

# Automated Vehicle Pilots: Avoiding Perfection being the Enemy of the Good

BY

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## Abstract

Automated vehicles (AVs) are gaining increased attention due to their potential to significantly improve safety. While current AV technology has not yet eliminated accidents, it shows promise in reducing them, with further advancements expected. This thesis addresses the optimal timing for AV pilot deployments, balancing the pursuit of perfection against the need for timely implementation to enhance social welfare. Delaying AV introduction until perfection may cause future harm, while early deployment may not initially maximize welfare. To navigate this trade-off, a mathematical framework is introduced that integrates AV safety, technological diffusion, and the effects of learning over time. This framework also incorporates social factors, offering three models that address different scenarios faced by social planners. A case study is presented to demonstrate how these models optimize for social welfare by managing trade-offs, such as initial higher failure rates counterbalanced by safety improvements over time. The results highlight how the framework allows social planners to adjust inputs and explore optimized pilot scenarios. The discussion emphasizes the framework's flexibility for customization and its capacity to represent key AV-related concepts. Finally, potential future refinements, such as variable weighting and iterative improvements, are proposed to enhance the framework's applicability.

## **Dedication**

This work is dedicated to my family, whose unwavering support provided a constant refuge throughout my academic journey. To my friends, your encouragement has been a source of strength. Together, this dedication symbolizes our collective pursuit of a better future—one where shared dreams and aspirations thrive.

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# Chapter 1

## Introduction

### 1.1 Motivation

Automated vehicles (AVs) constitute a developing field in transportation, with potential benefits that necessitate rigorous validation across various industries. This validation involves thorough testing, assessment, and verification to substantiate the tangible advantages. Recent studies explore AV impacts, including reduced parking demand, decreased environmental impact, and enhanced safety [1]. Among these advantages, a pivotal prospect is the potential decrease in accident rates attributed to AV deployment [2, 3, 4]. Notably, human error, identified as a leading cause of crashes, accounts for a staggering 93% according to a study conducted in 2008 [5, 6, 7]. A critical question looms despite the promise of accident reduction: when will these benefits materialize? The current AV technology is imperfect and has been implicated in accidents, as exemplified by an incident in Phoenix, Arizona [8]. This case involved a fatality where Uber’s AV system failed to identify a pedestrian within the crucial 5.6 seconds of detection. The incident relied on the backup driver, who did not intervene promptly. The repercussions of this accident were felt throughout the community and the automotive industry, prompting renewed inquiries into AV safety and testing protocols. The gravity of these questions was underscored by the cessation of Uber AV testing in Phoenix, and the fallout from this failure potentially reverberated across other companies involved in AV development [9]. Nevertheless, enhancing AV safety necessitates rigorous technology testing to establish a robust proof of concept. While setbacks and accidents may raise concerns, it is through systematic testing and refinement that AVs can evolve to fulfill their promise of enhanced safety on our roadways.

The debate on increasing safety remains a key driver of AV integration [10, 11, 12]. While it is often assumed that AVs will eliminate the majority of human error in collisions, the reality is far more complex. AV safety is inherently interdisciplinary, requiring careful consideration of factors such as legal liability, software vulnerabilities, hardware reliability, and more. Additionally, the presence of mixed traffic scenarios has further complicated safety assessments [12]. Given these numerous dimensions of safety, it is crucial to specify which aspects will be the focus of this study. For instance, if collisions are to be used as a metric for AV safety, they must be evaluated within the context of an AV pilot. This thesis presents a mathematical framework designed to determine the optimal timing for AV pilot implementation, integrating safety considerations to assess whether early deployment of imperfect AVs can contribute to a safer future. The framework advocated in this thesis supports a proactive approach to AV integration, acknowledging the trade-offs between pursuing perfection and ensuring timely deployment.

Several other concepts and information will be utilized to create such a framework. The detailed body of literature on AV pilot initiatives provides a resource for designing projects. Through synthesizing common attributes and interpreting limitations [13], researchers and policymakers can enhance AV pilot programs and their designs, providing some factors of interest for pilot design.

A key consideration is the diffusion of AVs throughout transportation networks, which presents a valuable research avenue: the transitional phase of AV adoption [14, 15, 16]. While studies explore the transformative impacts of AVs, not all projected outcomes are favourable, with certain scenarios indicating potential increases in travel times or contributions to urban sprawl [16, 17, 18, 19]. The complexity of AV diffusion, coupled with factors that challenge accurate forecasting, underscores its importance within the proposed framework of this thesis.

The question of “How Safe is Safe Enough?” frequently arises within the AV sector and other industries, invoking critical safety and ethical considerations in the context of AV pilot deployment [20, 21, 22]. Establishing a threshold for acceptable safety in AV operations is pivotal, as explored in Koopman’s recent work [23]. Koopman addresses key elements for determining ‘safe enough’ AV deployment, including the governance of deployment through stakeholder involvement, the explicit definition of safety expectations, and the integration of safety margins to account for uncertainties in risk assessment. Although specific quantitative measures were not provided in his presentation, the emphasis on setting a clear risk threshold underscores its fundamental role in defining safety standards.

Addressing safety may involve defining metrics such as crash occurrences (e.g., vehicle miles travelled and disengagements) and considering ethical concerns, such as the trolley

problem [24, 25, 26]. In the RAND report [6], the authors address three primary questions: quantifying the lives saved by AV implementation, evaluating the costs of waiting for improved AV safety, and examining the implications for consumer-oriented policies. The report assumes average improvements in AV safety of 10%, 75%, and 90% compared to human drivers, with clear thresholds for evaluation that align with Koopman’s ideas.

The RAND report advocates for a nuanced approach, balancing proactive measures with a wait-and-see stance. However, it encounters limitations related to societal systems external to its models, particularly concerning potential project termination due to societal crash costs. Additionally, defining safety based on crash rates introduces uncertainties, as improvements in AV technology may not address vehicles or infrastructure beyond the report’s scope. With these considerations in mind, the following section presents the research goals of this thesis.

## 1.2 Research goals

AV-related studies, such as the RAND report, provide a theoretical foundation for this thesis. The development of a mathematical framework, specifically designed to optimise AV pilot implementation, serves as a tool for evaluating pilot design. By incorporating key concepts such as AV safety and diffusion, the framework addresses critical issues outlined in the literature. For example, it introduces a numerical representation of social costs—an aspect that has not been incorporated into previous models [6, 23]—and redefines safety metrics by incorporating disengagements. Disengagements, which occur when the AV system fails to handle a driving task and requires human intervention, are crucial for evaluating AVs, as they reveal the limitations of the automation system and its ability to manage real-world scenarios. This consideration confines the focus to AV automation levels 3 and 4 [27], where disengagements are particularly relevant. Furthermore, the pilot-focused nature of this study presents different societal repercussions, as the risk is associated more with disengagements rather than crash rates, reflecting the formative stages of AV testing. The impact of social costs and safety considerations during early AV testing is especially critical for pilot deployment [28, 29].

The following objectives are defined:

- **Objective 1:** Utilize and define concepts essential for the framework within the context of an AV pilot. Core concepts such as diffusion, learning dynamics, AV safety, and risk will be emphasized.

- **Objective 2:** Develop the framework to minimize the risk within an AV pilot, with the minimization representing the optimal scenario for this study.
- **Objective 3:** Demonstrate the adaptability of the framework by testing a case study with models derived from the framework.
- **Objective 4:** Evaluate the effectiveness of the framework and the results produced by the models.
- **Objective 5:** Assess whether the framework addresses the balance between perfection and timely implementation, and propose potential improvements.

The achievement of these objectives contributes to the ongoing discourse on safety measurement [25, 26].

### 1.3 Research contribution

The proposed framework integrates the interconnected concepts of learning from AV metrics and managing risk through exposure, reflected in the disengagement rate. Technological diffusion, primarily driven by the specific goals of the pilot, significantly influences outcomes, differentiating between a limited pilot introduction and broader societal adoption. The framework introduces parameters such as discount factors, which reflect the utility derived by travellers from AVs, and factors that account for the social planner’s level of conservatism. Moreover, the inclusion of a proposed social cost aims to quantitatively capture social factors identified as limitations in the RAND report. By constructing a case study based on attributes from previous pilots, the framework can be practically applied and evaluated.

The outcomes derived from the case study provide valuable insights that should be approached with caution and thorough analysis. Direct implementation of the framework may encounter challenges associated with social factors, including the risk of social backlash, as highlighted in the RAND report. While the RAND report could mathematically justify a higher-than-average crash rate, such a rate may prove socially unacceptable, potentially hindering progress in the planning phases. The integration of the social cost concept within the thesis framework addresses these concerns; however, final approval still rests with a decision maker, referred to in this study as the social planner. This social planner, typically the stakeholder tasked with approving the pilot, must ensure that social factors are sufficiently addressed. Applying the framework’s results without proper

oversight risks repeating the social challenges identified in the RAND report, such as the potential termination of the pilot due to public resistance towards an elevated crash rate.

It is therefore essential for the social planner to carefully review the results before proceeding with the pilot, with flexibility to adjust the models during its implementation if necessary. Initial assessments may reveal a significant level of inherent risk, particularly shaped by travel patterns. However, greater pilot engagement can lead to risk mitigation, as increased utility is derived through the learning process. The social planner must also account for the potential persistence of failure rates and recognise the uncertainties involved in predicting these rates.

## 1.4 Thesis organization

Thus, the effort to establish a foundational conceptual framework that challenges the notion of perfection as the enemy of the good produces significant results. Section 2 outlines the key concepts employed, defining them within the context of AV pilots and reviewing relevant literature. Building on these insights, Sections 3 and 4 provide the mathematical derivations that contribute to the framework and model formulation. Section 5 presents an case study to demonstrate the practical application of the model. The outcomes of this case study are discussed in Section 6, followed by a detailed analysis in Section 7. Finally, Section 8 offers a conclusive synthesis of the findings, encapsulating the core contributions of the paper.

# Chapter 2

## Related literature

In this section, literature on key AV-related concepts, such as diffusion, safety metrics, learning models, social costs, and pilot data, is reviewed. The discussion outlines these concepts, explores their interconnections, and demonstrates how they collectively inform the design of a framework for evaluating AV pilots. Each section examines both theoretical and practical aspects, illustrating how these elements work together to minimize risks and enhance the successful integration of AV technology.

### 2.1 AV safety and learning dynamics

The principle “perfection is the enemy of the good” is particularly relevant in the context of modelling pilot studies for AVs. AVs, ranging from Level 3 to Level 5 on the SAE automation scale [27], undergo rigorous testing before broader integration into transportation networks. Pilot studies often serve as crucial preliminary tests that precede more extensive trials and eventual deployment. A significant concern during these phases is ensuring the safety of these pilot initiatives [30].

Clearly defining testing parameters for AVs is essential, given that safety requirements vary significantly across different automation levels. For instance, a Level 5 AV is expected to handle all driving tasks autonomously in any scenario, without human intervention. Conversely, a Level 3 AV, while capable of managing most driving tasks, may still require human assistance in complex situations such as traffic jams [27]. The higher expectations for Level 5 AVs necessitate more stringent safety thresholds compared to Level 3 AVs. Determining the optimal safety levels for each automation level and predicting when these thresholds will be met are crucial questions for researchers and planners.

The Model of Automated Vehicle Safety (MAVS) and the Robust Decision Making (RDM) model were employed to address these questions [6, 31]. This collaborative approach evaluates scenarios related to AVs and highlights how the pursuit of perfection can impede progress. The study compared AVs with safety performances exceeding those of the average human driver against crash rates. Key concerns include learning mechanisms, safety considerations, and external factors influencing AV-related scenarios.

The RAND study, which considers long-term impacts with a minimum evaluation period of 15 years [6], supports the notion of gradual technological improvement. This concept is supported by studies demonstrating how technology evolves and improves over time [32, 33, 34]. The S-curve model of technology development, which illustrates performance initially lagging but accelerating over time until reaching a peak, is essential for understanding these advancements [35]. Mathematically, several approaches have been utilized to represent this learning phenomenon. Some studies have opted for a linear model, encapsulating the “learning-by-doing” paradigm, where each incremental use of the technology contributes to its overall refinement and effectiveness [36, 37]. When applied to AVs, such a linear framework might suggest that increased operational mileage during pilot phases leads to proportional improvements in navigation accuracy, system calibration, and safety protocols. However, more nuanced approaches, such as the use of piecewise functions [38], offer flexibility in capturing varying rates of learning. For example, an initial phase of exponential improvement could be followed by a transition to slower, more incremental gains, effectively modelling the diminishing returns often seen in technological adaptation. This approach can be tailored to reflect different stages of AV deployment and the diverse challenges encountered as the technology scales.

