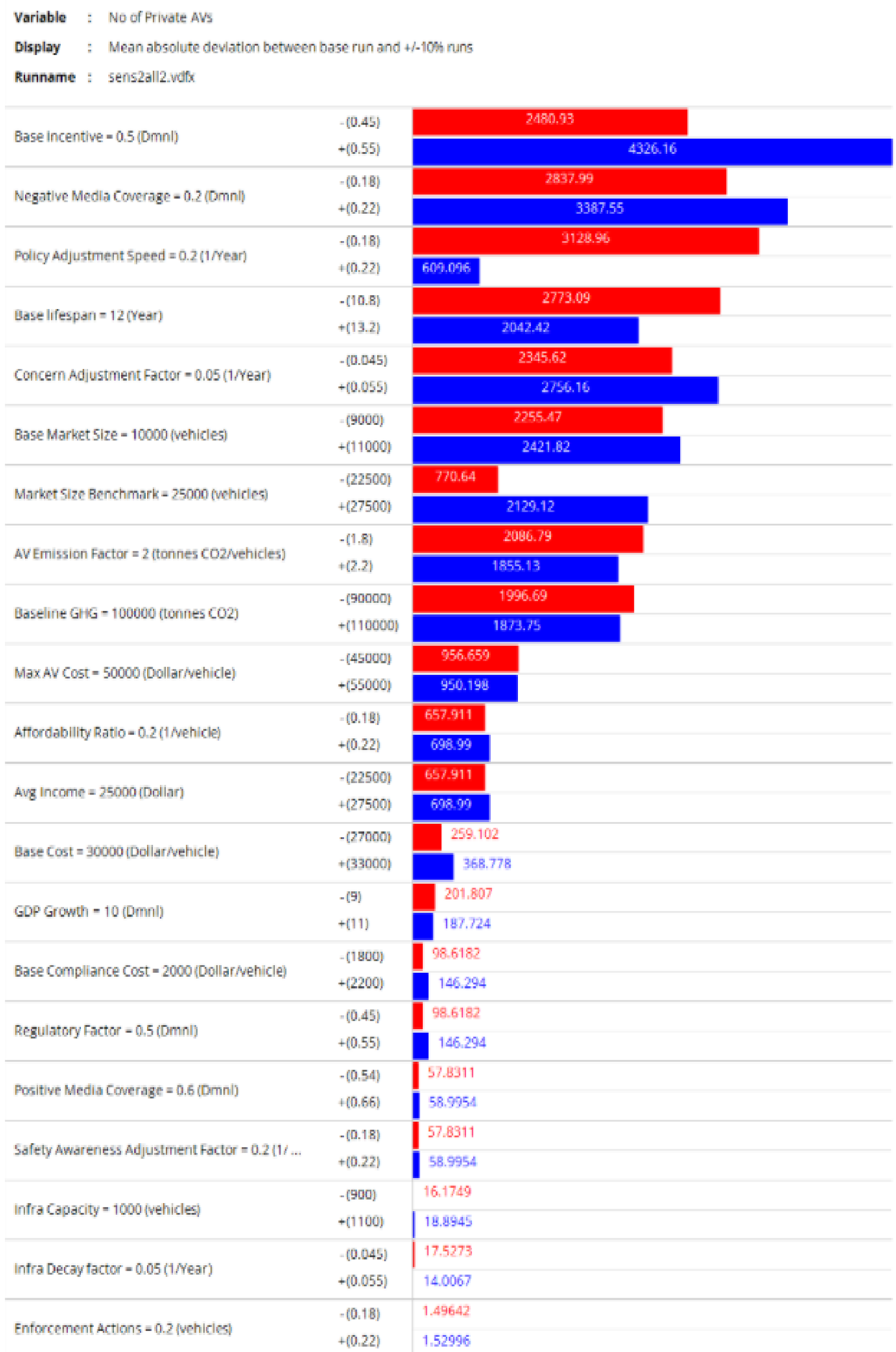


Figure 13: Sensitivity Analysis Report with regards to ‘No. of Private AVs’

# Chapter 4

# Results and Scenario Analysis

## 4.1 Overview of Simulation Scenarios

This section presents the simulation results derived from the developed system dynamics model, aimed at evaluating how varying levels of safety regulation stringency influence private autonomous vehicle (AV) adoption. Given the multidimensional nature of AV policy design, the simulations include a baseline scenario as well as three key policy scenarios that reflect different regulatory strategies. These scenarios are crafted to explore the trade-offs between enhancing public safety and accelerating the deployment of AVs, with emphasis on the resulting dynamics of public trust, AV accident rates, government incentives, and infrastructure readiness.

Each simulation run covers a 30-year time horizon, which is appropriate for observing the mid- to long-term impacts of policy decisions in an emerging technology market.

The simulation results are analyzed in terms of both quantitative model outputs (e.g., adoption rates, accident rates, public trust index) and qualitative behavioral patterns (e.g., reinforcing or balancing loop dominance, policy delays, non-linear dynamics). This dual focus allows for both evidence-based insights and system-level interpretation, in alignment with system dynamics principles[130].

### 4.2 Baseline Scenario: Natural Progression without Major Policy Intervention

The baseline scenario represents the evolution of private autonomous vehicle (AV) adoption over a 30-year period without any significant changes in government policy, regulatory stringency, or additional incentives. This scenario serves as the reference point against which other policy scenarios will be evaluated. It reflects a status quo in which the system dynamics evolve based on the internal structure of the model, capturing feedback loops between public trust, accident rates, infrastructure readiness, AV cost, and adoption behavior.

**Scenario Design Assumptions:**

- Regulatory stringency, government incentives, and infrastructure investment levels remain at their initial values throughout the simulation.
- Public trust fluctuates based on AV accident rates and media influence, but no targeted policy is implemented to sway perception. Initially, this index was kept at 0.1, assuming there is very little confidence among users about the AVs;
- The AV market is primarily driven by technological availability, consumer attitudes, and organic system behavior.
- No corrective measures are taken to counterbalance early resistance or misalignment in the adoption environment.

**Model Behavior and Observations:**

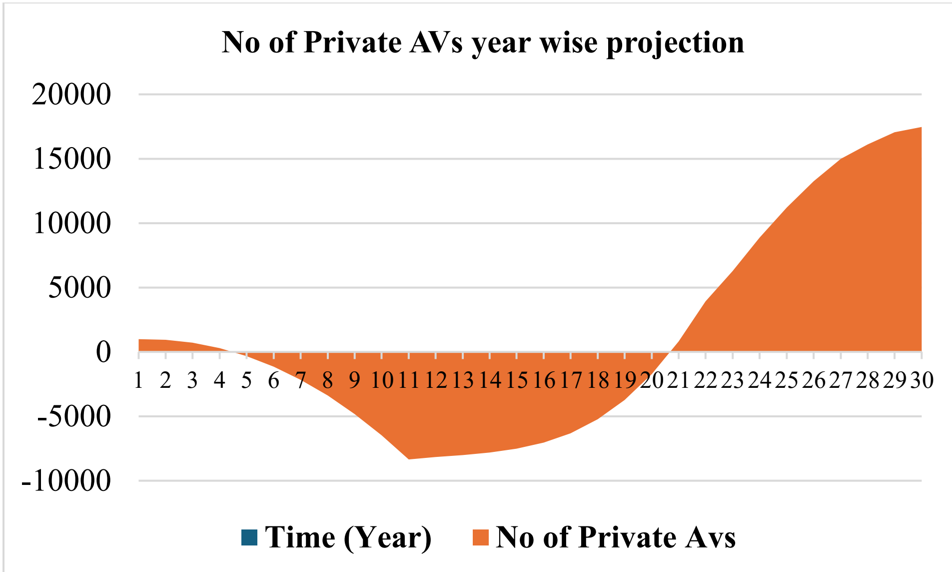


Figure 14: Private AV adoption under the baseline scenario

**1. Initial Decline and Negative Adoption Values (Years 1–20): As shown in the figure 10,**

- As shown in the figure, the number of private AVs begins at 1,000 in Year 1 but drops quickly, turning negative by Year 5 (−330) and reaching a low of around −8,348 by Year 11.

- This decline reflects strong balancing feedback loops driven by high AV accident rates, negative media coverage, low public trust, and inadequate infrastructure.

- The persistent negative values through Year 20 suggest that removals or rejections outweigh new AV purchases, indicating systemic resistance during the early phase.

- These outcomes highlight the consequences of early safety concerns and weak regulatory support, which suppress adoption despite initial momentum.