This concept is broadly applicable and particularly relevant for AVs, where pilot programs typically operate over shorter periods compared to the extended evaluations in studies such as RAND’s [6]. Although the RAND study’s long-term focus is likely more representative of the learning process—given that technological improvements occur progressively over time—it is important to recognise that even within shorter pilot durations, the benefits of learning can still be significant. Shorter pilots, while not capturing the full extent of AV evolution, can nonetheless contribute valuable insights, particularly regarding system optimisation, calibration, and early identification of critical performance issues. The learning gained in these shorter time frames may reveal early-stage improvements in navigation or reductions in disengagement, which can cumulatively lead to more substantial benefits over the long term. Thus, short-term gains can be viewed as foundational steps that gradually contribute to the broader trajectory of AV technology development. Evaluating the benefits of learning from AV technology still poses challenges due to difficulties in quantifying these advantages, particularly when factoring in societal changes or

future conditions, such as evolving legal frameworks [23, 13].

The link between technological advancement and AV safety informs the framework’s design. Given that AV technology is expected to improve through iterative development, there may be justification for the early deployment of incrementally improved AVs [31]. Such early deployment could potentially lead to long-term safety benefits by reducing crash rates and enhancing overall road safety.

Considering the early implementation of AVs presents a nuanced perspective: deploying AVs before they are fully perfected may yield better long-term outcomes. The initial deployment of imperfect AVs provides an opportunity to gather valuable data and insights, which can drive iterative improvements. This approach allows for real-world testing and learning, leading to refinements that can reduce failure rates over time. Waiting for a flawless pilot might delay the benefits of gradual advancements and practical insights gained from early implementations. However, this strategy also acknowledges potential backlash associated with the failures of imperfect technology, which could hinder progress. Understanding the perception dynamics surrounding AVs is crucial, as user experiences significantly shape perceptions and influence the diffusion and adoption of the technology [39]. While safety considerations are a key aspect of the “perfection is the enemy of the good” paradigm, they are particularly critical in AV pilot design due to their impact on technology perception and adoption.

The existing literature on AVs employs a range of methodologies for assessing and quantifying AV safety [30, 25, 40, 26]. A significant challenge in evaluating future AV safety is the necessity of extrapolating specific metrics to estimate future safety values. One method to address this challenge involves the use of surrogate safety measures (SSMs) [26]. This approach requires advanced simulation software to support the extrapolation process and predict future safety outcomes [41, 42].

Another approach to quantifying AV safety involves a detailed analysis of the vehicle’s components and associated issues [43]. For instance, addressing perception errors due to limited camera range may necessitate advancements in camera technology integrated into the AV [44]. Recognising that a failure in one component can lead to system-wide failures, the literature presents various methods for estimating AV safety, each with its unique approach. Developing robust methods to measure and project AV safety is crucial not only for enhancing safety assessment but also for ensuring accurate projections. Effective safety measurement facilitates the identification and resolution of current safety issues while supporting the projection of future safety improvements, which is essential for the design and evaluation of AV pilot studies.

Despite these advancements, a cohesive framework for AV safety remains under devel-

opment [45]. The definition of what constitutes a safe AV is still unresolved, reflecting the current state of policies—or the lack thereof, such as the absence of numerical safety thresholds in existing regulations [13]. While some studies highlight the potential long-term benefits of AVs, such as reduced crash mortality rates, these metrics may not be as relevant for shorter-term AV pilot studies. The immediate impact of the technology during a pilot study, particularly in terms of public perception, can be significant. High crash rates in a pilot study could affect acceptance and hinder the study’s progression to broader deployment. In this context, the concept presented in the “Enemy of the Good” report is particularly relevant [6].

The MAVS and RDM reports illustrate the relationship between AVs’ Vehicle Miles Travelled (VMT) and changes in AV safety performance [6, 31]. This approach integrates exposure metrics, such as VMT, with safety performance assessments [46, 30]. Historical studies have employed VMT alongside collision data to evaluate safety impacts [47], and recent analyses have correlated increased AV usage with overall VMT effects within transportation networks [6, 48]. These metrics form a basis for comparing safety improvements over time, as increased exposure is expected to provide more insight into both the potential for crashes and system failures.

Disengagement reports provide a method for estimating the frequency of disengagements per mile, linking these occurrences to safety considerations [6, 49]. Disengagements occur when an AV’s automation system fails to execute a driving task, necessitating human intervention. This metric is particularly relevant for AVs operating at Levels 3 and 4, where the system manages most driving tasks but still requires occasional human oversight [27]. These levels are prone to disengagements due to their reliance on human drivers when the automation system encounters scenarios beyond its capabilities. While disengagements reflect areas for system improvement and learning, they are often less costly in immediate terms compared to crashes. Crashes have far-reaching consequences, including significant project delays, regulatory scrutiny, and negative public perception, which can considerably impact AV development efforts [30, 3].

Utilizing disengagement data enables the evaluation of risk exposure relative to VMT [50]. Disengagements, though indicative of system vulnerabilities, generally involve no physical harm, whereas crashes entail substantial financial and social costs. Consequently, a high disengagement rate may be perceived as less damaging to an AV pilot than crashes. It is crucial to recognize that AV technology is expected to meet higher standards compared to conventional vehicles. For AVs to be deployed, their performance should exceed that of an “average” driver, a benchmark that may include less ideal behaviors such as driving under the influence [23]. This high standard necessitates more rigorous safety measures and continuous system improvements. A successful pilot that minimizes both disengagements

and crashes will advance AV technology and contribute to safer, more reliable deployments in the future.

## 2.2 Social planners and AV deployment

Social planners, who may include AV vendors, companies, or governing bodies, play a pivotal role in managing AV pilot studies [13]. Their involvement is crucial as they can adjust the pilot to align with its objectives. Typically, pilots are designed with specific goals, such as addressing last-mile travel challenges or enhancing integration with public transit systems. Social planners are expected to have a thorough understanding of these objectives.

However, implementing a pilot study can be complex, requiring social planners to navigate existing laws and regulations [13, 51]. While the pilot’s goals provide a basis for evaluating its performance, the concept of success or failure may not always be clearly defined. For instance, a pilot aimed at meeting a local community’s last-mile travel needs might vary in scale depending on demand, user expectations, and available resources. A social planner might initially deploy a limited fleet of AVs in a high-demand area to assess user reactions and gather data before considering a broader rollout.

The concept of AV learning over time is relevant to this discussion [35, 33]. As the scale of AV deployment increases, exposure and risk levels also vary. For example, a pilot involving five AVs compared to one involving twenty AVs over the same period—assuming each vehicle travels the same distance—will yield different results in terms of disengagements and associated risks. While a smaller fleet may experience fewer disengagements overall, a larger fleet, covering a larger total distance, might reveal more issues due to increased usage. The term “supply distance” can be used to refer to the distance travelled by an individual AV. In the context of a pilot, this can be evaluated cumulatively for the entire fleet or for a subset of the fleet throughout the pilot’s duration. This distinction is important for understanding both the learning process and the potential benefits of scaling up to identify and address challenges more quickly.

Larger pilots are generally expected to carry more initial risk, not only due to the number of vehicles but also because increased exposure may lead to more disengagements. These disengagements can highlight issues that require attention, such as problems with road sensors. Addressing these issues can reduce disengagements over time, illustrating the connection between learning, safety, and AV deployment. This relationship is a critical element of the framework, offering valuable insights for social planners as they weigh the risks and benefits associated with scaling AV pilots.

## 2.3 Diffusion of AVs and technology

Defining the diffusion of AVs into the transportation network involves understanding it as the gradual integration of AVs into the existing fleet of vehicles. This process can be characterised by the replacement of human-driven vehicles (HVs) with AVs or by the addition of AVs to the current vehicle pool [27, 3]. As AVs become more prevalent, their diffusion reflects both the pace at which they replace conventional vehicles and the extent to which they are incorporated into new and existing transportation infrastructures.

In contemplating future scenarios, the gradual diffusion of AV technology into the transportation network over time corresponds to a concept observed in the literature, which applies to various technologies [52]. The concept of exposure in AV pilots can be linked to the diffusion of AV technology within a fleet or in public settings. However, the diffusion of AV technology may not always yield positive outcomes, as it may lead to increased travel distances and potential sustainability issues [53]. For instance, increased demand for AVs might impact parking infrastructure or contribute to greenhouse gas emissions, depending on the technology and usage patterns.

Several factors influence the diffusion rate of AV technology, including:

- **Technological readiness:** The maturity of AV technology affects its rate of diffusion. For example, the transition from Level 3 to Level 4 AVs, which require less human intervention, may accelerate adoption due to improved safety and reliability [27, 54].
- **Regulatory environment:** Government policies and regulations play a crucial role in the diffusion of AVs. For instance, regions with supportive legislation and clear regulatory frameworks, such as California’s extensive testing regulations, may experience faster diffusion compared to areas with restrictive or ambiguous policies [3, 13].
- **Public perception:** The acceptance of AVs by the public can significantly impact their diffusion. Positive perceptions, driven by successful pilots and media coverage, can enhance adoption rates [39, 13, 34]. Conversely, concerns about safety and privacy can hinder diffusion.
- **Economic factors:** Kaplan [55] explores how economic factors influencing AV diffusion include the high initial costs of technology, investment in R&D, and broader market conditions. The high cost of AVs can restrict early adoption to high-income

individuals or commercial fleets. Increased investment in R&D and supporting infrastructure can accelerate technological advancements and reduce costs, making AVs more accessible. Economic conditions, such as periods of economic growth or recession, also affect the diffusion rate by influencing available investment and consumer purchasing power.

- **Infrastructure compatibility:** The readiness of existing infrastructure to support AVs, such as road sensors and communication systems, influences diffusion. Areas with well-developed infrastructure for AVs may see quicker integration compared to regions that require significant upgrades [56, 57, 58].

The diffusion of AV technology often follows S-curves, similar to learning models. Initially, adoption may be slow due to high costs and technological limitations, but as the technology matures and becomes more affordable, adoption rates accelerate before eventually levelling off as the market saturates [59, 60, 61, 62, 63]. This S-curve pattern highlights how both learning and diffusion processes can exhibit similar growth trajectories, reflecting gradual improvements followed by rapid uptake.

Scaling effects are also significant in the context of AV diffusion. A high disengagement rate may be more detrimental in a scenario with widespread AV adoption compared to a situation where AVs are still in the early stages of diffusion. For example, if disengagements are frequent in a market with a high density of AVs, the overall safety and public perception may suffer more severely than if disengagements occur in a market with only a few AVs. As the number of AVs increases, the impact of each disengagement becomes more pronounced, potentially leading to greater scrutiny and more stringent regulatory responses.

Historical examples of technology diffusion, such as the adoption of mobile phones or electric vehicles, provide valuable insights into the potential trajectories for AV technology. For instance, the rapid adoption of smartphones illustrates how technological improvements and decreased costs can accelerate diffusion. As AVs become more affordable and feature-rich, similar dynamics are expected to drive their widespread adoption. Moreover, just as learning and iterative improvements contributed to the advancement of smartphones and electric vehicles, continuous learning and refinement in AV technology will likely enhance its performance and acceptance. This interplay between learning and diffusion underscores the importance of iterative development in shaping the future trajectory of AVs [54, 61].

Quantitative models, such as the Bass Diffusion Model or Logistic Growth Model, are often employed to predict diffusion rates and outcomes [59, 60]. The MAVS considers different cases of AV diffusion rates in its scenarios [6]. Additionally, understanding AV diffusion is crucial for predicting technological impact and informing policy and planning [3,

55, 56]. The diffusion of AV technology has implications for overall welfare, costs, adoption rates, and user characteristics. Identifying and addressing gaps in current research on AV diffusion will be essential for adapting policies and strategies to match future scenarios [60].

Insights gained from understanding diffusion will inform the framework for evaluating the broader impacts of AV technology. As the discussion progresses to the social costs associated with AV diffusion, it will be important to consider how these factors influence societal outcomes and the necessary measures to address potential negative consequences.

## 2.4 Social effects of AVs

Perception plays a crucial role in developing AV pilots, as it impacts public sentiment and influences simulation outcomes [6, 56]. The growing body of research on public perception of AV technology underscores its importance for technology adoption and usage [64, 39, 65, 66]. Stakeholders’ perceptions of AV safety are influenced by factors such as age, education, commuting costs, experience with technology, and previous encounters with AVs [39]. Understanding these factors and addressing safety concerns are critical for developing and implementing effective AV plans [66, 65]. Public outreach efforts, such as those by the City of Toronto’s AV pilot [67], highlight the importance of ensuring AVs meet public expectations and safety requirements before their introduction on the roads.

Assigning a numerical value to social costs, such as those resulting from a crash with fatalities, is complex. While it is feasible to estimate the direct economic impact, capturing the intangible effects—such as the impact on public perception and the potential for AV pilot shutdowns—is more challenging. Risk averseness among the public, driven by safety concerns and perceived risks associated with AVs, represents a significant social cost. This averseness can influence the success of AV pilots and impact overall technology adoption [68]. However, the benefits of travelling autonomously, such as increased convenience and reduced human error, also represent social benefits. These advantages contribute positively to the overall assessment of AV technology. Like social costs, quantifying these benefits can be challenging, as they often involve subjective factors and long-term impacts that are difficult to measure precisely.