**2. Recovery and Accelerated Growth (Years 21–30)**

- A shift occurs around Year 21, when net AV adoption becomes positive (813) and begins to climb steadily.
- The curve follows a typical S-shaped diffusion pattern [160], with adoption reaching ~17,468 by Year 30.
- This turnaround suggests that positive feedback loops, from improved public trust, fewer accidents, favorable media sentiment, and enhanced infrastructure, begin to dominate.
- The results imply that once the system passes a tipping point, self-reinforcing adoption dynamics take hold and drive sustained growth.

**3. Interpretation and Implications**

- The extended initial decline underscores the importance of early-stage policy support to counteract public skepticism and system fragility.
- Without intervention, the model shows that it could take two decades for AV adoption to recover organically, risking loss of public and political momentum.

- The baseline scenario serves as a reference case to evaluate how different policy interventions might reduce resistance and accelerate adoption earlier in the timeline.

**Key Takeaways:**

- The baseline scenario highlights inherent instability and potential failure in early adoption without proactive regulatory or policy intervention.
- Despite the eventual uptrend, waiting for organic adoption dynamics to self-correct could take decades, during which public and political support for AVs might erode.
- The early negative values act as a warning signal that misaligned or weak early system conditions can lead to prolonged resistance.

This baseline result serves as a crucial reference to evaluate the effectiveness of subsequent policy interventions in correcting the system's early imbalances and accelerating sustainable AV adoption.

### 4.3 Policy Scenario 1: High Regulatory Stringency with Minimal Government Incentives

This scenario explores the effect of a strict regulatory environment on private AV adoption in the absence of meaningful government incentives. It aims to simulate a real-world case where authorities impose rigorous safety and compliance standards for AV operation, such as advanced certification, stricter liability laws, or extensive testing, without any accompanying financial support for adoption.

**Scenario Design Assumptions:**

- **Regulatory Stringency Level: High** – Regulations around AV safety, compliance, and technical standards are significantly tightened.
- **Government Incentives: Minimal** – No subsidies, tax breaks, or promotional programs are provided.
- Other factors (e.g., media influence, accident dynamics, and infrastructure readiness) evolve naturally based on the model structure.
- Public Confidence reacts endogenously to safety improvements but is not actively enhanced through incentives or outreach.

**Model Behavior and Observations:**

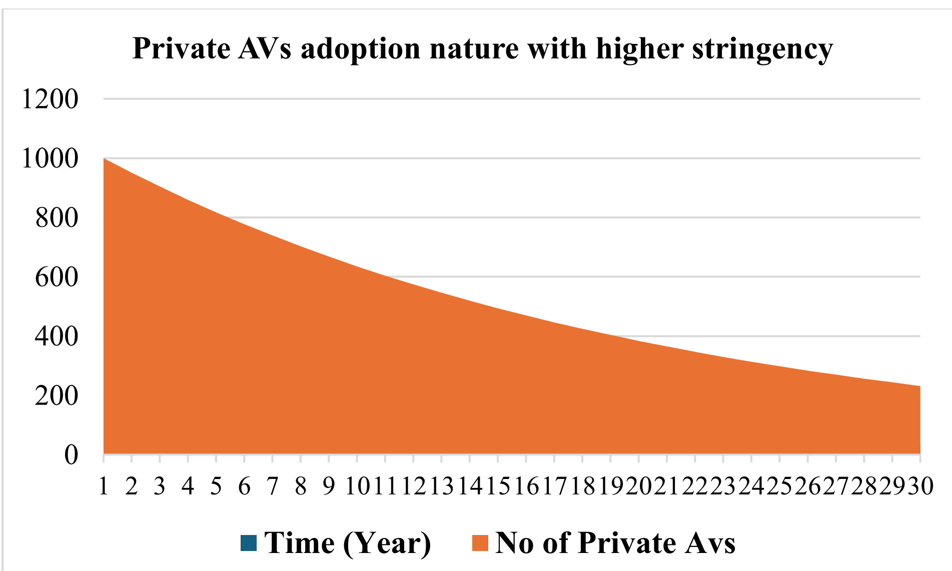


Figure 15: Private AVs adoption nature with higher stringency level (Scenario 1)

**1. Steady and Gradual Decline in AV Adoption (Years 1–30):** As shown in the figure above,

- Starting from 1,000 private AVs in Year 1, adoption decreases consistently over the 30-year period, falling to 231.7 AVs by Year 30.
- This slow but persistent erosion reflects the cumulative burden of high regulatory stringency without compensatory incentives.
- Unlike the baseline, which eventually recovers, this scenario shows a controlled but irreversible decline, suggesting that regulatory pressure alone is enough to suppress long-term adoption.

**2. Lack of Reinforcing Growth Dynamics:**

- The model shows no signs of recovery or positive feedback loops throughout the simulation.
- Public trust, infrastructure readiness, and other potential reinforcing mechanisms appear muted or blocked due to stringent regulations and minimal policy support.
- As a result, the AV market fails to gain momentum, remaining locked in a downward trajectory.

**3. System Behavior and Policy Insights:**

- The simulation is dominated by balancing feedback loops, where rising AV costs, regulatory compliance burdens, and public hesitancy outweigh adoption drivers.

- Without financial incentives or supportive infrastructure, consumer willingness to adopt AVs steadily diminishes.
- Even if regulations improve safety, their deterrent effect, unaccompanied by enabling policies, stalls adoption.

**Key Takeaways**

- A strict regulatory regime without incentives leads to gradual disengagement from AV ownership.
- The model highlights the risk of over-regulation in isolation, which can stall technological transitions despite safety gains.
- This scenario underscores the need for regulatory-policy balance: supportive incentives are essential to mitigate adoption resistance caused by strict rules

This scenario serves as a cautionary case: without incentives to counterbalance the deterrent effect of high regulatory burden, AV adoption may stagnate or erode, ultimately delaying the transition to autonomous mobility.

### 4.4 Policy Scenario 2: High Government Incentives with Minimal Regulatory Stringency

This scenario simulates a policy environment where government provides strong financial and strategic support for AV adoption (e.g., subsidies, tax relief, public campaigns), but regulatory oversight remains minimal. The goal is to observe how aggressive incentivization affects AV adoption when safety standards are relaxed or underdeveloped.

**Scenario Design Assumptions:**

- **Government Incentives: High** – Subsidies, tax credits, promotional programs, or easy financing options are maximized to boost AV ownership.
- **Regulatory Stringency: Low** – Safety, liability, and certification requirements are kept at a minimum, reducing barriers to AV entry.
- Public trust evolves endogenously but is not externally boosted by strong safety standards or regulatory assurance.
- The AV market experiences minimal friction in terms of cost and adoption process.

**Model Behavior and Observations:**

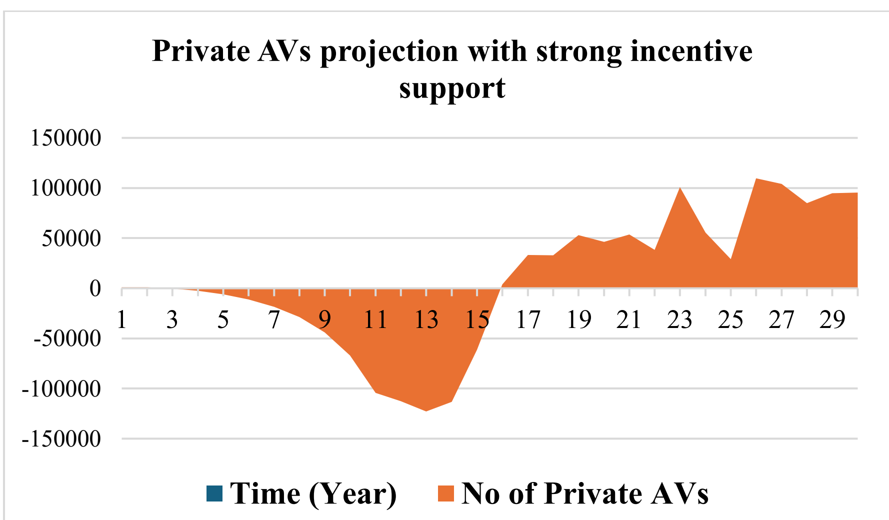


Figure 16: No. of Private AVs over the years, with strong incentive support from the government.