For example, a crash involving a self-driving shuttle, even if the shuttle was operating in manual mode at the time, can influence public perception and potentially lead to the discontinuation of the pilot. This situation exemplifies how social costs, including risk averseness and the broader effects on public trust, can affect the viability of AV initiatives

[69, 70]. The RAND report emphasises the importance of considering perception factors in evaluating technological impacts [6].

The complexity of quantifying social costs underscores the necessity for comprehensive frameworks that address both the economic and qualitative dimensions of these impacts. By incorporating social costs, such as risk averseness, and benefits, such as the advantages of autonomous travel, the thesis aims to build upon existing literature and provide a more nuanced understanding of the broader societal effects of AV technology [68, 71]. This approach enhances the framework by considering not only direct economic impacts but also the societal and perceptual factors that influence the success and acceptance of AV pilots.

## 2.5 Existing AV pilot characteristics

While the previous sections discuss concepts related to the design of the framework, it is crucial to examine how these concepts can be operationalised. This section explores existing AV pilot literature, focusing on the characteristics of these pilots and their relevance to the framework. AV pilots often build upon a foundation of existing knowledge, and social planners typically review past pilot information and observe other designs to inform their approaches [72, 73, 74]. Additionally, qualitative metrics such as user satisfaction surveys may be employed to assess the pilot’s impact [75], which can be valuable for quantifying social costs and benefits within the framework. Access to this data facilitates ongoing refinement of the framework as the pilot progresses.

This analysis begins with Canadian AV pilot studies due to the current relevance of these initiatives within Canada’s developmental context. Several provinces in Canada are actively engaged in planning and preparing for AV integration [76, 77, 78, 79]. By examining these national efforts, it is possible to assess the characteristics of AV pilots in Canada and compare them with those from other countries.

Table 2.1 categorizes Canadian pilot information, providing examples of AV pilots and their locations. The selected categories aim to maintain consistency in the available information across various pilots despite geographical differences. Notable categories for the framework’s concepts include operation dates, which may be used to estimate pilot durations; AV providers, which may be queried regarding disengagement rates; and route lengths, which may be used to estimate supply distances. It is important to note that while these attributes are common, additional attributes may become prevalent as pilots progress. For example, the DMV of California has been recording disengagements, which

may become more common over time [80, 81]. Each pilot involves a partnership between local governments and various entities, including research funding companies or manufacturers. Additionally, several pilots integrate with public transit systems, serving as last-mile services through designated routes. A common feature across these pilots is the use of automated shuttles for testing, many of which operate at speeds not exceeding 20 km/h due to safety concerns.

Table 2.1: Reviewed Canadian AV pilots.

| Project Owner(s)                                                   | City, Province     | Operating Date              | AV Provider  | Route Length   | Operating Speed | Purpose                                                                  | Reference            |
|--------------------------------------------------------------------|--------------------|-----------------------------|--------------|----------------|-----------------|--------------------------------------------------------------------------|----------------------|
| Transdev and City of Montreal                                      | Montreal, Quebec   | Fall 2018                   | EasyMile     | 1.4 km         | 15 km/h         | Testing consumer acceptance                                              | Company news [74]    |
| Transdev and City of Montreal                                      | Montreal, Quebec   | June 21, 2019 - Aug 4, 2019 | EasyMile     | 1.4 km         | 15 km/h         | Testing consumer acceptance                                              | Company news [74]    |
| Durham Region Transit, Town of Whitby and others                   | Whitby, Ontario    | 2021 - 2022                 | Local Motors | 6 km           | 20 km/h         | Assess benefits and implications                                         | Government news [82] |
| Area X.O, Transport Canada and City of Ottawa                      | Ottawa, Ontario    | Nov, 2020                   | EasyMile     | 1.5 km         | 15 km/h         | Assess performance and gain insight on planning                          | Company news [83]    |
| University of Waterloo, Robosense and others                       | Waterloo, Ontario  | Unknown                     | EasyMile     | 2.7 km         | 20 km/h [84]    | Testing AV technology [84]                                               | University news [85] |
| City of Calgary, University of Calgary and others                  | Calgary, Alberta   | Sept, 2018                  | EasyMile     | 1 km           | 12 km/h         | Testing AV technology and long-term feasibility                          | Government news [86] |
| City of Toronto, TTC and Metrolinx                                 | Toronto, Ontario   | Fall, 2021                  | Local Motors | Less than 5 km | Unknown         | Testing AV technology to connect residents to rapid transit and planning | Government news [87] |
| City of Hamilton, Autonomous Vehicle Innovation Network and others | Hamilton, Ontario  | Said to be 2020 - 2022      | Unknown      | Unknown        | Unknown         | Testing AV technology with road users                                    | Government news [88] |
| City of Candiac, and others                                        | Candiac, Quebec    | 2018 - 2019                 | NAVYA        | 2 km           | 25 km/h         | Testing road safety and social acceptance of AVs                         | Media news [89]      |
| City of Stratford, and others                                      | Stratford, Ontario | 2020                        | Unknown      | Unknown        | Unknown         | Testing smart infrastructure and AVs                                     | Media news [90]      |
| City of Beaumont, and others                                       | Beaumont, Alberta  | 2019                        | EasyMile     | 1 km           | 15 km/h         | Learn how electric AVs operate with residents and traffic                | Media news [91]      |

AV pilots may have different goals, as evidenced in Table 2.1. For instance, the pilot in Montreal with Transdev focused on user acceptance [74], while Toronto’s West Rouge Trial aimed to test AV technology for connecting residents to the rapid transit system, familiarising them with AVs, and investigating planning procedures [87]. These varying objectives influence the extent of user feedback required and the level of public exposure.

Public and private pilots often differ significantly in terms of the availability and scope of information. Public pilots, such as Toronto’s West Rouge Trial, may be subject to more stringent transparency requirements, leading to more detailed and accessible data on pilot outcomes. In contrast, private pilots, such as Montreal’s pilot with Transdev, may limit the dissemination of information, focusing on internal assessments and proprietary data. Consequently, the availability of information can vary greatly between pilots, impacting the ease with which comparisons can be made.

For example, Calgary’s trial provided comprehensive data on passenger numbers, trips made, distance travelled, and energy consumption via the ELA website [92]. This data facilitates detailed analysis and comparison. However, comparing this data with results from Toronto’s trial is challenging due to the latter’s closure to the public and restricted information access. Similarly, Montreal’s pilot with Transdev faces similar limitations, with available information being private and less accessible. These discrepancies highlight the challenges in comparing public and private AV pilots, emphasising the importance of considering information availability when evaluating pilot outcomes.

To gain a broader perspective on pilot attributes, it is necessary to examine pilots outside Canada, as domestic pilots provide only a limited view of the technology’s usage and performance data. Table 2.2 presents examples of international pilots, formatted similarly to the previous table. Many of these pilots offer information in categories that are comparable across different settings. However, due to the large number of pilots worldwide, not all could be included. Criteria were used to select the most relevant pilots for comparison, focusing on those involving test beds, automated cars, shuttles, and buses.

Table 2.2: Pilots outside Canada.

| Project Owner(s)                              | Location                 | Operating Date        | AV Provider               | Route Length                  | Operating Speed     | Purpose                                                        | Reference             |
|-----------------------------------------------|--------------------------|-----------------------|---------------------------|-------------------------------|---------------------|----------------------------------------------------------------|-----------------------|
| City of Arlington, May Mobility and others    | Arlington, Texas         | Mar, 2021 - Unknown   | May Mobility              | Service Area (1 sq mile) [93] | 25 km/h [93]        | Testing on-demand ride-sharing and AVs for safe transportation | Government news [94]  |
| City of Arlington, EasyMile and others        | Arlington, Texas         | Aug, 2017 - Aug, 2018 | EasyMile                  | Service area of unlisted size | 15 mph              | Testing AVs and educating the public                           | Government news [95]  |
| Waymo, City of Phoenix and others             | Phoenix, Arizona         | Public Tests 2017     | Waymo and FCA             | Service area of unlisted size | Max of 45 km/h [96] | For safety                                                     | Company news [97]     |
| Land Transport Authority and others           | Jurong Island, Singapore | 2021 [98]             | STROBO Series 12 Bus [99] | Unknown                       | 25 km/h [100]       | Create jobs, test safety and optimize road space               | Government news [101] |
| City of Seoul, Hyundai Motor Group and others | Seoul, South Korea       | Unknown               | Hyundai Motor Group       | Unknown                       | Unknown             | Testing AV technology for improvement                          | Company news [102]    |
| City of Madrid, Indra and others              | Madrid, Spain            | 2017                  | AUTO C-ITS                | 10 km [103]                   | Unknown             | Testing AV technology in different scenarios                   | Company news [104]    |
| City of Lisbon, C-Roads and others            | Lisbon, Portugal         | Unknown               | Unknown                   | Service area of unlisted size | Unknown             | Testing AV technology in different scenarios                   | Company news [103]    |
| City of Santiago, Transdev and others         | Santiago, Chile          | 2019 - 2020           | EasyMile                  | Unknown                       | Unknown             | Testing AV technology for last mile scenarios                  | Company news [105]    |
| City of Hwaseong-si, Transdev and others      | Hwaseong-si, South Korea | Unknown               | Unknown                   | Unknown                       | Unknown             | Testing AV technology                                          | Government news [106] |
| Oxbotica and others                           | Europe                   | May, 2022             | Oxbotica                  | Unknown                       | Unknown             | Testing AV technology                                          | Company news [107]    |
| City of Helsinki, Fabulos and others          | Helsinki, Finland        | May, 2022             | Oxbotica                  | Unknown                       | Unknown             | Testing AV technology and last mile transportation             | Company news [108]    |

Preference was given to projects with publicly available information. These criteria establish a benchmark for the standard set of information that pilot projects should aim to provide and how it can be incorporated into the framework. In some cases, information on these pilots required supplementation from press releases or news articles rather than being readily accessible to the public. Nevertheless, even with this additional information, significant differences between these pilots and Canadian pilots remain.

While some international pilots may have commenced around the same time, notable differences arise in the types of pilots and their attributes. For instance, pilots in Phoenix, Arizona [97] and Arlington, Texas [94] are not shuttle pilots but rather ride-service pilots utilizing smaller automated vehicles, in contrast to the range of shuttles deployed by Canadian pilots. Waymo, which has transitioned from a pilot stage to a fully operational business, also provides open datasets on its AVs, contrasting with the more restricted data access often encountered in Canadian pilots. Additionally, pilots conducted in Madrid, Spain, and Lisbon, Portugal, are accompanied by academic literature explicitly referring to these projects [109, 110].

The attributes commonly observed in AV pilot studies have implications for the framework, though they also underscore a significant issue regarding the availability of comprehensive data. While full transparency may not always be feasible, increasing the accessibility of data could be advantageous. For instance, disengagement rates—an attribute integral to the framework—are not typically reported among the standard attributes in the reviewed pilots. Furthermore, other critical factors, such as AV safety requirements for components, fleet sizes, route lengths, and anticipated demand, are often considered in pilot evaluations but are not uniformly disclosed.

Availability of pilot results facilitates comparative analysis between observed outcomes and initial predictions [93]. Incorporating certain attributes into the framework could incentivise greater transparency, potentially establishing benchmarks for future research. Table 2.3 presents a list of attributes that could be standardised to enhance data availability and comparability.

Table 2.3: Possible attributes of AV pilot programs and their descriptions.

| Attribute                  | Description                                                                                           |
|----------------------------|-------------------------------------------------------------------------------------------------------|
| Vehicle type               | Type of vehicle used in the pilot (e.g., shuttle, sedan, bus).                                        |
| Pilot purpose              | The main goal or objective of the pilot (e.g., technology testing, user acceptance).                  |
| Service area type          | The type of area where the pilot operates (e.g., urban, suburban, rural).                             |
| Route length               | The length of the routes covered during the pilot (e.g., 1 km, 5 km).                                 |
| Fleet size                 | The number of AVs participating in the pilot.                                                         |
| Disengagement rate         | The frequency or rate of system disengagements during the pilot.                                      |
| Public transit integration | The extent to which the AVs are integrated with existing public transit systems.                      |
| Operation hours            | The hours during which the AVs are operational (e.g., 24/7, business hours).                          |
| Operating speed            | The speed at which the AVs operate (e.g., 20 km/h, 50 km/h).                                          |
| Passenger capacity         | The number of passengers that the AVs can accommodate.                                                |
| Safety measures            | The safety protocols and features implemented during the pilot.                                       |
| Data collection methods    | The methods used to collect data during the pilot (e.g., sensors, surveys).                           |
| Public campaigns           | Any public awareness or engagement campaigns associated with the pilot.                               |
| AV provider                | The company or organization providing the AV technology.                                              |
| Regulatory compliance      | The adherence to relevant regulations and standards.                                                  |
| Costs                      | The financial aspects of the pilot, including budget and funding sources.                             |
| User demographics          | The demographics of users participating in the pilot.                                                 |
| Data security              | Measures taken to protect data privacy and security.                                                  |
| Success metrics            | Criteria used to evaluate the success of the pilot (e.g., user satisfaction, operational efficiency). |
| Operational challenges     | Specific challenges faced during the pilot (e.g., weather conditions, technical issues).              |
| Future tests               | Plans for future testing or expansion based on pilot results.                                         |

The attributes identified from the reviewed AV pilot literature offer a crucial foundation for evaluating AV pilots and the available data. Integrating these attributes—such as disengagement rates, fleet sizes, route lengths, and safety requirements—into the framework can aid in the standardisation of data reporting and analysis in future studies. This standardisation will enhance the comparability and reliability of pilot evaluations across different contexts. The pilot data presented in the tables highlights common elements, providing a valuable basis for deeper analysis. As efforts towards data standardisation progress, the insights gained will help refine the framework and support the broader adoption and optimisation of AV technologies.

## 2.6 Research contribution

The preceding sections of this review have detailed key concepts essential for designing a framework to assess AV pilots. From understanding the connections between learning and safety to examining the diffusion of AV technology and the intricacies of public perception and social costs, these elements collectively inform how AV pilots can be optimally structured and evaluated.

Central to this framework is the concept of safety, particularly as defined by disengagements. Disengagements—instances where the human driver must take over from the AV—serve as a critical measure of both the safety and reliability of AV systems. The frequency and context of disengagements provide insights into the AV’s learning curve and areas for technological improvement. Models of learning and improvement, such as iterative development and S-curve growth patterns, are instrumental in understanding how AV technology evolves and how safety can be enhanced over time.

Diffusion models, including those employing distributions and mathematical frameworks, offer valuable tools for predicting and analysing the spread of AV technology. For instance, the Bass Diffusion Model and Logistic Growth Model provide insights into how AVs might penetrate the market and influence safety outcomes as their adoption scales. These models help in estimating how quickly AVs will replace conventional vehicles and what impact this might have on overall safety and public perception.

Pilot information, as outlined in the reviewed literature, provides a substantial dataset for refining and validating the proposed framework. Key attributes such as disengagement rates, operational metrics, and other relevant factors are critical for assessing the effectiveness and risks associated with AV pilots. By integrating these data points, a case study can be synthesized to model various scenarios and outcomes, thus facilitating a more nuanced understanding of AV technology in practice. This methodology not only contributes

to standardising the assessment of AV pilots but also establishes benchmarks for future research and improves the comparability of pilot outcomes.

Ultimately, the integration of these concepts—safety metrics defined by disengagements, learning models, diffusion theories, and pilot data—forms a robust foundation for designing a framework aimed at minimizing risks and optimizing AV deployment. Figure 2.1 presents a simplified flowchart illustrating the relationships between these concepts. While the framework’s full development is a forthcoming step, the current exploration of these concepts directly addresses the research objectives: defining essential concepts within the context of AV pilots, laying the groundwork for a risk-minimization framework, and preparing for case studies using past pilot information. This approach not only sets the stage for practical pilot evaluation but also contributes to the broader discourse on AV integration, paving the way for more informed and effective policy and planning decisions.

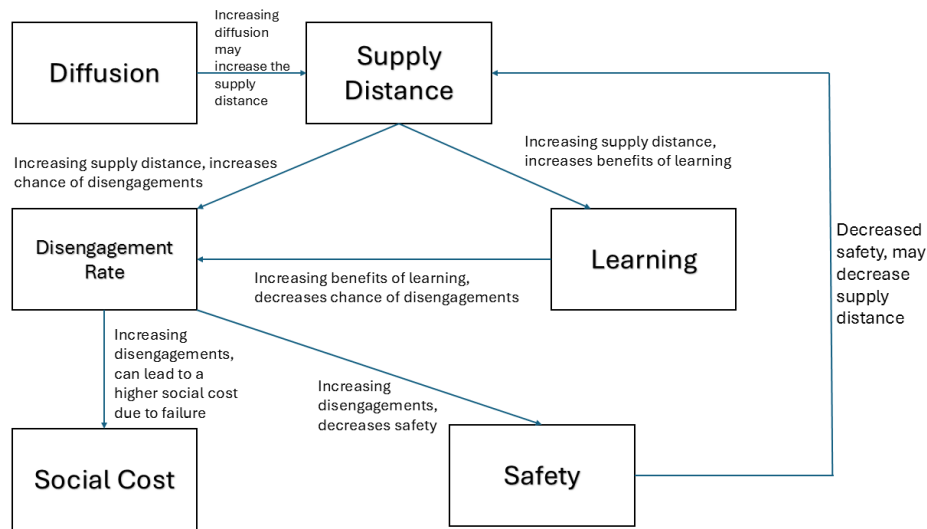


Figure 2.1: A flowchart showing possible relationships between supply distance, learning, safety, disengagements, and social costs.

# Chapter 3

## Mathematical framework outline

This chapter presents a mathematical framework tailored for social planners engaged in the development of AV pilot programs. The primary challenge addressed is integrating various concepts from the literature—such as safety, learning, diffusion, and public perception—into a cohesive model. This framework aims to balance the ideal aspirations with practical constraints, reflecting the principle that “perfection is the enemy of the good.” By tackling this challenge, the framework provides a structured approach to evaluating and optimizing AV pilot programs, facilitating more informed decision-making and effective implementation.

### 3.1 Diffusion modelling adaptation

In the given context, a scenario is considered where a social planner must devise a strategy for deploying AVs over  $T$  time units, denoted by  $t$ , which may extend over several months or years. The primary objective is to initiate and progressively expand an AV pilot program while ensuring compliance with safety regulations established or accepted by the social planner. This analysis begins with the formulation of the diffusion model that is central to the mathematical framework.

Diffusion modelling serves as a predictive tool for forecasting the spread of technology or ideas over time. Previous implementations of diffusion modelling include using a modified logistic growth model to evaluate the adoption rate of advanced traveller information systems [111] and applying diffusion models to simulate the market penetration of hydrogen fuel cell vehicles [112]. This approach has been extensively utilized across various contexts,

including studies on the proliferation of ideas [113, 114]. Drawing on recent research that employed a market penetration model to project the adoption of AV technology based on price differentials between AVs and conventional vehicles [115], the diffusion process can be approximated using a function that incorporates variables such as  $Q$ ,  $Q_1^a$ ,  $t$ , and  $\phi$ . This simplified representation of the diffusion model is given by:

$$q_t^a = g(Q, Q_1^a, t, \phi) \quad \forall t \in T \quad (3.1)$$

Here,  $Q$  denotes the total diffusion across the transportation network, with  $q_t^a$  representing the diffusion of AVs at time  $t$ , and  $q_t^h$  representing the diffusion of HVs at time  $t$ . The relationship between AV and HV diffusion is expressed as  $q_t^a + q_t^h = Q$ . The variable  $Q_1^a$  indicates the initial AV demand at  $t = 1$ , while  $\phi_t$  represents the cost differential between AVs and HVs at time  $t$ . This formulation provides a basis for approximating how these variables influence the diffusion process and can be adapted for more detailed modelling.

$\phi_t$  represents the difference between the cost of HVs, denoted as  $C_t^h$ , and the cost of AVs, denoted as  $C_t^a$ , as follows:

$$\phi_t = C_t^h - C_t^a \quad \forall t \in T. \quad (3.2)$$

Although  $\phi_t$  can be negative, indicating that AVs might cost more than HVs, this formulation is intended as a conceptual component within the framework. This potential negativity does not pose a problem for the model, as it assumes that AVs are generally considered beneficial. If AVs were not deemed to offer any potential benefits, there would be no reason for comparison in the first place. Subsequent analyses will decompose the cost components further, including social factors, to offer a more detailed understanding of the costs involved. The use of  $\phi_t$  as a difference in cost is crucial to the diffusion model and serves as a foundational concept rather than a definitive limitation of the framework.

Utilizing the difference in costs, which influences demand as supported by prior research [116, 117], the demand functions can be defined as follows:

$$D_a(\phi_t) = q_t^a \quad \forall t \in T, \quad (3.3)$$

$$D_h(\phi_t) = Q - D_a(\phi_t) = q_t^h \quad \forall t \in T. \quad (3.4)$$

These equations represent the demand functions for AVs ( $D_a$ ) and HVs ( $D_h$ ). Furthermore, the inverse of the AV demand function, which denotes the perceived benefit received by AV users at time  $t$ , is expressed by:

$$D_a^{-1}(q_t^a) = \phi_t. \quad (3.5)$$

Finally, a supply-demand condition is defined to ensure that the distance travelled by the travellers does not exceed the distance provided by the pilot:

$$q_t^a L \leq x_t \quad \forall t \in T, \quad (3.6)$$

where  $L$  represents the average trip length of the travellers, and  $x_t$  denotes the supply distance of the pilot. The choice of average trip length rather than total trip length is made to provide a more generalizable measure that can be adjusted based on the specific needs and constraints of the social planner. This average trip length allows for flexibility in adapting to varying trip patterns and pilot conditions. Establishing the diffusion of the mathematical framework sets the groundwork for exploring other essential concepts in its development and future models.

## 3.2 Travel demand and comfort

Building upon the previously discussed concepts related to cost, as outlined in the RAND report and perceptions of users, the subsequent section of the framework will further explore these elements. The cost of travelling in a HV is denoted by  $C_t^h$ , while the cost of travelling in an AV is represented by  $C_t^a$ . A unified cost of travel, including time and financial tolls, is denoted as  $c$ , which applies to both transportation modes. For AVs, travellers might gain utility from not having to drive, captured by a discount factor,  $\alpha$ . Additionally, travellers may display risk aversion due to perception of AV disengagements, which can be accounted for by introducing a discomfort factor,  $\beta$ . The cost functions can thus be formulated as:

$$C_t^h = g(c) \quad \forall t \in T, \quad (3.7)$$

$$C_t^a = g(c, \alpha, \beta, r_t) \quad \forall t \in T. \quad (3.8)$$

The parameters  $\alpha$  and  $\beta$  hold particular importance in the context of this study. Specifically,  $\alpha$  represents a discount factor for travellers, reflecting the additional comfort and convenience associated with not having to drive. This increased comfort may translate into

more time for passengers to engage in alternative activities or focus on other pursuits. Similarly,  $\beta$  is a factor that captures the hesitancy of travellers to adopt AV technology, based on anticipated failure rates. It is assumed that travellers are aware of these failure rates. Additionally,  $r_t$  denotes the disengagement rate, which will be discussed in greater detail in the subsequent section. While the framework can be expanded to incorporate more detailed and nuanced cost considerations, the current model employs these parameters to maintain simplicity.

### 3.3 Consideration of safety and failure

Previously, the concept of failure was introduced in the context of understanding  $\beta$ . Within this discussion, safety is conceptualized as a reduction in these failures, characterized specifically as the number of disengagements within  $T$ . The count of disengagements is typically modelled using a Poisson distribution with a rate of  $r_t$ , known as the failure rate. However, to maintain a more general framework, alternative distributions may be considered for modelling disengagements. For instance, diffusion models discussed by [118] and [119] offer various approaches for modelling stochastic processes, which can be applicable for different types of failure distributions. Incorporating the rate of disengagements with the AV pilot supply distance ( $x_t$ ) and cumulative supply distance ( $X_t$ ), the number of failures at time  $t$ , denoted as  $n_t$ , can be estimated accordingly. This random variable is expressed as:

$$n_t \sim P\{r_t x_t\} \quad \forall t. \quad (3.9)$$

Considering the stochastic nature of the number of failures associated with the deployment of AVs, the social planner establishes critical safety thresholds in the form of minimum and maximum acceptable levels of disengagements for the new AV technology. This strategic approach aims to control the range of disengagements, thereby managing social risks in the design of AV pilot programs. The formulation of this safety criterion is defined as follows:

$$\text{Prob}\{n_t \geq \xi\} \leq \theta \quad \forall t, \quad (3.10)$$

The safety constraint ensures that the probability of the number of failures exceeding a predefined threshold, denoted as  $\xi$ , remains below a specified level  $\theta$ . The parameters  $\xi$  and  $\theta$  represent the social planner's tolerance for risk and safety conservatism.  $\xi$  is defined

as the minimum number of failures the social planner is willing to accept—meaning that if the number of failures is lower than  $\xi$ , this is seen as a positive outcome. Since  $\theta$  acts as an upper bound on risk, it is essential to recognize that a higher risk threshold may lead to increased social costs. Specifically, the social cost, denoted as  $C$ , is intrinsically linked to  $\theta$ : higher values of  $\theta$  correspond to a higher potential for failures, thereby increasing the associated social cost. The relationship can be conceptualized as  $C \cdot \theta$ , where a higher  $\theta$  would imply a higher cost due to an increased frequency of failures.

The assumed value of  $C$  will be factored into the objective function and reflects the social planner’s tolerance for acceptable risk. Estimating  $C$  is challenging, as it involves measuring various factors associated with failure costs, including potential accidents. This challenge aligns with observations from the RAND report, which advocated for incorporating social costs into the framework but did not provide a concrete methodology for its implementation.