**1. Severe Instability and Negative Spiral (Years 3–15):**

- After a stable start, AV ownership plummets into negative values by Year 3 (hypothetically), bottoming out in around Year 13.
- This indicates a clear model breakdown and nonphysical behavior, likely driven by:
    - Excessively strong reinforcing loops (e.g., incentives → trust → adoption) without dampening controls.
    - Absence of regulatory oversight, allowing exaggerated growth in adoption despite mounting risks.
    - Missing balancing loops, such as those accounting for AV accidents, trust shocks, or infrastructure overload.
- The system lacks safety safeguards or risk containment, causing AV adoption to spiral unrealistically.

**2. Rapid Recovery and Oscillating Growth (Years 16–30):**

- The model rebounds sharply in Year 16, entering a volatile phase of exponential and erratic growth:
    - From 3,760 AVs in Year 16 to over 100,000 AVs by Years 23 and 26, with sharp dips and rebounds.

- AV ownership sees wild fluctuations:
    - Peaks in Years 23 and 26, followed by declines (Years 24–25), and another upswing toward Year 30 (~95,600 AVs).
- These fluctuations point to unstable positive feedback loops, where adoption is driven largely by incentives and public trust, but without sufficient structural or safety checks.

**3. System Dynamics Interpretation:**

- The simulation is dominated by uncontrolled reinforcing feedback, likely from loops such as:
    - Incentives → Adoption → Word of Mouth/Public Trust → More Adoption
- However, the system fails to introduce critical balancing feedback, such as:
    - Accident feedback or safety incidents that reduce trust
    - Infrastructure readiness constraints
    - Budget limitations on prolonged incentive spending
    - Quality degradation from insufficient regulation

**Key Takeaways:**

- Over-incentivization without regulatory moderation leads to extreme instability, including nonphysical negative values and volatile overshooting behavior.

- The AV market in this scenario exhibits high short-term responsiveness, but poor long-term stability.
- This suggests that unregulated growth, even if driven by generous policies, may eventually erode public trust or policy credibility, causing unpredictable market responses.

While incentives are powerful tools to accelerate AV adoption, without regulatory guardrails, the system becomes volatile and unsustainable. Balanced policy design, where financial support is coupled with minimum safety standards and infrastructure planning, is essential for fostering stable, realistic AV adoption**.**

### 4.5 Policy Scenario 3: Balanced Regulatory Stringency and Government Incentives (Moderate-Moderate)

This scenario simulates a balanced policy approach, where both regulatory safety standards and government incentives are maintained at moderate levels. The aim is to assess whether a middle-ground strategy can promote stable and sustainable adoption of private AVs over time.

**Scenario Design Assumptions:**

- **Government Incentives: Moderate** – Adequate support is provided through financial aid, tax benefits, or awareness programs, but not to the extreme level of aggressive subsidization.
- **Regulatory Stringency: Moderate** – AV manufacturers must meet baseline safety, reliability, and performance standards. Regulatory feedback from public trust and AV incidents exists but is not overly restrictive.

- Public trust builds gradually through a balance of incentive-driven visibility and trust in safety mechanisms.
- Infrastructure and government budget constraints are partially considered.

**Model Behavior and Observations:**

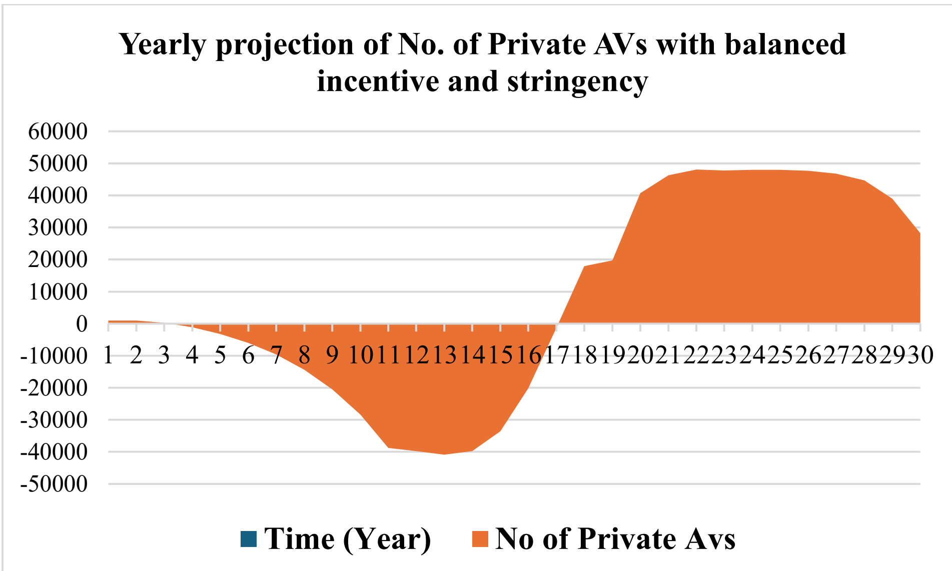


Figure 17: Projection of private AV adoption with moderate incentives and balanced stringency level

**1. Initial Decline and System Strain (Years 1–17):**

- The AV population begins at 1,000 units in Year 1 but enters a steep negative trajectory, hypothetically reaching the lowest reduction in the vehicle numbers in around Year 13.
- This sustained decline reflects early-stage systemic friction caused by:
    - Residual public distrust and safety concerns,
    - Lag in infrastructure readiness,

    - Limited momentum from only moderate incentives,
    - Time delay in policy effectiveness and public response.
- However, compared to Scenario 2, this decline is more controlled and shows signs of stabilization by Year 14 onward.

**2. Reversal and Entry into Positive Territory (Years 15–18):**

- The system begins to recover, rising from -33,540.9 in Year 15 to -1,311.55 in Year 17, indicating:
    - The slow but steady impact of moderate regulations restores trust,
    - Infrastructure catching up to deployment needs,
    - AV safety records and media narratives are beginning to shift positively.
- A major turning point occurs in Year 18, with the system moving into positive adoption territory (17,983.7 AVs), marking the onset of viable diffusion.

**3. Steady and Controlled Growth Phase (Years 18–27)**

- AV ownership climbs from 17,983.7 in Year 18 to a peak of ~47,989.6 AVs in Year 24, with only slight fluctuations afterward.
- Unlike Scenario 2, the growth is:
    - Smooth, stable, and realistic,
    - Free of extreme spikes, crashes, or negative values,

    - Indicative of a system governed by well-balanced reinforcing and balancing feedback loops.
- Public trust, infrastructure, and incentives are in harmony, resulting in controlled exponential growth followed by a plateau.

**4. Plateau and Soft Landing (Years 27–30)**

- A gradual decline begins post-peak:
    - From 46,827.7 AVs in Year 27 to 28,233.6 AVs by Year 30,
- This soft landing reflects:
    - Possible policy shifts e.g., reduced public incentives as the market matures,
    - Budget reallocation toward long-term infrastructure,
    - Early adopter saturation,
    - Natural market stabilization effects from regulatory maturity and reduced novelty.

**Key Takeaways:**

- This scenario most closely mirrors a real-world S-curve of technology adoption, with:
    - Initial resistance,
    - Gradual uptake,

    - Sustained growth,
    - Followed by a plateau and mild tapering.
- Moderate policies fostered stable adoption, avoided volatility, and kept public trust, regulatory oversight, and government spending in balance.
- Negative values early in the simulation reflect real-world lags and delays in behavioral and systemic adaptation, but the recovery trajectory validates the policy mix.

**Policy Insight:**

- A balanced strategy, neither overly aggressive nor overly cautious, proves the most effective and sustainable for long-term AV adoption.
- Moderate incentives drive interest without destabilizing budgets, while moderate regulations secure public safety and trust without deterring adoption.
- This validates the hypothesis that policy synergy, rather than policy extremity, is key to fostering responsible innovation and public acceptance in AV diffusion.

The balanced approach in Scenario 3 proves to be the most effective policy mix in promoting sustainable and stable AV adoption. Neither over-regulation nor over-incentivization is necessary; a harmonized strategy provides the most robust and manageable growth in private AV ownership. This supports the hypothesis that policy synergy, rather than extremity, is key to enabling long-term technology diffusion and public acceptance.

### 4.6 Behavioral Comparison of the Scenarios

The following comparison highlights the differing system behaviors across four policy scenarios based on variations in government incentive levels, regulatory stringency, and regulatory factors. All scenarios evolve with an endogenous Public Confidence in AV Safety variable, which dynamically responds to accidents, regulations, and trust loops.

Each scenario produces distinct adoption trajectories for private AVs due to these varying inputs:

- Baseline Scenario shows gradual S-shaped growth, suggesting natural adoption through internal feedback mechanisms without external push or pressure.
- Scenario 1 (Strict Regulation, No Incentives) exhibits a consistent and steady decline, indicating that high regulatory pressure with no supportive incentives significantly suppresses AV adoption.
- Scenario 2 (High Incentives, Loose Regulation) generates an unstable boom-bust cycle. Aggressive incentives spark rapid growth, but insufficient regulation leads to public trust breakdown and collapse in adoption.