Empirical observations from AV pilots substantiate that the failure rate experiences a decline with increasing total distance travelled as driving algorithms mature and learn to circumvent prior errors [6, 120]. Let  $f(X_t)$  be defined as a learning function, where  $0 \leq f(X_t) \leq 1$ , characterizing the reduction in the failure rate from  $r_{t-1}$  to  $r_t$  at time  $t$ , given a cumulative supply distance of  $X_t$ . Drawing inspiration from the characteristics of the S-curve learning trend [35], the following two properties are imposed on the learning function. Firstly,  $\partial f(X_t)/\partial X_t < 0$  signifies a decrease in the failure rate as  $X_t$  increases for any given  $t$ . Additionally,  $\partial^2 f(X_t)/\partial X_t^2 > 0$  indicates diminishing returns in learning, representing a progressively smaller reduction in the failure rate as  $X_t$  increases. Consequently, the failure rate at time  $t$  can be expressed as:

$$r_0 = R, \tag{3.11a}$$

$$r_t = Rf(X_t) \quad \forall t \in \{1, \dots, T\}, \tag{3.11b}$$

Where  $R$  signifies the initial failure rate established by the original equipment manufacturer (OEM) before deploying their AV fleet for a pilot. The iterative multiplication depicted in Equation (3.11b) establishes a connection between the advantages of the learning function and the initial failure rate. The progression of learning throughout the pilot duration influences the failure rate. As the  $f(X_t)$  approaches zero, indicating an increase in learning,  $r_t$  also tends toward zero. The specific definition of the learning function holds significance in shaping the characteristics of the failure rate.

### 3.4 Worked example of the framework

Consider an AV pilot program where the initial failure rate  $R$  is set at 0.05 failures per mile, as defined by the OEM. The cumulative supply distance  $X_t$  represents the total miles driven by the AV fleet at time  $t$ .

For this example, let the learning function  $f(X_t)$  be defined as:

$$f(X_t) = \frac{1}{1 + 0.1X_t}, \quad (3.12)$$

which represents the reduction in failure rate as the AV system learns from cumulative driving experience.

#### Initial Conditions

At the start of the pilot program,  $X_t = 0$ , so the failure rate is:

$$r_t = R \cdot f(X_t) = 0.05 \cdot f(0) = 0.05 \cdot 1 = 0.05 \text{ failures per mile.} \quad (3.13)$$

#### After Driving 1000 Miles

After driving a cumulative distance of  $X_t = 1000$  miles, the learning function updates as:

$$f(1000) = \frac{1}{1 + 0.1 \times 1000} = \frac{1}{101}. \quad (3.14)$$

Thus, the new failure rate becomes:

$$r_t = 0.05 \cdot \frac{1}{101} \approx 0.000495 \text{ failures per mile.} \quad (3.15)$$

#### Probability of Exceeding the Safety Threshold

Suppose the social planner has established a minimum safety threshold  $\xi = 1$  failures, indicating that the number of failures should not drop below this level. The risk tolerance

$\theta = 0.01$  represents the maximum acceptable probability of having more than this minimum number of failures.

We now estimate the probability that the number of failures  $n_t$  exceeds this threshold using the Poisson distribution. After the AVs drive an additional 2000 miles, the expected number of failures is:

$$\lambda = 2000 \times 0.000495 \approx 0.99. \quad (3.16)$$

Given that  $\lambda$  is slightly below the threshold of 1, the probability of having fewer than  $\xi$  failures (i.e., less than 1 failure) is still acceptable under the planner's considerations. However, we can calculate the probability of observing exactly 1 or more failures (i.e.,  $n_t \geq 1$ ) using the Poisson cumulative distribution function.

Using a Poisson distribution with  $\lambda = 0.99$ , we calculate the probability of having more than 1 failure:

$$\text{Prob}(n_t \geq \xi) = 1 - \text{PoissonCDF}(\lambda = 0.99, \text{threshold} = 1). \quad (3.17)$$

## Conclusion of the Example

In this case, the social planner's tolerance is satisfied, as the probability of exceeding the minimum failure threshold  $\xi = 1$  is still within the acceptable risk level, and the framework shows that driving further would likely remain within acceptable safety limits.

This example illustrates how the framework can be applied to assess risk, showing that even when the expected number of failures is low, the framework accommodates the social planner's minimum risk considerations. However, it's essential to remember that these values are for illustrative purposes, and real-world calibration would be needed to validate the results. The next section will focus on adapting this framework to demonstrate its flexibility and meet various objectives.

# Chapter 4

## Customizing the general framework: three models for social planners

Section 3 has established the foundational concepts for the equations and parameters within the proposed framework. This section will now present specific examples tailored for application within the context of this study. The equations introduced in this thesis will be extended to account for various scenarios encountered in an AV pilot program. The social planner’s objective is to optimize social welfare by minimizing potential costs, using equations that can be adapted based on the planner’s understanding of the specific conditions.

### 4.1 Failure, risk and learning equations

Earlier, it was stated that the failure rate could be modelled using a probability distribution. Given the nature of AV disengagements, we select the Poisson distribution, as it is well-suited for modelling non-negative, discrete events that occur independently and are memoryless over time [121]. This is ideal for AV disengagements, where failures occur sporadically and independently of one another. The Poisson distribution accurately reflects the randomness of such events within the deployment period, capturing the likelihood of discrete failures. Thus, the failure rate at time  $t$  is given by:

$$n_t \sim \text{Pois}\{r_t x_t\} \quad \forall t. \quad (4.1)$$

In the context of Equation 3.10, the previously established constraints for  $n_t$  continue to apply. The concept of acceptable risk, denoted as  $\theta$ , is closely linked to the notion of social cost,  $C$ . A higher acceptable risk threshold might lead the social planner to accept a greater social cost, reflecting a trade-off between risk tolerance and societal impact. Furthermore, the failure rate at time  $t$  is shaped by the initial failure rate,  $R$ , and the learning function. To model the learning process, a logit model is employed, drawing on methodologies discussed in the literature [6, 31]. This model effectively captures the dynamic where  $f(X_t)$  approaches zero, signifying improved learning, which in turn causes  $r_t$  to converge towards zero. The learning function is expressed as follows:

$$f(X_t) = \frac{1}{0.5 + 0.5 \exp(\frac{X_t}{A})} \quad \forall t. \quad (4.2)$$

In the provided learning function  $f(X_t)$ , the parameter  $A$  dictates the rate at which the failure rate  $r_t$  approaches zero as the cumulative supply distance  $X_t$  increases. Although  $A$  does not directly scale the function, it influences the curvature of the learning process, determining how rapidly improvements occur as additional distance is accumulated. This logistic form is consistent with the S-curve learning dynamics discussed in the relevant literature [6, 31, 35]. The flexibility of  $f(X_t)$  allows for further refinement, such as the introduction of a  $\gamma$  parameter to adjust the elasticity of the function and better accommodate different technological learning environments. In this study, the scenario in which the social planner's maximum acceptable risk,  $\theta$ , remains constant over time is referred to as the special case of the general model. This particular case has been selected for analysis as it represents a distinct operational condition where the planner does not vary the acceptable risk threshold, offering a focused framework for examining consistent risk management. The implications and outcomes of this special case will be further explained in Section 6.

## 4.2 Travel demand, cost and comfort

The simplification of the transportation network into HVs and AVs, allowing for a clear division of demand, is adopted in this study. The incorporation of additional travel modes is not considered in this analysis. Furthermore, the cost functions are simplified and may be subject to adjustments in future models. Initially, the cost of an HV is assumed to be represented by the cost of travel time or financial tolls, denoted as  $c$ . It is posited

that AVs must provide some benefit to offset this cost, introducing the discount factor,  $\alpha$ , which modifies the cost for AVs. The scenario where  $\alpha$  is less than 1 is explored, indicating that AVs are more likely to be deployed when a utility benefit is present. This context is essential, as a higher cost for AVs would negate their usage unless balanced by benefits reflected in  $\alpha$  and the discomfort factor,  $\beta$ , which accounts for travellers' reactions to the failure rate. Thus, incorporating these factors, the costs for HVs and AVs can be expressed as:

$$C_t^h = c \quad \forall t \in T, \quad (4.3)$$

$$C_t^a = \alpha c + \beta r_t \quad \forall t \in T. \quad (4.4)$$

### 4.3 Diffusion modelling equations and the simplified diffusion model

Given that previous diffusion models have employed logistical growth models to explore adoption rates, we adopt a modified approach inspired from previous works [115]. We tailor the equation towards AVs and attempt to capture the S-shaped adoption curve. The diffusion of AVs in the pilot is related to the diffusion during the previous time unit (and the pilot's initial start). By accounting for the preceding time interval, we acknowledge that the diffusion process is influenced by historical and current factors. Additionally, the cost difference between AVs and HVs plays a role in the diffusion of AVs. If AVs offer a clear benefit represented by the cost differential, it can be reflected in this adoption rate. This approach integrates cost dynamics, diffusion patterns, and AVs, which culminates in the following equation:

Building on previous diffusion models that have employed logistic growth frameworks to investigate adoption rates, this study adopts a modified approach informed by earlier research [115, 6, 31]. The equation is specifically tailored to AVs to effectively capture the S-shaped adoption curve characteristic of technology diffusion [59, 60]. The diffusion of AVs within the pilot program is inherently linked to the diffusion observed in the preceding time unit, as well as the initial deployment phase of the pilot. By incorporating the historical context of the previous time interval, this approach acknowledges that the diffusion process is influenced by both past trends and current conditions. Furthermore, the differential in costs between AVs and HVs significantly impacts the adoption rates of AVs. Should AVs provide a discernible advantage as indicated by the cost differential, this benefit can be

reflected in the adoption rate. This methodology synthesises cost dynamics, diffusion patterns, and the unique characteristics of AVs, resulting in the following equation:

$$q_t^a = \frac{QQ_1^a}{Q_1^a + (Q - Q_1^a) \exp(-\phi_t t)} \quad \forall t \in T, \quad (4.5)$$

The value  $Q$  significantly influences the behavior of the exponential function in the equation, potentially driving it towards 0 depending on the sensitivity of the model's parameters. Specifically, as  $Q$  increases relative to  $Q_1^a$ , the denominator may become dominated by the term involving  $\exp(-\phi_t t)$ , resulting in a decrease in the overall adoption rate  $q_t^a$ . Initial model tests that exclude  $Q$  could yield contrasting results, highlighting the importance of this parameter in determining adoption dynamics. This aspect warrants further exploration, particularly in the context of sensitivity analysis to understand the implications of varying  $Q$ . Furthermore, the difference function  $\phi$  can be simplified based on the previously defined cost functions, allowing for a more streamlined analysis of its impact on the diffusion of AVs. Additionally, the difference function,  $\phi$ , can now be simplified based on our defined cost functions as:

$$\phi_t = C_t^h - C_t^a = c(1 - \alpha) - \beta r_t \quad \forall t \in T. \quad (4.6)$$

While the demand functions and the supply-demand constraint remain unaltered in this model, an important modification is introduced concerning the diffusion equation. Specifically, this addresses scenarios where the traveller's discount factor,  $\alpha$ , is not constant but instead varies over time. This variability introduces an additional level of uncertainty, particularly when the social planner is unaware of the initial diffusion rate. In such instances, the discount factor may be derived based on evolving system dynamics. By incorporating the failure rate,  $r_t$ , and the discomfort factor,  $\beta$ , the discount factor can be expressed as:

$$\alpha_t = \frac{\beta r_t}{c} \quad (4.7)$$

This relationship is derived by assuming that the cost can be linked to diffusion via the established relationship between cost and demand [115]. Here, the failure rate and discomfort factor directly influence the perceived utility of AVs, modifying the discount factor  $\alpha$  accordingly. As the failure rate increases, the demand for AVs decreases, reflected in a higher discount factor, thereby capturing the dynamic interaction between cost and diffusion in the model.

In light of the uncertainty surrounding initial diffusion and  $\alpha$ , a linear diffusion model is appropriate. When initial adoption and the discount factor are unknown, this linear approach offers simplicity and flexibility. It directly relates the diffusion of AVs to real-time cost changes without requiring complex assumptions about initial conditions. This leads to the following simplified diffusion model, which assumes a direct linear relationship between the adoption of AVs and the cost differential [122, 118]:

$$q_t^a = Q(1 - \frac{\beta r_t}{c}) \quad (4.8)$$

As the diffusion model is modified to account for changes in the discount factor, corresponding adjustments are reflected in the objective function. This modified approach, however, does not incorporate the initial diffusion. Instead, it calculates diffusion at each time unit by relying on the failure rate, discomfort factor, and cost ( $c$ ). While this equation is simpler than the previous diffusion equation (3.10), deviations may arise from the exclusion of initial diffusion, which can influence the adoption process. By simplifying the calculations, some precision is traded for practicality in modelling the diffusion. This approach is referred to as the simplified diffusion model for this case.

## 4.4 Objective functions

In this model, the objective function aims to minimize the total cost incurred by travellers, encompassing costs associated with AVs and HVs, as well as social costs represented by  $\theta$ . This cost minimization is intrinsically linked to the reduction of disengagements, as fewer disengagements correspond to higher safety levels and, consequently, enhanced social welfare. The equation governing  $q_t^a$  reflects the interplay of factors affecting adoption rates, where changes in  $\alpha$  directly influence the cost dynamics. The constraint relating to  $r_t$  and its formulation emphasizes the dependence on the failure rate and other parameters, thereby integrating these crucial aspects into the objective function.

By incorporating the changes outlined in this section along with the initial mathematical framework, the policymaker minimizes the total travellers' cost by solving the following mathematical model referred to as the general model:

$$\min_{x_t, \theta_t} \quad q_t^a(\alpha c + \beta r_t) + \sum_t (c(Q - q_t^a)) + \sum_t (C\theta) \quad (4.9a)$$

$$S.t. : \quad q_t^a = \frac{Q Q_1^a}{Q_1^a + (Q - Q_1^a) \exp \left( -t \left( c(1 - \alpha) - \beta r_t \right) \right)} \quad \forall t \in T, \quad (4.9b)$$

$$q_t^h = Q - q_t^a \quad \forall t \in T, \quad (4.9c)$$

$$x_t \geq q_t^a L \quad \forall t \in T, \quad (4.9d)$$

$$r_t = Rf(X_t) \quad \forall t \in T, \quad (4.9e)$$

$$Prob\{Pois(r_t x_t) \geq \xi\} \leq \theta_t \quad \forall t \in T. \quad (4.9f)$$

In this formulation,  $x_t$  represents the control variable tied to the operational capacity and directly influences the system's response to demand fluctuations. The objective function, expressed in the first equation, aims to minimize the combined costs of AV operations, the difference between total demand and AV adoption, and the associated social costs, thereby aligning with the policymaker's goal of optimizing travel costs and enhancing social welfare.

The constraint for  $q_t^a$  in the second equation captures the adoption dynamics of AVs, reflecting the influence of historical and current factors on adoption rates. The third equation states the relationship between total demand and AV adoption, ensuring that the model accurately reflects the supply-demand interactions. The fourth equation establishes a capacity constraint based on the operational level, while the fifth equation relates the failure rate to system performance, further integrating safety considerations into the model. Lastly, the sixth equation incorporates a probabilistic constraint that ties social costs to the acceptable risk level determined by the social planner.

This framework results in an optimization problem characterized by non-linear and dynamic elements, accompanied by multiple constraints. To effectively address this minimization within the optimization process, a thorough understanding of the functional relationships among the various components is essential. Moreover, this model incorporates probabilistic elements to represent real-world scenarios, acknowledging that actual costs may entail consequences beyond the scope of the mathematical framework.

The general model incorporates the social cost,  $C$ , linked to the social planner's maximum acceptable risk within the objective function. By including this cost, the model seeks to mitigate situations where the prioritization of maximizing supply distance could overshadow other important considerations in AV deployment strategies. Minimizing traveller

costs, in turn, is intrinsically tied to reducing disengagements, which can enhance overall social welfare.

In the special case of the general model, where the social planner's maximum acceptable risk,  $\theta$ , remains constant, the objective function's structure is preserved. However, with  $\theta$  fixed, the optimization may result in a scenario where AV deployment maintains a steady rate that meets the risk threshold, potentially allowing for more aggressive or faster adoption if AVs consistently operate within the acceptable risk level. This removal of dynamic risk adjustment may favor a strategy that prioritizes maximizing adoption rates under the assumption that the risk constraint is already met.

The modified diffusion model, referred to as the simplified diffusion model, introduces alterations to the discount factor equation, thereby impacting the cost equation from Equation 4.4. Consequently, the adjusted objective function for this model is formulated as follows:

$$\begin{aligned}
\min_{x_t, \theta_t} \quad & \sum_t \left( q_t^a (\beta r_t * \frac{(1-\beta r_t)}{2}) + (Q - q_t^a c) \right) + \sum (c(Q - q_t^a)) + \sum (C\theta) & (4.10a) \\
S.t. : \quad & q_t^a = Q(1 - \frac{\beta r_t}{c}) & \forall t \in T, \\
& & (4.10b) \\
& q_t^h = Q - q_t^a & \forall t \in T, \\
& & (4.10c) \\
& x_t \geq q_t^a L & \forall t \in T, \\
& & (4.10d) \\
& r_t = Rf(X_t) & \forall t \in T, \\
& & (4.10e) \\
& Prob\{Pois(r_t x_t) \geq \xi\} \leq \theta_t & \forall t \in T. \\
& & (4.10f)
\end{aligned}$$

Although the objective function is termed "simplified," it retains the characteristics of an optimization function akin to the general model. The alterations made to the diffusion equation result in a model that continues to embody non-linear and dynamic factors, which may pose challenges for computational methods. Each equation in this formulation serves a critical role: the first equation captures the total cost minimization, considering both the costs associated with AV adoption and the social costs; the second equation delineates the

adoption dynamics based on the adjusted diffusion framework; the third equation ensures the integrity of the supply-demand relationship; the fourth equation establishes capacity constraints; the fifth equation relates the failure rate to system performance; and the sixth equation incorporates a probabilistic constraint on acceptable risk.

The results produced by the simplified diffusion model will differ inherently from those generated by both the general model and its special case. As a result, direct comparisons between these outcomes must be treated with caution, acknowledging the distinct methodologies applied in each case. However, these comparisons are significant in the context of this thesis, as they highlight how variations in diffusion frameworks influence overall system performance and inform decision-making processes. By integrating these insights, this approach makes a substantial contribution to the literature on AV deployment strategies and social costs, offering policymakers and stakeholders a deeper understanding of the trade-offs involved in AV adoption. This work enhances the theoretical foundation by bridging the gap between diffusion models and practical deployment scenarios, providing valuable tools for guiding the transition towards AV integration in real-world systems.

# Chapter 5

## Case study and solution method

To exemplify the application of the models, a case study will be conducted utilizing fundamental data derived from potential pilot scenarios along with necessary assumptions. This approach aims to simulate a scenario wherein a social planner employs the models to evaluate a pilot before deployment. As the model's variables are not calibrated, primary data becomes essential for generating possible trends that a social planner might anticipate. The base case will be implemented across the models outlined in Section 4. Additionally, the solution method utilized in MATLAB will be described, providing insight into the computational approach taken in this case study.

### 5.1 Background, safety, failure and learning considerations

The planning phase of AV pilots is critical for implementing the models presented in this paper. A prior study on Canadian pilots [13] documented various pilot projects, many of which operated for several months, with some extending up to a year. The West Rogue Trial [67] serves as a relevant reference point. Therefore, it is reasonable for the social planner to establish a general pilot duration for observation using the models. In this case study, a ten-month pilot duration is assumed, aligning with the operational timelines observed in the aforementioned study [13]. Given that the West Rogue Trial was scheduled from summer 2021 to February 2022, rounding to ten months is deemed appropriate for scenarios in which AV pilot services are initiated in a designated area. During such instances, vendors

supplying AVs are expected to engage in comprehensive planning phases with stakeholders regarding shuttle operations and routing.

Additionally, in light of new regulations in Ontario [13, 81] and the necessity for empirical data, vendors are likely to gather information on disengagements and other operational issues, such as service reliability and user acceptance. The social planner is presumed to have access to vendor data or prior disengagement reports, which can be utilized to construct the Poisson distribution in Equation (4.1). This integration, alongside various supply distances, enables the social planner to effectively assess safety considerations.

In the case study, a ten-month duration is examined to assess long-term effects, utilizing a deliberately set higher-than-average failure rate to adopt a conservative stance in the analysis. For context, Waymo’s disengagement rate in 2021 was approximately one disengagement per 12,000 miles [80, 123]. The initial average failure rate, denoted as  $R$ , for this theoretical case is conservatively estimated at one failure for every mile, assuming the vendor is experienced, akin to Waymo. This choice to employ a higher failure rate reflects a precautionary approach, accounting for potential discrepancies in performance across different vendors, particularly in the absence of transparent data for Canadian pilots [13]. While Waymo’s publicly available information serves as a reference, it is acknowledged that other manufacturers and vendors may exhibit higher failure rates, as indicated by data collected from the State of California [80, 123]. Given the absence of calibration and the potential variability in defining failure, this estimate may be subject to refinement in future studies. To illustrate the application of the model, complete calibration may not be requisite.

To establish a baseline for the social planner’s expectations, a Poisson distribution is assumed to account for the number of accidents per time unit, denoted as  $n_t$  in Equation 3.10. In this context, the social planner’s level of conservatism, denoted as  $\xi$ , is set to one. This choice signifies a cautious approach, reflecting the planner’s intent to err on the side of safety when making predictions about potential outcomes. Additionally, the risk level, denoted as  $\theta$ , is maintained as a constant value of one for the special case of the general model. A  $\theta$  value of one implies that the social planner is willing to accept a baseline level of risk, establishing a threshold for decision-making. Holding  $\theta$  constant introduces a shift in the model’s results, but it allows for easier interpretation and analysis. In both the general model and the simplified diffusion model, the social planner retains the flexibility to assess  $\theta$  dynamically throughout the pilot duration, thereby facilitating optimal decision-making based on their assessments.

## 5.2 Travel demand and comfort considerations

Subsequently, the social planner is required to address considerations related to travel demand and user comfort. This can be accomplished through perception surveys designed to gauge users' perspectives on safety and the relative comfort associated with the utilization of AVs. Additionally, community engagement initiatives, such as town hall meetings, may serve as effective methods for collecting pertinent data. For both the general and special cases, it is assumed that  $\alpha = 0.65$ , reflecting an enhanced user comfort level, as the utility derived from using an AV typically serves as a significant incentive. The social planner may opt to designate specific areas where AVs are best suited, aligning with contextual factors, similar to the rationale behind the selection of the West Rogue Trail's location to coincide with existing train schedules [67]. In the simplified diffusion case, the parameter  $\alpha$  is not required as an input. The value of  $\beta = 3$  is adopted to represent the assumed reluctance stemming from failures, thereby influencing the discomfort factor. This value is not tied to a specific scale; rather, it serves as a relative measure of discomfort, indicating a moderately high level of reluctance to use AVs in the event of failures. It is acknowledged that these parameters are subject to refinement based on the social planner's insights into the user demographic and the prevailing social climate.

While an increase in the accident threshold may be appropriate for certain areas, such as Durham, where a previous pilot experienced an incident [70, 69], maintaining a threshold of three for this generic case study serves as a suitable starting point for initial analysis. The perception surrounding the incident can significantly influence the pilot's initial parameters, as evidenced by the outcome of the Durham pilot, which may have contributed to its termination. Another critical variable to consider within the models is the cost parameter, denoted as  $c$ , which is assumed to be 10. A higher cost parameter would further accentuate the distinctions between the costs associated with utilizing AVs versus HVs and is contingent upon the preferences of the social planner's target user base. The choice of a general cost of 10 is justified as it allows for a balance where the costs of AVs are competitive with HVs, thus providing utility without discouraging usage. Given that the model requires calibration, initiating with a value that allows for easy adjustment is prudent.

Furthermore, the social cost, denoted as  $C$ , integrated into the objective functions of the models, operates under a similar rationale. In urban areas characterized by higher population densities, the social cost of an accident is anticipated to be elevated. A negative impact resulting from a failure could jeopardize the viability of a pilot serving an area capable of accommodating it at a higher capacity. Therefore, a value of  $C = 20$  is assumed. The final consideration regarding demand is predicated on the understanding established between the social planner, users, and AV suppliers. The models presume an

asymmetrical balance between the demand for HVs and AVs. Given that AV routes may provide additional connectivity to transit systems or serve areas lacking adequate transit options, often referred to as “transit deserts” [13], it is assumed that approximately five percent of the total demand would be allocated to AVs at the outset.

While the initial demand figure may appear modest, it reflects the anticipated shifts associated with the pilot and may yield significant effects contingent upon the pilot’s outcomes. The highest demand is anticipated in scenarios where autonomous vehicles AVs replace HVs; however, pilots may also facilitate the introduction of new routes tailored specifically for AVs. The initial demand for AVs is instrumental in determining supply constraints and shaping the social planner’s initial risk parameters, which are particularly critical in the early stages of implementation. Notably, within the simplified diffusion model, the initial diffusion parameter is not an explicit input, as the model operates primarily on the travellers’ discount factor. This approach underscores the necessity for tangible results at the onset of the pilot project. The social planner retains the flexibility to negotiate this initial demand figure based on the unique characteristics of the pilot. Nevertheless, it is positioned as a general expectation for a comprehensive transition to AVs over the long term.

### 5.3 Diffusion considerations

Finally, the diffusion considerations for the models will be adjusted according to the collaboration between the social planner and the AV supplier. In both the general and special case models, the adoption rate of AVs is influenced by the benefits associated with using AVs in the previous year (or the anticipated benefits in the first year). This requires an assessment of the changes in total demand within the transportation network and a comparison of the cost differences between AVs and HVs. The demand function for AVs and HVs will be derived from the diffusion and cost functions and will be subject to constraints imposed by Equation (3.6), which depends on the average traveller distance.

The social planner must strive to align the pilot’s provision with the demand of travellers. However, this presents a catch-22 situation: the social planner cannot accurately gauge the demand until the pilot is conducted. This uncertainty necessitates an initial estimate, which may require adjustment based on observed demand during the pilot. Therefore, while aiming to match demand, the social planner must anticipate potential discrepancies and adapt strategies accordingly.