- Scenario 3 (Balanced Strategy) displays realistic, stable S-curve behavior. After an initial decline due to inertia, adoption picks up and stabilizes, showing the benefits of a moderate, harmonized policy approach.

Table 6: Behavioral Comparison of Scenarios

| **Behavioral Comparison of the Graphical Results** | | | | |
|---|---|---|---|---|
| **Output Metric** | **Baseline** | **Scenario 1** | **Scenario 2** | **Scenario 3** |
| Initial Trend (Years 1–10) | Decline | Gradual decline | Sharp collapse | Decline |
| Mid-term Trend (Years 11–20) | Rebound | Continued decline | Oscillatory rebound | Gradual rebound towards the end of the decade |
| Long-term Trend (Years 21–30) | S-curve to around 20K | Down to 231.7 | Overshoot to 1M, then upswing towards the end | Growth to ~47K, soft decline to 28K |
| Curve Shape | S-shaped | Linear decay | Oscillatory, unstable | Smooth S-shaped |
| Stability & Realism | Stable, Realistic | Realistic | Unrealistic | Stable, realistic |

This behavioral comparison supports the conclusion that Scenario 3's balanced regulatory and incentive approach is most effective in achieving long-term, stable AV adoption while maintaining public trust and systemic sustainability.

# Chapter 5

# Discussion and Implications

The growing interest in autonomous vehicles (AVs) presents both an opportunity and a challenge for policymakers. This study set out to explore a key policy dilemma: how to balance regulatory safety standards to encourage private AV adoption. Using a system dynamics (SD) modeling approach, this research simulated the effects of regulatory stringency, government incentives, infrastructure readiness, public trust, and AV-related accidents over a 30-year horizon.

The simulation in this study was structured around three distinct policy scenarios, ranging from strict safety-focused regulation to incentive-heavy, growth-driven approaches. The resulting behavioral patterns were evaluated for realism, sustainability, and policy relevance. These insights contribute to a more nuanced understanding of how interrelated feedback loops in AV policy environments drive long-term system behavior.

This chapter discusses the key findings in depth, interprets their implications for AV adoption policies and system dynamics theory, and highlights the limitations of the study. The aim is to provide a coherent narrative linking simulation outcomes with actionable lessons for researchers and policymakers working on emerging transportation systems.

### 5.1 Key Findings and Interpretations

This section synthesizes the simulation results and scenario behaviors, highlighting key dynamics observed across the model outputs. Each finding is interpreted in terms of its theoretical significance and policy relevance.

#### 5.1.1 Trade-off Between Regulatory Stringency and Adoption Rate

Across all scenarios, an inverse but smooth relationship was observed between regulatory stringency and the private AV adoption rate. Higher stringency led to increased compliance costs, lowering affordability and slowing adoption, especially in the first two decades. However, over time, regulatory pressure helped stabilize public trust and safety outcomes.

This dynamic confirms existing theoretical expectations from system dynamics and innovation diffusion literature, that excessive early regulation may deter adoption, but the absence of oversight can trigger safety concerns and public backlash [130][160].

Policymakers must phase in regulatory measures gradually while balancing safety concerns with economic feasibility, particularly during the early stages of market diffusion.

#### 5.1.2 Role of Public Trust and Media Influence

The Public Confidence in AV Safety variable emerged as a key driver of adoption behavior. This trust was found to be highly sensitive to media narratives and accident rates, both of which were influenced by regulatory stringency and technological maturity.

This aligns with prior findings that perceived safety, not just actual performance, affects public uptake of new mobility technologies[162][163].

Governments and AV manufacturers must proactively shape public perception through transparent reporting, responsible media engagement, and visible safety demonstrations.

### 5.1.3 Delayed but Crucial Infrastructure Feedback

Infrastructure readiness displayed lagged but crucial effects. In early simulation years, high government incentives boosted AV adoption. However, insufficient infrastructure capacity caused bottlenecks in the mid-to-late periods, triggering soft declines in adoption under certain scenarios.

This delay illustrates the “shifting the burden” archetype in system dynamics, where symptomatic solutions (incentives) temporarily mask structural deficiencies (infrastructure) [164].

Strategic and anticipatory investment in charging, maintenance, and AV traffic systems must complement financial incentives to ensure long-term scalability.

### 5.1.4 Oscillatory Behavior Under Imbalanced Policies

Scenario 2 (over-incentivization with lax regulation) led to an unsustainable overshoot and crash behavior. Rapid adoption outpaced safety development, causing accidents to rise and trust to collapse. This resulted in public and regulatory backlash, leading to a sharp drop in adoption after peaking.

This validates warnings from AV policy studies that excessive early growth without regulatory guardrails can destabilize the market[63][78]. A balanced co-evolution of regulation and market incentives is essential to avoid boom-bust cycles in AV adoption.

### 5.1.5 S-Curve Adoption and Behavioral Realism

The baseline and Scenario 3 both showed realistic S-curve adoption patterns, influenced by gradual saturation, trust buildup, and budget reallocation from incentives to infrastructure over time.

This reflects classical innovation diffusion behavior, where adoption accelerates after early trust and affordability barriers are overcome, then stabilizes as market saturation approaches[106] .

Policies should expect and accommodate nonlinear uptake, with flexible mechanisms that can evolve across early, mid, and late adoption stages.

## 5.2 Implications for Policy and Practice

This section outlines the actionable insights derived from the system dynamics simulations, guiding policymakers and AV stakeholders. The findings suggest the need for nuanced, adaptive policymaking rather than one-size-fits-all solutions.

### 5.2.1 Phase-In Regulatory Stringency Gradually

The model demonstrated that imposing strict safety regulations too early can stall AV adoption due to increased purchase costs and compliance burdens. Conversely, delayed regulatory action can erode public trust through higher accident rates. Thus, a phased regulatory strategy, beginning with soft standards and evolving toward stricter mandates as the market matures, is optimal. A tiered safety framework should be developed that increases in stringency over time, calibrated to AV market maturity and public readiness[77] [104].

### 5.2.2 Align Incentive Structures with Infrastructure Development

While public incentives initially drive AV uptake, long-term adoption is constrained by infrastructure bottlenecks (e.g., charging, AV-friendly roads). A dual strategy is needed, one that balances short-term subsidies with parallel investments in long-term infrastructure.

AV incentive programs should be integrated with infrastructure planning at the city and regional levels to avoid adoption plateaus[78] [165]

### 5.2.3 Build and Maintain Public Trust Proactively

Public trust emerged as a dynamic, nonlinear variable influenced by both AV performance and media narratives. Simulations showed that once trust collapses (as in Scenario 2), it takes significant time and effort to rebuild. This highlights the fragile nature of trust in emerging technologies.

Concerned authorities should implement transparency mandates for AV performance data and encourage regular, independent safety assessments. Partner with media outlets and public institutions to promote fact-based communication[162][25].

### 5.2.4 Avoid Over-Reliance on Subsidies

Over-incentivization without proper oversight (as modeled in Scenario 2) may trigger unsustainable growth, resulting in backlash. A balance must be struck between stimulating early adoption and maintaining long-term viability through sustainable market conditions.

We should design incentive policies with sunset clauses, gradually tapering benefits as the market stabilizes, and redirecting resources toward system-level improvements[63][166]

### 5.2.5 Use Dynamic Modeling for Policy Forecasting

The complexity of the AV ecosystem, with interlinked social, technical, and institutional feedback loops, makes static policy tools insufficient. The system dynamics approach proved highly effective in testing multiple policy pathways and forecasting unintended consequences.

System dynamics and other simulation-based tools should be incorporated into urban mobility and AV policy planning to ensure robust scenario testing and adaptive strategies [134][130].

## 5.3 Real World Applications and Case Comparison

While our simulation model offers valuable insights into the potential outcomes of various policy scenarios, grounding these findings in real-world contexts enhances the model's credibility and relevance. In this section, real-life examples from cities and countries that have adopted different autonomous vehicle (AV) policies are examined to assess how closely these experiences align with the model's projections. By exploring both successful and problematic implementations, we can better understand how the interplay of regulatory stringency and government incentives shapes AV adoption dynamics in practice. These examples not only validate the balanced policy scenario identified in this study as the most stable and sustainable but also highlight critical pitfalls that can emerge from misaligned or overly extreme policies. The aim is to bridge the gap between theoretical insights and practical governance by evaluating how actual policy choices have influenced the trajectory of AV adoption globally.

### 5.3.1 Policy Illustrations: Good Policy vs Bad Policy

The regulatory landscape for autonomous vehicles (AVs) varies significantly across jurisdictions, with vastly different outcomes. A cautionary case is Austin, Texas, which adopted an almost entirely hands-off regulatory stance under a 2017 preemption law. This permissive framework allowed companies like Waymo, Cruise, and Tesla to deploy AVs with minimal oversight, limited only by basic insurance and DMV registration requirements [167]. While this relaxed approach rapidly attracted AV deployments and businesses, it soon led to mounting public concern. Local agencies received over 70 complaints from residents and first responders within just a few months. ranging from erratic behavior, near-miss collisions, to emergency vehicles being blocked and AVs failing to heed police directions [168]. One firefighter described the situation as “alarming,” with AVs coming within five feet of fire trucks despite emergency signals being activated. This lack of robust oversight illustrates the risks of an overly permissive policy: rapid deployment may generate innovation but can undermine public trust and create safety hazards.

In contrast, California is exemplified by a more balanced regulatory framework. The state enforces comprehensive testing permits and mandates extensive crash reporting, safety-driver requirements, and performance thresholds for AV deployment[169]. This has fostered a more cautious rollout of AVs, with companies like Waymo and Mercedes-Benz obtaining permits aligned with concrete safety standards and highway-only operating conditions[167]. While California's stricter approach may slow innovation, it promotes structured growth, builds public trust through transparency, and ensures measurable safety outcomes.

Similarly, Arizona offers a case of moderate regulation. The state adopted clear insurance, operational, and liability guidelines, creating a predictable yet flexible environment for AV testing. This framework has attracted sustained investment and pilot programs without incurring the community backlash seen in Austin. By providing oversight monitors safety indicators while allowing innovation to proceed, Arizona presents a model aligned with the balanced scenario identified in this thesis, pairing moderate regulations with enabling policies to achieve stable and safe AV adoption.

These contrasting examples illustrate that overly lenient policies, while potentially accelerating innovation in the short term, often backfire by eroding trust and amplifying safety risks. Conversely, balanced regulatory frameworks, such as those in California and Arizona, can foster sustainable AV adoption while maintaining public confidence, supporting the thesis argument that moderate regulation, paired with thoughtful incentives, is the most robust policy approach for the future of urban autonomous mobility.

### 5.3.2 Real-Life Examples of Balanced Policy Cases:

Following the identification of the balanced scenario, moderate regulatory stringency paired with sustained but reasonable government incentives, as the most effective policy strategy in the simulation model, it is important to explore whether such a balance has been achieved in real-world settings. A balanced policy approach aims to simultaneously promote innovation in AV technologies and ensure public safety, infrastructure readiness, and trust. Unlike extreme policy positions, either over-regulation that stifles innovation or unchecked incentivization that risks public backlash, balanced frameworks attempt to harmonize stakeholder interests and foster gradual, stable adoption. This subsection highlights regions that have embraced such policy equilibrium and examines the extent to which their outcomes reflect the model's prediction of a smooth, S-shaped adoption curve.

- **Case of Singapore:** Singapore offers a compelling real-world example of a "balanced scenario" where moderate safety regulations are harmoniously paired with structured incentives and infrastructure readiness, closely aligning with the balanced policy archetype modeled in this thesis.

  Beginning in 2014, Singapore launched its "Smart Nation" initiative, embedding AVs into a broader urban mobility and sustainability vision. Singapore's 2014 AV roadmap underlined its ambition to become a testbed for future transport technologies, enabling pilot trials and R&D collaboration among agencies and industry partners [170]. By 2017, the city-state enacted the Road Traffic (Autonomous Motor Vehicles) Rules, which established a regulatory sandbox allowing AV testing to proceed under clearly defined operational boundaries, safety-driver requirements, insurance mandates, and accident-reporting protocols[170]. Rather than imposing overly stringent restrictions, this adaptive regulatory model emphasized gradual expansion of testing zones, from closed campuses to selected public roadways, as vehicle performance and public comfort evolved.

Simultaneously, Singapore deployed targeted incentives and support measures to build AV infrastructure and amplitude. In 2019, the city released Technical Reference 68, setting national standards for vehicle behavior, functional safety, cybersecurity, and data interoperability, providing certainty for AV developers while fostering industry confidence [171]. Strategic trials of Level 4 AV shuttles, autonomous buses, street sweepers, and logistics vehicles have been rolled out in controlled environments across active testbeds like Western Singapore, Resorts World Sentosa, and one-north [172]. These pilots were launched with a safety driver onboard and backed by co-investment partnerships, public-sector support, and active local stakeholder engagement, ensuring that both infrastructure and mobility systems were ready for integration.

The outcomes mirror the modeled balanced scenario. Public trust in AV systems has steadily increased, with surveys demonstrating widespread acceptance thanks to transparent governance and carefully staged deployments [173]. Meanwhile, AV penetration has been gradual and stable, marked by incremental growth rather than boom-and-bust cycles. The infrastructure's gradual scaling up (AV-ready lanes, charging points, 5G support) and phased expansion of operating areas have helped sustain a smooth S-curve in adoption, precisely the diffusion trend seen in our balanced policy simulations.

In summary, Singapore's approach to AV development, characterized by progressive regulation, targeted standardization, strategic infrastructure deployment, and transparent pilots, aligns closely with the thesis's balanced policy scenario. As such, it offers empirical validation that integrated, moderate, and feedback-aware policy frameworks can catalyze stable AV adoption while safeguarding safety and fostering system readiness.

- **Case of Shenzhen, China**: Shenzhen exemplifies a "balanced" regulatory approach that mirrors the moderate regulation–moderate incentives strategy simulated in this thesis. In March 2021, the Shenzhen Municipal People's Congress enacted the first local regulations for intelligent connected vehicles (ICVs) in China, the "Regulations on the Administration of ICVs", that came into effect on August 1, 2022. These rules clarified operational scope, testing zones, liability assignment, data security, and insurance requirements for AVs, enabling controlled yet substantive on-road deployment (Shenzhen Congress, 2021) [174][175].

  Under this regulatory framework, Shenzhen permitted Level 4 autonomous mini-buses and robo-taxis to operate in designated zones, starting in early 2023 across multiple districts. As of mid-2024, 944 km of public roads were opened for AV testing, covering highways and urban streets, with over 1,000 test permits issued to 14 companies, including Pony.ai and AutoX [176]. These deployments operate within tightly defined geofenced areas, under on-board safety supervision and standard cybersecurity protocols [177].

Critically, Shenzhen's policy didn't just control testing, it linked AV rollout to strategic infrastructure investments and incentive programs. The city implemented "vehicle–road–cloud" integration pilots by mid-2024, deploying 5G-V2X-enabled roads, intelligent traffic signals, and public charging facilities to support AV functionality [178][179][180]. Moreover, subsidies and administrative support were offered to AV operators who met safety and performance benchmarks within these infrastructure-enhanced corridors.

These efforts have produced robust and stable AV advancement: hundreds of AVs are now operating with zero reported major incidents, and test permit volumes continue to rise incrementally, confirming steady growth without explosion or collapse. Shenzhen's experience validates the thesis's balanced policy outcome, where moderate regulation, coupled with targeted incentives and infrastructural readiness, supports a sustained S-shaped adoption curve without compromising safety or system stability.

- **Case of Germany:** Germany provides a strong illustration of the balanced policy scenario, implementing moderate regulations accompanied by structured incentives and technical standards, supportive of safe and gradual

AV adoption. In July 2021, Germany passed the Act on Autonomous Driving, a significant amendment to the Road Traffic Act, legalizing Level 4 autonomous vehicles in defined operating zones, such as highways and specific urban areas, as long as vehicles are accompanied by a “technical oversight” system and meet stringent safety and data protection requirements. This legal framework also mandates accident-avoidance systems with prioritization of human life and non-discrimination in crash scenarios [181].

Complementing this regulatory foundation, Germany has introduced targeted incentives and support measures for AV development. Federal agencies, including the Federal Ministry for Digital and Transport (BMDV), launched funding programs for autonomous vehicle pilots, especially in public transport and smart city contexts, under the broader CCAM (Cooperative, Connected and Automated Mobility) initiative. These pilots are conducted in interconnected urban regions, such as Munich. where vehicles operate within designated digital corridors supported by real-time traffic and communication infrastructure [182].