For this case study, an average trip length,  $L$ , of one mile is assumed. Although the West Rogue Trial’s pilot area was approximately three miles [13], a one-mile assumption is

chosen here for ease of interpretation and to simplify the model. This is because the actual area covered in the West Rogue Trial may not have been fully utilized, and a larger pilot area necessitates more intricate planning and consideration. The initial demand values for the network,  $Q$ , and initial AV demand,  $Q_1^a$ , are set at 0.05 and 1 (representing 5% and 100%, respectively), reflecting an introductory scenario where AVs are expected to cater to 5% of the network demand while diffusion of the technology unfolds.

As a metric for social welfare, social planners may use the inverse of the cost functions to represent the received benefit. Minimizing the potential costs associated with the technology is crucial for enhancing social welfare, aligning with common objectives in pilot programs [13]. By incorporating concepts of learning, diffusion, and safety, social planners can leverage the models to understand and project the general outcomes of their pilot deployments.

## 5.4 Summarized information of the models and solution method

Model 1 represents the general model, encompassing various attributes required for evaluating a pilot project, as outlined in the preceding section. Table 5.1 presents the attributes associated with this general model, excluding the special case considerations.

Table 5.1: Attributes for the general model (Model 1).

| Variable | Description                                | Value  |
|----------|--------------------------------------------|--------|
| $T$      | Pilot operating period (months)            | 10     |
| $R$      | Initial failure rate for every mile        | 1      |
| $\xi$    | Social planner's conservation level        | 1      |
| $\theta$ | Social planner's maximum risk              | varied |
| $\beta$  | Travellers' reluctance due to failure      | 3      |
| $\alpha$ | Comfort factor for not driving             | 0.65   |
| $c$      | Cost factor                                | 10     |
| $C$      | Social cost factor                         | 20     |
| $L$      | Average trip distance (miles)              | 1      |
| $Q$      | Total transportation demand in the network | 1      |
| $Q_1^a$  | Initial AV demand                          | 0.05   |
| $A$      | Rate of improvement in the learning        | 5      |

Model 2 represents a special case of the general model, specifically tailored for scenarios where the social planner's maximum risk,  $\theta$ , is set to a fixed value of 1. This adjustment simplifies the model for particular applications, providing a focused analysis based on this constant parameter. The attributes for this special case are detailed in Table 5.2, which highlights the distinction in the  $\theta$  value compared to the general model.

Table 5.2: Attributes for the special case of the general model (Model 2).

| Variable | Description                                | Value |
|----------|--------------------------------------------|-------|
| $T$      | Pilot operating period (months)            | 10    |
| $R$      | Initial failure rate for every mile        | 1     |
| $\xi$    | Social planner's conservation level        | 1     |
| $\theta$ | Social planner's maximum risk              | 1     |
| $\beta$  | Travellers' reluctance due to failure      | 3     |
| $\alpha$ | Comfort factor for not driving             | 0.65  |
| $c$      | Cost factor                                | 10    |
| $C$      | Social cost factor                         | 20    |
| $L$      | Average trip distance (miles)              | 1     |
| $Q$      | Total transportation demand in the network | 1     |
| $Q_1^a$  | Initial AV demand                          | 0.05  |
| $A$      | Rate of improvement in learning            | 5     |

Model 3 refers to the simplified diffusion case, which operates under a different set of assumptions compared to the general model. In this case, the model simplifies the initial setup by reducing the number of attributes required. Specifically, the discount factor and initial diffusion rate are determined by the model's functions, rather than being predefined inputs. This adjustment allows for a focus on diffusion dynamics with fewer parameters at the outset, facilitating an alternative analysis for the pilot project. The specific attributes for Model 3 are detailed in Table 5.3.

Table 5.3: Attributes for the simplified diffusion model (Model 3).

| Variable | Description                                | Value |
|----------|--------------------------------------------|-------|
| $T$      | Pilot operating period (months)            | 10    |
| $R$      | Initial failure rate for every mile        | 1     |
| $\xi$    | Social planner’s conservation level        | 1     |
| $\beta$  | Travellers’ reluctance due to failure      | 3     |
| $c$      | Cost factor                                | 10    |
| $C$      | Social cost factor                         | 20    |
| $L$      | Average trip distance (miles)              | 1     |
| $Q$      | Total transportation demand in the network | 1     |
| $A$      | Rate of improvement in the learning        | 0.01  |

### Model 1: general model’s solution method

In the first model, the adoption rate is governed by a general diffusion process where the planner aims to minimize social welfare costs while balancing the adoption rate with safety risks, measured through failure rates ( $R$ ), and associated costs. The adoption fraction,  $q_t^a$ , evolves over time based on  $r(t)$ , which starts at the initial failure rate  $R$ , and the planner adjusts this rate dynamically as cumulative supply distance increases

To solve this optimization, MATLAB’s `fmincon` was employed with both upper and lower bounds on decision variables, reflecting the need to keep the adoption fraction within feasible limits. The upper bound for the adoption rate was left unconstrained, allowing for exploration of aggressive adoption scenarios. However, bounds were applied to other variables, such as those related to safety, ensuring that failure rates and safety targets adhered to the predefined constraints. This aligns with the planner’s objective to minimize disengagements while maximizing  $q_t^a$ .

Non-linear constraints (`nonlcon`) were also introduced to enforce safety standards using a Poisson distribution, ensuring that disengagement rates met an acceptable threshold  $\theta$ . This created a necessary trade-off between safety and adoption rates, factoring in variable costs and risks.

### Model 2: special case of the general model’s solution method

Model 2 builds upon the first model but simplifies the problem by fixing the maximum acceptable risk at  $\theta = 1$ . This transforms the model into a special case where the planner

no longer adjusts risk dynamically but instead works within a constant risk ceiling.

In this scenario, the removal of the upper bound on adoption rates plays a crucial role. With the maximum acceptable risk fixed, if AVs meet this safety threshold, it implies that there are no additional safety constraints to limit adoption. The planner, therefore, is free to explore scenarios of mass adoption without worrying about exceeding safety targets. This reflects a scenario where, once the risk is managed and capped, the main objective becomes maximizing the adoption rate to take full advantage of the AVs' potential.

The use of the `fmincon` function with non-linear constraints ensures that safety outcomes adhere to the fixed risk ceiling, and the optimization focuses on maximizing adoption within the set constraints. The removal of the upper bound reflects an optimistic scenario where the planner assumes that, once AVs meet the required safety standards, they can be widely adopted without significant risks, leading to potentially higher diffusion rates compared to Model 1, where risk management was more dynamic.

### **Model 3: simplified diffusion model's solution method**

In the third model, a linear adoption function is employed, further simplifying the diffusion process. The adoption fraction  $q_t^a(t)$  depends directly on the cost and the dynamically adjusted failure rate  $r(t)$ , which starts from the initial value  $R$ , without requiring the complex diffusion terms seen in the previous models.

Upper bounds were introduced in this model, particularly concerning variables related to disengagement risk, ensuring that safety remained within stricter limits. While the adoption rate itself remained unbounded, signaling a more optimistic approach to AV deployment, the application of these bounds emphasized the need for cautious expansion of the adoption process, in contrast to Model 2, where no upper bounds were imposed.

This model also simplified the non-linear constraints used in the optimization. Though the Poisson distribution remained a central safety mechanism, additional safeguards were added to prevent  $q_t^a(t)$  from becoming negative, accounting for the linear nature of this model. The objective of minimizing social welfare costs continued to guide the optimization, but the reduced complexity led to a more constrained and cautious exploration of adoption dynamics.

### **Summary of MATLAB implementation**

Across all three models, the use of MATLAB's `fmincon` function allowed for flexibility in exploring AV adoption scenarios, balancing  $q_t^a$ , safety risks, and associated costs. The non-

linear constraints played a central role in ensuring that safety targets were consistently met. Notably, the absence of upper bounds in Model 2 allows for unrestricted growth in  $q_t^a$ , in contrast to the bounds applied in the other models.

The differing assumptions about risk, safety, and adoption constraints led to varied optimization outcomes across the models. These assumptions, as well as their implications for AV adoption, will be explored in detail in the subsequent sections.

# Chapter 6

## Results

This section models fundamental parameter changes and scenarios for comparison utilizing the general model (Model 1), building upon the baseline scenario detailed in Section 5. Several trends emerge when employing the assumed values from the previous section as a baseline, and these variations will be compared through multiple figures presented in this section.

An overview of the results obtained from the three different models will be provided. A comparative analysis will be conducted between Model 1 and the special case (Model 2), as illustrated in Table 6.1. Concurrently, insights and observations regarding the simplified diffusion model (Model 3) will be presented, as depicted in Figure 6.1. This comprehensive examination aims to detail the implications of parameter adjustments and diverse modelling approaches, thereby contributing to a refined understanding of the case study. Furthermore, this section addresses Objectives 3 and 4 by demonstrating the adaptability of the framework through the analysis of varying results and insights derived from the models, emphasizing the effectiveness of the framework in practical applications.

## 6.1 Model comparisons

This section describes the distinctions among the three models within the case study. A comparative analysis will primarily focus on Model 1 and Model 2, as both employ the same underlying equations, thereby facilitating a more straightforward comparison. In contrast, Model 3 necessitates separate consideration due to its reliance on a different set of equations and assumptions, including a linear diffusion process and unknown  $\alpha$ . These differences complicate direct comparisons with Models 1 and 2, as Model 3 lacks the same dynamics and structural intricacies inherent in the other two models. This examination aims to highlight the unique characteristics and outcomes that arise from the diverse modelling approaches applied in the case study, contributing to a comprehensive evaluation of the results.

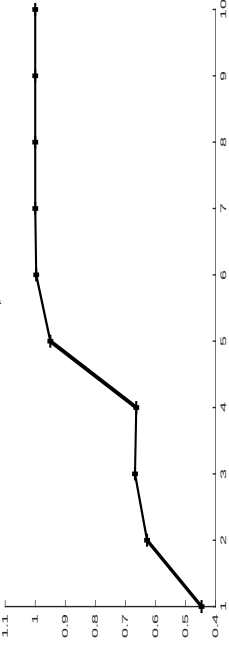
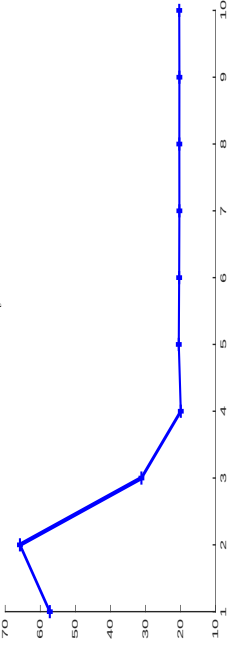
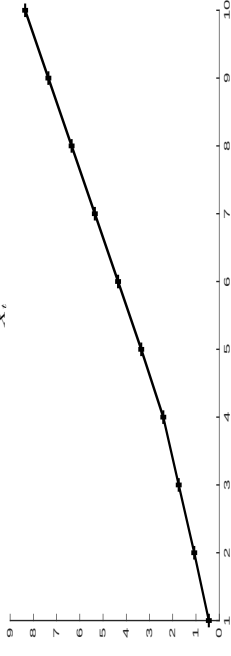
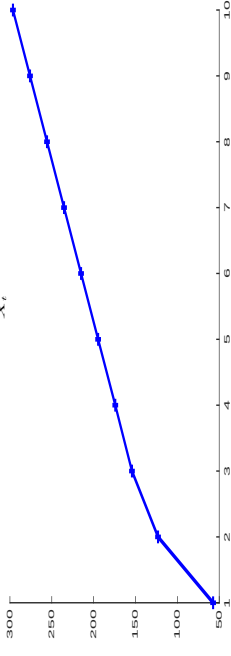
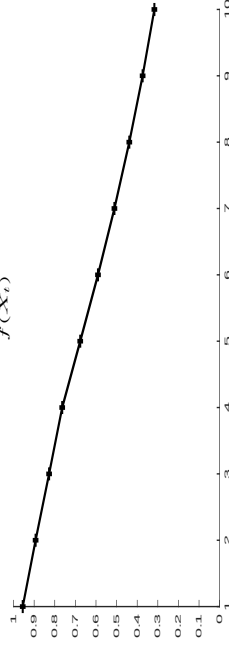
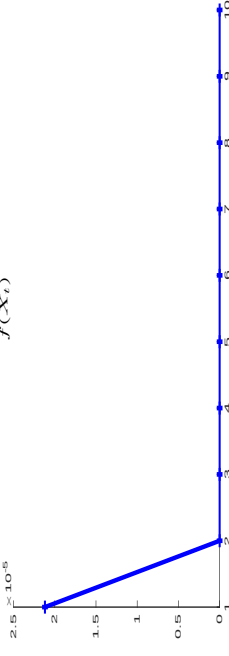
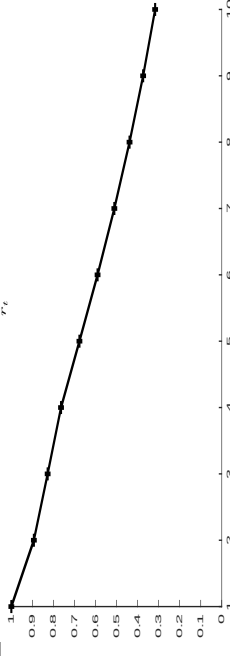
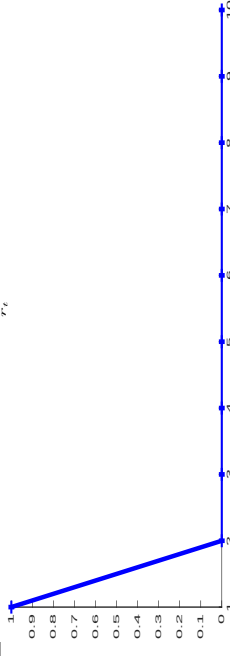
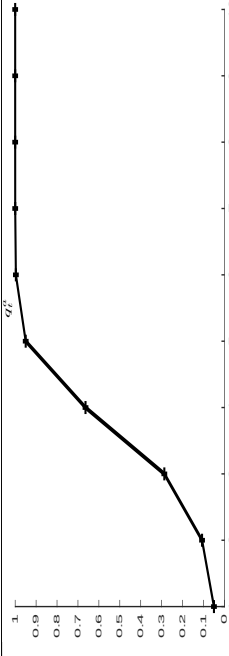
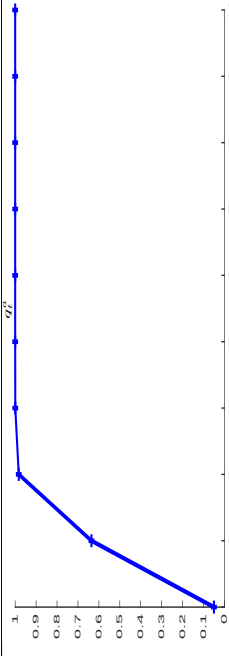
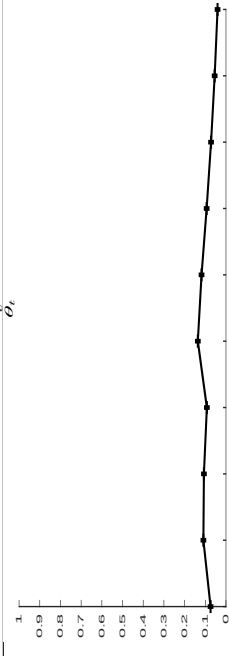
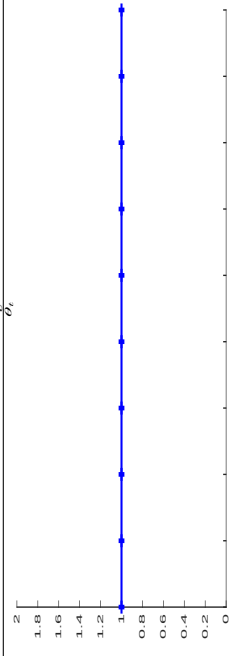
### The results of the general and special case models (Model 1 and 2)