Early outcomes reflect stability and measured growth: deployment zones remain limited to specific corridors, technical supervisors oversee remote operations, and permits are granted conditionally, with strong insurance and liability frameworks in place [183]. Public trust is being carefully cultivated through structured, well-controlled trials, and incremental integration into public transport fleets is underway, particularly in Munich's shared AV shuttle deployments (autonomous mobility-on-demand services)[184].

Germany's approach reflects the thesis-modeled "balanced scenario": comprehensive yet flexible regulations, technology-enabling standards and standards-compliant infrastructure, moderate incentives for pilots, and systematic oversight that aligns with safety objectives. This coordinated framework supports a measured diffusion of AVs, consistent with the thesis's predicted smooth S-shaped adoption curve, while simultaneously safeguarding public safety and maintaining system responsiveness.

The examined cases of China, Singapore, and the Germany collectively illustrate how a balanced policy approach, grounded in moderate regulatory oversight and sustained, targeted incentives, can facilitate stable and scalable autonomous vehicle adoption. These regions demonstrate that fostering AV innovation does not require compromising on safety or infrastructure planning. Instead, a coordinated policy ecosystem that evolves with technological maturity and public readiness can generate sustained growth, public trust, and meaningful market penetration. The observed real-world outcomes from these countries validate the core findings of this study: that a harmonized policy strategy is not only theoretically sound but also practically effective. As AV technologies continue to mature, the balanced policy path offers a replicable and resilient framework for cities and nations seeking long-term success in autonomous mobility.

### 5.3.3 Possible AV Failure Prevention Through Balanced Policy

Several high-profile autonomous vehicle (AV) incidents suggest that careful, feedback-driven policy frameworks, like those proposed in this thesis, could have mitigated or even prevented some of these failures. A central example is the fatal Uber autonomous vehicle crash in Tempe, Arizona, in March 2018, where a self-driving Uber struck and killed pedestrian Elaine Herzberg. The National Transportation Safety Board (NTSB) identified multiple contributing factors: (1) the safety driver was distracted, watching streamed shows on her phone over 30% of the time before the crash; (2) emergency braking was disabled during autonomous operation; and (3) Uber's internal safety culture lacked robust risk management and data oversight (NTSB, 2019) [185].

Politically, Arizona's virtually nonexistent AV regulatory regime, lacking permit requirements, mandatory risk assessments, or human oversight, facilitated rapid but uncoordinated AV deployment [186]. The incident triggered an immediate, albeit reactive, policy response: Governor Doug Ducey suspended Uber's testing privileges, and the NTSB recommended mandating risk management plans, human attention monitoring, retention of emergency brakes, and enforcement of safety culture measures for all test operators nationwide [187].

Several of these policy adjustments align closely with the balanced feedback-aware design proposed in this thesis. Specifically:

- Pre-deployment of risk management plans and mandatory crashes and data reporting would establish structural accountability, reducing reliance on reactive fixes.
- Enforced attention monitoring systems (e.g., cameras, sensors) could reduce automation complacency, where operators become distracted when technology seems infallible, addressing a critical failure mode seen in Uber's crash.
- Reactivation of emergency braking functionality within autonomous mode, combined with cyber-physical system audits, would maintain safety when software decisions fail.

Academic analyses support the effectiveness of these policy tools. Taeihagh and Lim emphasize the importance of risk governance frameworks and regulatory culture in preventing AV-related failures [188], whereas Kohli and Chadha demonstrate how computer vision enhancements, mandated through vehicle certification, could detect pedestrians more reliably in low visibility [189].

These corrective measures bear striking similarity with the policy feedback loops in the balanced scenario: dynamic regulation, attention to enforcement, and continuous infrastructure and safety feedback. If fully implemented before testing, such policies may have prevented the Tempe tragedy. Indeed, the Uber incident and subsequent license suspension exemplify how neglecting coordinated oversight and ignoring feedback can lead to preventable human harm and delay public trust, an outcome directly addressed by the balanced policy scenario outlined in this thesis.

Another recurring example is Tesla's misuse of its Partial Automation (Autopilot) system, which has been linked to at least 13 fatal collisions between 2016 and 2023 [190]. Criticism centers on insufficient system monitoring, misleading marketing, and weak regulation. Scholars have argued for policy interventions similar to those in this thesis: mandatory driver monitoring, crash data reporting, and limits on system marketing and use, enforced through clear performance thresholds. Though Tesla incidents did not involve fully autonomous vehicles, they reflect similar governance gaps and feedback voids.

In summary, policy design improvements mirroring the balanced model, combining moderate but proactive regulation, attention systems, and data-driven enforcement, could have forestalled or mitigated high-profile AV failures. These cases validate the thesis's core argument: feedback-rich, adaptive policy frameworks are essential for ensuring safe, sustainable AV deployment. Without such structures, AV systems may cause harm, degrade trust, and ultimately stall adoption.

## 5.4 Theoretical Contributions

This section explores how the study's findings advance the theoretical understanding of autonomous vehicle (AV) adoption dynamics, particularly through the lens of system dynamics modeling, technology diffusion theory, and socio-technical systems thinking.

### 5.4.1 Extension of Technology Diffusion Theory

Classical diffusion models [160] typically assume a smooth S-shaped adoption curve driven by innovator and early adopter behavior. However, this study demonstrates that in the case of AVs, a complex, safety-critical, and disruptive technology, adoption is heavily mediated by regulatory, psychological, and infrastructural feedback loops. The findings suggest that diffusion is not simply a matter of technological readiness or market pull but is shaped by evolving public trust, media narratives, and government policy shifts.

AV adoption does not follow a classical linear or logistic pattern but exhibits systemically driven, multi-phase transitions, validating calls for more complex, endogenous models of diffusion[191].

### 5.4.2 Contribution to Socio-Technical Transitions Literature

The study reinforces the perspective that AVs represent not just a technological innovation but a transformation within a broader socio-technical system. By integrating public perception, regulatory feedback, infrastructure dynamics, and government budgeting into a unified model, the research provides a clearer picture of the co-evolution of technology and society.

The dynamic interaction of human factors (trust, safety perceptions), policy mechanisms, and technical change highlights the importance of feedback-driven models in analyzing socio-technical transitions[192].

### 5.4.3 Advancement in System Dynamics Modeling of AVs

While previous AV-related system dynamics models have explored individual factors like cost or emissions[193] this study advances the methodology by incorporating multiple reinforcing and balancing feedback loops across time. The model contributes to SD theory by demonstrating how policies, trust, and infrastructure jointly determine long-term system behavior. This work supports the value of endogenous structure modeling in transportation innovation, contributing a robust framework that other scholars can adapt to similar disruptive mobility technologies[130] [134]

### 5.4.4 Policy Feedback as a Central Mechanism in AV Adoption

The inclusion of regulatory stringency as a variable that both influences and is influenced by accident rates and public pressure reveals a significant theoretical insight: policy is not an exogenous force but an endogenous actor in technology adoption. This recursive role of policy introduces complexity often absent in standard economic or logistic models.

AV adoption processes involve not only consumer and market dynamics but also adaptive policymaking cycles contributing to theories of policy feedback and dynamic governance [194][195].

## 5.5 Study Limitations

While this study offers valuable insights into the dynamic interplay between regulatory safety standards and private AV adoption, several limitations should be acknowledged to contextualize the results and inform future research.

### 5.5.1 Simplification of Real-World Complexity

System dynamics models, by design, abstract from real-world complexity to focus on structure and behavior. Several influential factors, such as regional cultural differences, global supply chains, and manufacturer-specific technological advancements, were not included due to scope constraints.

**Limitation:**

This abstraction may limit the direct applicability of the results to specific regional contexts or heterogeneous consumer groups [130].

### 5.5.2 Assumptions and Hypothetical Parameters

Due to the emerging nature of AV technology, many parameter values were assumed based on theoretical reasoning and stylized facts rather than empirical calibration. For instance, variables like the Public Trust Index or Regulatory Stringency were simulated with hypothetical scales and relationships.

**Limitation:**

The results illustrate plausible dynamics rather than predictive accuracy. Empirical validation would require access to future real-world data or stated preference surveys[134][133].

### 5.5.3 Exclusion of Shared and Commercial AV Scenarios

The model focuses strictly on private AV ownership and does not account for dynamics introduced by shared AV fleets or commercial AV operations (e.g., robotaxis, delivery bots). These use cases may respond differently to regulatory and infrastructure conditions.

**Limitation:**

The findings may not generalize to other AV deployment models that may have distinct safety, economic, and infrastructure implications[196].

### 5.5.4 Linear Trade-off Assumption in Budget Allocation

The government budget allocation in the model assumes a simplified linear trade-off between infrastructure investment and public incentives. In reality, budget decisions are often influenced by political cycles, lobbying, macroeconomic constraints, and emergency reallocations.

**Limitation:**

This may underrepresent the uncertainty and non-linearity present in real-world fiscal policymaking [197]

### 5.5.5 Limited Consideration of Social Equity and Ethics

The model does not explicitly address ethical concerns, such as unequal access to AVs, potential job displacement, or algorithmic bias. These social dimensions can profoundly shape public trust and policy responses over time.

**Limitation:**

Future extensions should integrate social equity indicators and ethical feedback loops to better reflect the broader societal impact of AV adoption[29][198].

## 5.6 Chapter Summary and Transition to Conclusion

This chapter presented the key findings derived from the dynamic simulation of private autonomous vehicle (AV) adoption under varying levels of regulatory safety stringency and government incentives. The simulation demonstrated that:

- Moderate regulation, when paired with sustained public incentives, fosters long-term, stable AV adoption with realistic and smooth behavioral patterns.

- Excessively strict regulations can trigger sharp collapses in adoption due to rising costs, delayed technological deployment, and declining public trust.
- Conversely, lenient regulatory environments may initially accelerate adoption but risk public backlash and policy overcorrections in response to safety incidents.

From a policy standpoint, the findings suggest that a phased and balanced regulatory strategy, complemented by a front-loaded public incentive scheme and long-term infrastructure investment, is likely to yield the most stable and sustainable adoption trajectory. This aligns with recent academic and policy literature emphasizing regulatory flexibility and adaptive governance in AV transitions[63][198]

In terms of theoretical contributions, the study integrates social, economic, regulatory, and technological dimensions into a single dynamic framework. This contributes to the growing body of system dynamics literature focused on transportation and emerging technologies, highlighting the importance of feedback loops, time delays, and policy trade-offs.

Despite its strengths, the study is bounded by several limitations, including simplified budget structures, the exclusion of shared AV dynamics, and hypothetical parameter values. These open pathways for future work that can enrich, validate, and extend the model through empirical calibration, stakeholder involvement, and inclusion of social justice considerations.

# Chapter 6

# Conclusions and Future Work

This study sets out to explore the complex interplay between regulatory safety standards and the adoption rate of private autonomous vehicles (AVs) using a system dynamics (SD) approach. Motivated by growing interest in AV technology and the crucial role of public policy in shaping its diffusion, this research aimed to investigate how various levels of regulatory stringency and government incentives could influence the trajectory of private AV ownership in urban settings over a 30-year simulation period.

The central research question addressed was: "How do changes in safety-related regulatory stringency and government incentives interact to influence the long-term adoption dynamics of private autonomous vehicles in a city?"

To answer this, the study developed a comprehensive system dynamics simulation model grounded in the feedback-rich structure of AV ecosystems. The model incorporated multiple interconnected subsystems, including:

- Regulatory Stringency Subsystem, capturing how safety concerns and AV accidents influence policymaking.
- Adoption Dynamics Subsystem, modeling AV diffusion as a function of incentives, cost, public trust, and infrastructure readiness.
- Public Trust and Media Feedback Subsystem, which shaped societal perceptions based on accident rates and media portrayal.

- Infrastructure and Budget Allocation Subsystem, representing government trade-offs between infrastructure investment and direct incentives.
- GHG Emission and Environmental Feedback, which indirectly affected policy responses via emissions-linked incentives.

Simulation scenarios included:

- A baseline case with moderate regulations and incentives,
- A high-regulation scenario with stringent safety requirements,
- A high-incentive scenario with aggressive subsidies and tax reliefs, and
- A balanced scenario with phased regulations and adaptive incentive policies.

Each scenario was evaluated on key performance metrics such as AV ownership numbers, regulatory burden, public trust index, infrastructure readiness, and AV accident rates over a 30-year horizon. The behavioral patterns of these outputs were analyzed to identify nonlinear dynamics, threshold effects, and the efficacy of various policy combinations.

The system dynamics methodology proved particularly suited to this research due to its ability to simulate feedback loops, time delays, and emergent system behaviors. As Sterman [130] emphasized, SD modeling enables policy experimentation in complex socio-technical systems, where traditional linear approaches may fall short. This research contributes to that tradition by applying

SD to the relatively underexplored domain of regulatory policymaking for AV adoption.

### 6.1 Summary of Key Insights

The simulation results and scenario analyses revealed several important insights into the dynamics of private AV adoption under varying policy environments. These findings offer both theoretical contributions and practical relevance for policy design in emerging autonomous mobility systems.

- **Regulatory Stringency has a Nonlinear Impact on Adoption:** A major insight is that increasing regulatory stringency does not produce a linearly negative effect on the adoption of AV. Instead, adoption follows an S-shaped trajectory where moderate regulations initially build public trust, leading to stable adoption, but excessive regulation suppresses adoption due to rising costs, approval delays, and reduced manufacturer flexibility. This aligns with earlier system dynamics work on technology diffusion, where thresholds and tipping points often define system behavior[130]. Over-regulation beyond a critical threshold creates diminishing returns, echoing concerns in AV policy literature about balancing innovation and safety [77].
- **Incentive Policies are Effective but Require Timing and Phasing:** The results also indicate that financial incentives (subsidies, tax reliefs, and rebates) are effective in accelerating early adoption of private AVs. However, their long-term effectiveness depends on timely phase-outs and complementary investments in infrastructure. The “high incentive” scenario

led to overshooting and instability when incentives remained unchecked, while the balanced scenario showed stable growth when incentives were phased out as adoption reached critical mass. This finding is supported by previous research emphasizing the importance of smart phasing of subsidies and avoiding lock-in effects[199]. It suggests that policymakers should not only introduce incentives but also plan their sunsetting aligned with technology maturity.

- **Public Trust Emerges as a Pivotal Mediator:** The Public Trust Index, influenced by both accident rates and media portrayal, emerged as a critical variable affecting adoption. In scenarios where accident rates dropped due to regulatory measures, public trust increased steadily, reinforcing adoption. Conversely, spikes in accidents or negative media created delays or reversals in AV uptake, despite favorable incentives or infrastructure. This insight supports theoretical frameworks that emphasize perceived safety and public perception as essential factors in autonomous technology acceptance[200] [201]. The feedback loop between public trust and policy reaction (regulatory tightening) was central in determining long-term dynamics.

- **Infrastructure Readiness Moderates Adoption Saturation:** The model showed that as AV ownership increased, so did the demand for charging, maintenance, and smart infrastructure. Scenarios with early emphasis on incentives but delayed infrastructure spending faced adoption slowdowns in later years. The balanced scenario, which gradually shifted the government budget from incentives to infrastructure investment, performed best in maintaining sustained adoption. This reflects real-world challenges in scaling electric and autonomous vehicles, where infrastructure bottlenecks (e.g., charging deserts, connectivity gaps) pose practical constraints [202]. It underscores the need for forward-looking infrastructure planning in tandem with demand-side policies.

- **Environmental Co-benefits Can Reinforce Incentive Justification:** The model's inclusion of a GHG Emission Index showed that higher AV penetration led to reduced emissions, especially under scenarios with a clean energy grid. These emission reductions created justification for maintaining moderate incentives even in later years, as part of a broader sustainability strategy. This confirms policy arguments that climate goals can be aligned with AV promotion under the right regulatory and infrastructural conditions[203][204]. The model suggests that emission-based incentives (like carbon credits or congestion pricing relief) can be useful tools alongside direct financial subsidies.

These insights not only validate the conceptual assumptions of the system dynamics model but also offer practical levers for policymakers to balance safety, trust, infrastructure readiness, and environmental goals in their AV adoption strategies.

### 6.2 Policy Implications

The simulation findings offer multiple actionable implications for policymakers who are navigating the complex trade-offs between ensuring safety and accelerating the adoption of private autonomous vehicles (AVs). The following implications emerge from the study's behavioral outcomes and systemic feedback insights:

- **Calibrate Regulatory Stringency to Avoid Overreach:** The model shows that excessive regulatory tightening can inadvertently suppress adoption by increasing AV costs and development delays. Thus, policymakers should:
    - Avoid abrupt regulatory escalations in response to isolated incidents.
    - Implement adaptive regulatory frameworks that evolve based on cumulative AV safety performance and maturity level.
    - Use performance-based regulation (e.g., outcome-focused rather than design-prescriptive rules) to provide flexibility while maintaining accountability.

  This mirrors the recommendations by OECD [205] and SAE[206] who advocate for "graduated autonomy" policies that scale with demonstrated system reliability.

- **Design Incentives with Built-In Exit Strategies:** Incentives like subsidies, tax exemptions, or purchase rebates should not be open-ended. Based on model behavior:

- Early generous incentives help overcome initial adoption inertia.
- A tapering approach, where incentives reduce increased AV penetration, avoids market distortions and fiscal burden.
- Linking incentive eligibility to emission reductions or safety records can reinforce policy alignment with broader goals.

This is consistent with findings by Li[207] and Zhang & Guhathakurta[208] , who argue that incentive efficiency diminishes over time and must evolve.

- **Prioritizing Public Trust Through Transparent Communication and Risk Management:** The study highlights the central role of public trust as a mediator of adoption. Therefore:

    - Governments and AV firms must proactively communicate accident data, safety updates, and risk mitigation efforts.
    - Public campaigns should emphasize improvements in AV safety over time, backed by third-party evaluations.
    - Develop mechanisms to counter misinformation, especially during crises or media-driven events.

    As emphasized by Bansal[133], societal perception and legitimacy are as important as technical performance in determining AV success.

- **Budget Rebalancing Toward Infrastructure Readiness:** The model recommends a strategic shift from incentives to infrastructure investment as AV adoption grows. Key measures include:

- Expanding smart traffic infrastructure, including vehicle-to-infrastructure (V2I) systems.
- Enhancing AV-specific maintenance and charging facilities in urban and suburban corridors.
- Coordinating with municipalities to ensure last-mile accessibility and equitable infrastructure deployment.

As suggested by Brown[209], infrastructure is often the “hidden bottleneck” to AV scalability, and its neglect can slow momentum even in favorable policy environments.

- **Use Environmental Co-benefits as Policy Justification:** The GHG Emission Index dynamics show that AV adoption can align with sustainability goals when supported by green energy systems. Policymakers can:
  - Introduce emission-based incentives (e.g., rebates for AVs operating on clean electricity).
  - Highlight emission savings in policy narratives to build public and political support.
  - Consider integrating AV promotion into national climate strategies, especially under international obligations (e.g., Paris Agreement goals).

This reinforces positions by Creutzig[203] and IEA [202], which advocate for technology convergence policies to tackle both mobility and climate objectives simultaneously.

Together, these policy implications suggest that a systems approach—informed by feedback, timing, and multi-sector coordination—is vital to successfully managing the regulatory and adoption journey of private AVs.

### 6.3 Theoretical Contributions

This study makes several theoretical contributions to the evolving literature on autonomous vehicle (AV) adoption, regulatory design, and system dynamics modeling in policy research.

- **Advancing the Understanding of Regulatory Trade-offs:** While existing literature often examines AV adoption from either a technological or policy lens, this study introduces a system-level perspective by modeling how regulatory stringency dynamically interacts with public trust, government incentives, and infrastructure investment. The system dynamics approach elucidates how tightening safety standards, while improving perceived safety over time, may initially suppress adoption due to increased costs and reduced affordability, highlighting a temporal trade-off rarely captured in static or linear models[210][62].
- **Public Trust as a Mediating Construct:** Another key contribution is the formalization of public trust in AV safety as a stock variable influenced by accidents, media coverage, and regulatory efforts. While public perception

has been acknowledged in behavioral studies[162] [133], few models endogenously represent how it evolves over time and shapes adoption. The trust index developed here helps bridge behavioral and policy dynamics by linking safety regulation to perception-driven demand elasticity.

- **Feedback Loops in Policy-Induced Behavioral Change:** This research also contributes to theory by highlighting the feedback-rich nature of AV policy environments. Policies such as incentives or oversight are not one-directional levers but part of loops where the outcomes feed back into policymaking through indicators like accident rates, GHG emissions, and infrastructure pressure. These insights align with Forrester's[85] notion of systems thinking in policy design, emphasizing the importance of balancing short-term gains and long-term sustainability.

- **Contribution to System Dynamics Applications in Emerging Mobility:** Methodologically, this study extends the application of system dynamics to a relatively nascent policy domain, private AV ownership in urban contexts. Most existing SD models in transportation focus on conventional modal shift or infrastructure planning[211] . By integrating technological evolution, media narratives, and adaptive policy levers, this work enriches the toolkit for researchers exploring technology policy diffusion in complex urban systems.

### 6.4 Recommendations for Future Research and Policy Design

Based on the simulation results and insights generated through the system dynamics approach, several actionable recommendations can be drawn for both future academic research and practical policy formulation.

- **Policy Recommendations**

  - **Adopt a Phased Regulatory Strategy**

    The results suggest that overly stringent safety regulations introduced too early in the AV adoption lifecycle can dampen market growth. Policymakers should consider a phased approach, initially promoting adoption through incentives while gradually increasing safety requirements as technology matures and public trust stabilizes. This aligns with findings by Bansal and Kockelman [133], who emphasized the need for temporal calibration in AV policy rollout.

  - **Balance Incentives and Infrastructure Investment**

    Government resources should be strategically allocated to both consumer incentives (e.g., tax credits) and infrastructure development (e.g., AV-friendly roads, charging stations). Simulation results show that infrastructure readiness becomes increasingly critical in the later phases of adoption, necessitating a shift in funding priorities over time.

- **Institutionalizing Public Trust Mechanisms**

  Policies aimed at increasing transparency, education, and media engagement should accompany regulatory enforcement. This includes regular safety audits, public-access accident data, and responsible media messaging. Building public trust is not a by-product but a key enabler of adoption, particularly in the early years.

- **Use Dynamic Indicators for Policy Feedback**

  Regulators should not rely solely on static benchmarks (e.g., adoption rates), but incorporate dynamic indicators such as real-time accident trends, GHG emissions, and media sentiment analysis to adjust policy levers proactively. This approach is in line with adaptive governance strategies proposed by van der Voort[212].

- **Recommendations for Future Research**

  - **Incorporate Real-World Behavioral Data**

    While the current model used conceptual, assumed relationships to simulate adoption dynamics, future work should integrate empirical behavioral datasets, such as consumer surveys or real adoption rates across cities, to validate and refine feedback structures.

  - **Explore Heterogeneity in Adoption Patterns**

    Future models could segment the population by socioeconomic status, geographic location, or digital literacy to investigate how AV adoption and regulatory perception vary across demographic groups. Such granularity would improve policy targeting and equity outcomes[121].

- **Test Policy Scenarios under Crisis Conditions**

  Extending the model to simulate shock events, like a major AV accident, cybersecurity breach, or sudden budget cuts, would help test the resilience of current policy recommendations under extreme conditions. This could reveal tipping points or unintended side effects.

- **Model Shared AV and Mobility Integration**

  Although this study focused on private AV ownership, future research can expand the model to include shared AVs, public transport integration, and mobility-as-a-service (MaaS) to understand systemic interactions across the full mobility ecosystem[63].

### 6.5 Closing Summary

This study employed a system dynamics modeling approach to investigate the regulatory trade-offs between safety stringency and private autonomous vehicle (AV) adoption in urban settings. The model incorporated key feedback loops related to government incentives, regulatory pressure, infrastructure readiness, accident trends, and public trust to simulate AV adoption over a 30-year horizon.

Through a series of scenario-based simulations, the findings highlighted that:

- Excessive early regulatory stringency can significantly suppress AV adoption, even if safety outcomes improve.
- Well-timed government incentives, especially in the early and mid-phases, are effective in accelerating adoption but need to be balanced with long-term infrastructure investments.
- Public trust emerged as a central mediator, strongly influenced by accident rates and media narratives, and in turn influenced both adoption and regulatory pressure.
- The most effective policy configuration appeared to be one that dynamically adapts based on real-time indicators, gradually shifting focus from monetary incentives to institutional and infrastructural support.

From a theoretical perspective, this research contributes to literature by modeling AV adoption as a complex, adaptive system and providing a framework for understanding how feedback effects, policy delays, and behavioral variables interact over time. It complements earlier empirical studies by offering a dynamic simulation-based platform for policy experimentation.

Practically, the study offers valuable insights for policymakers on the importance of phased regulatory design, adaptive governance, and maintaining the delicate balance between safety enforcement and market growth. It also opens several avenues for future research, such as integrating shared AVs, disaggregating user populations, and simulating disruptive events.

In conclusion, as cities and governments worldwide prepare for the era of autonomous mobility, this study offers a foundation for both researchers and decision-makers to navigate the trade-offs inherent in regulating a rapidly evolving technological landscape, aiming for safe, sustainable, and inclusive adoption of autonomous vehicles.

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