The optimization results of the two models yield significant findings, as illustrated in Table 6.1. Initially, Model 1 demonstrates a supply distance that begins at a low value and gradually approaches the average traveller distance as a maximum. In contrast, Model 2 exhibits a supply distance that starts at a considerably larger value, with an initial increase over the first month followed by a subsequent decline. The critical distinction between the two models lies in the maximum acceptable risk,  $\theta$ , which significantly influences the outcomes of the case study. The assumption of a constant  $\theta$  in Model 2 represents a relaxed constraint, contributing to the initially higher supply distance if the safety constraint is met. Conversely, Model 1's fluctuating  $\theta$  values result in an overall smaller supply distance, highlighting the impact of risk dynamics on the pilot's performance.

The increased supply distance in Model 2 facilitates a more rapid diffusion process compared to Model 1, resulting in a more pronounced S-shaped curve in the latter. This acceleration is particularly evident in the faster diffusion rate,  $q_t^a$ , observed in the special case. The implications extend to the learning function,  $f(X_t)$ , and the failure rate,  $r_t$ , which are intricately linked. As the cumulative supply distance,  $X_t$ , increases substantially, both functions experience a rapid decline. While Model 1 demonstrates a gradual decrease from the initial failure rate, Model 2 exhibits a sharp drop from the outset of the pilot.

However, the unbounded upper limit in Model 2's faster diffusion raises potential concerns regarding the maximization of adoption while ensuring compliance with safety constraints. Rapid adoption, while advantageous in theory, can lead to considerable risks

Table 6.1: Results from Model 1 and Model 2 for the case study.

|                                      | General Model                                                                        | Special Case                                                                        |
|--------------------------------------|--------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Supply Distance ( $x_t$ )            |    |    |
| Cumulative Supply Distance ( $X_t$ ) |    |    |
| Learning Function ( $f(X_t)$ )       |    |    |
| Failure Rate ( $r_t$ )               |   |   |
| Diffusion Rate ( $q_t^a$ )           |  |  |
| Maximum Failure Rate ( $\theta$ )    |  |  |

in practice, particularly as the benefits derived from the learning function may exhibit volatility. To address this issue mathematically, one approach could involve introducing an upper limit on the diffusion rate or refining the parameters governing the learning function to better align with safety outcomes. Additionally, implementing tighter bounds on the maximum acceptable risk,  $\theta$ , or utilizing a dynamic adjustment mechanism based on real-time safety data could further strengthen the model’s robustness. Such adjustments would promote a more balanced approach to adoption and safety, mitigating the risks associated with accelerated diffusion and ensuring that safety considerations are not compromised in pursuit of rapid adoption.

The social planner, equipped with the capability to generate predictive models for the case study, must recognize that the results produced, particularly from the Model 2, may appear unrealistic upon closer examination. In contrast, the outcomes from Model 1 may align more closely with anticipated benefits, especially as the learning function exhibits a more gradual decrease. This necessitates the verification of results, placing a responsibility on the social planner to potentially adjust expectations in the special case, such as changing constraints. An initially large supply distance may not be sustainable given the pilot’s available resources. By conducting trials with different equations, the planner can explore various scenarios and evaluate acceptable risks, thereby enhancing the robustness of the decision-making process and ensuring alignment with practical constraints.

## **The results of the simplified diffusion model (Model 3)**

The comparison of Model 3 with the preceding models necessitates a distinct analysis due to variations in their underlying equations. Unlike Models 1 and 2, Model 3 does not require the discount factor,  $\alpha$ , as an input; instead,  $\alpha$  is derived from the model’s formulation. This approach not only streamlines the inputs needed from the theoretical pilot but also allows for the calculation of  $\alpha$ . The ability to solve for the discount factor provides additional insights into the dynamics of adoption, enhancing the model’s utility in evaluating various scenarios within the case study.

The results from Model 3, as shown in Figure 6.1, exhibit a more streamlined structure, with most graphs displaying curved shapes where the cumulative supply is represented by the derivative of  $x_t$ . The absence of fluctuations observed in Model 1 stems from the fundamental difference in the diffusion mechanisms. While there may be apparent similarities in certain outcomes, the underlying mathematical structures differ significantly—Model 1 incorporates a more complex learning dynamic and variable safety constraints, while Model 3 employs a linear diffusion process with a solved-for discount factor,  $\alpha$ . These differences

alter both the objective function and diffusion equations, making direct comparison challenging across varied scenarios. This distinction implies that while Model 3 might yield similar results in this case study, applying the same logic across different cases could lead to inaccuracies. Over time, the social planner would observe a decline in the maximum acceptable risk, alongside reductions in  $f(X_t)$  and  $r_t$ . This trend indicates that the pilot may initially pose higher risks, but learning benefits gradually mitigate those uncertainties. Despite potential drawbacks, the findings underscore the adaptability of Model 3 and its capacity to inform decision-making under different diffusion assumptions.

The interpretation of these findings is critical. The social planner possesses significant influence over the outcomes by selecting formulas that align with their understanding of the case study. This flexibility introduces a potential bias in the interpretation of results. While adapting the model may yield more beneficial long-term outcomes, further examination of this topic will be presented in Section 7.

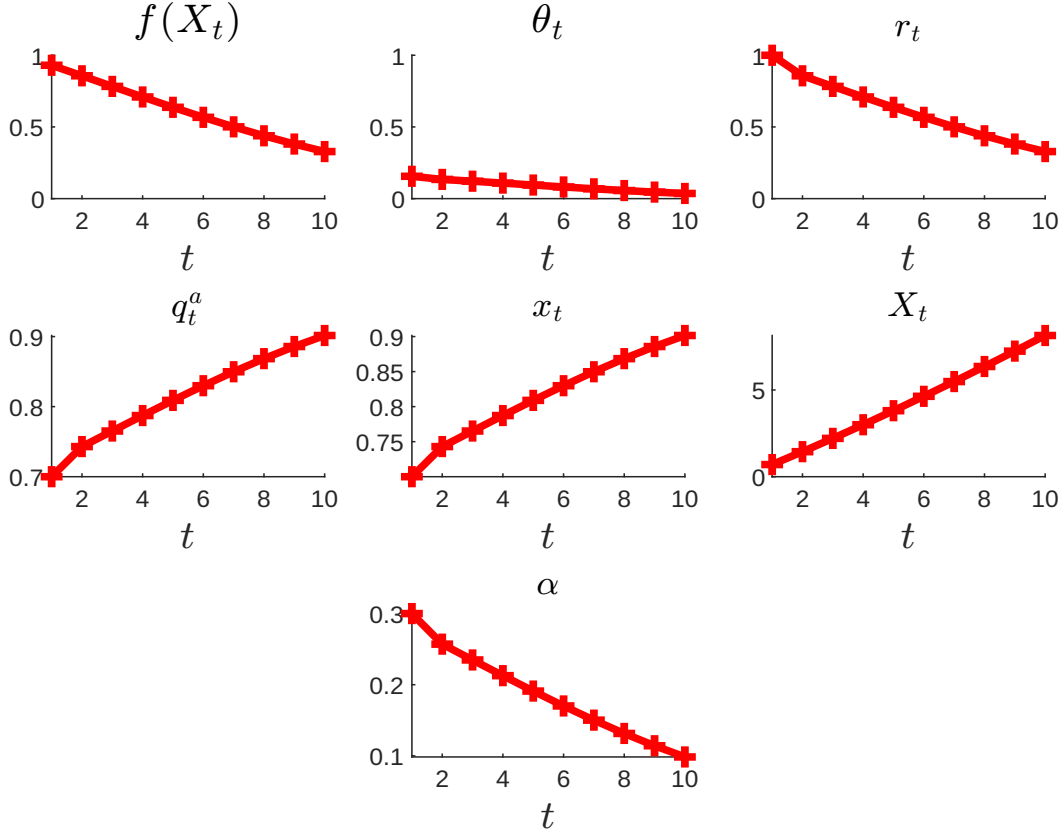


Figure 6.1: Model 3's results from the case study.

## 6.2 Single parameter results

In analyzing the outcomes of Model 1, variations may emerge; however, general expectations can be inferred by assessing the influence of adjustments to individual parameters. Model 1 was selected for detailed analysis due to its broader applicability and flexibility compared to Model 2 and Model 3. While Model 2 is a special case with a fixed cap on acceptable risk, and Model 3 employs a different diffusion model that alters the objective function, Model 1 offers a more comprehensive understanding of system dynamics. This is achieved by allowing for variable risk parameters and incorporating a more detailed diffusion equation. The following results provide insight into the intuitive effects and anticipated changes, driven by the principles embedded within the framework of Model 1. Thus, the focus will be on examining variations in response to changes within this general model.

### Discomfort factor, $\beta$ parameter

Regarding the discomfort factors for travellers, certain expectations can be established within the model framework. For example, an increase in  $\beta$  is expected to lead to slower public acceptance, which may delay the diffusion of AVs. In scenarios where the population is highly risk-averse, this could result in limited public engagement with AV pilots during the initial phases. Modifying the  $\beta$  parameter in the general model, given its sensitivity, allows for an examination of these trends, as illustrated in Figure 6.2.

A higher value of  $\beta$  results in a slower diffusion within the network, as evident in the diffusion graph ( $q_t^a$ ), whereas a lower  $\beta$  facilitates quicker diffusion. Furthermore, an increase in  $\beta$  does not necessarily correlate with a rapid increase in the supply distance. For instance, when  $\beta$  is set to one, the cumulative distance,  $X_t$ , is higher later in the pilot's life than when  $\beta$  is set to two, but lower at the start. This phenomenon is influenced by the initial supply distance, as shown in the graph of  $x_t$ . The trade-off in risk is clear in the graph of  $\theta$ , where a higher  $\beta$  shows elevated risk early on but less risk after four months. However, this early advantage is outweighed by the other cases later in the pilot, as the learning function improves with increased usage, lowering risk at later stages. Managing traveller preferences early on can contribute to successful pilot deployments. As a future step, weighting these variables could provide further insight into balancing diffusion, risk, and system performance over time.

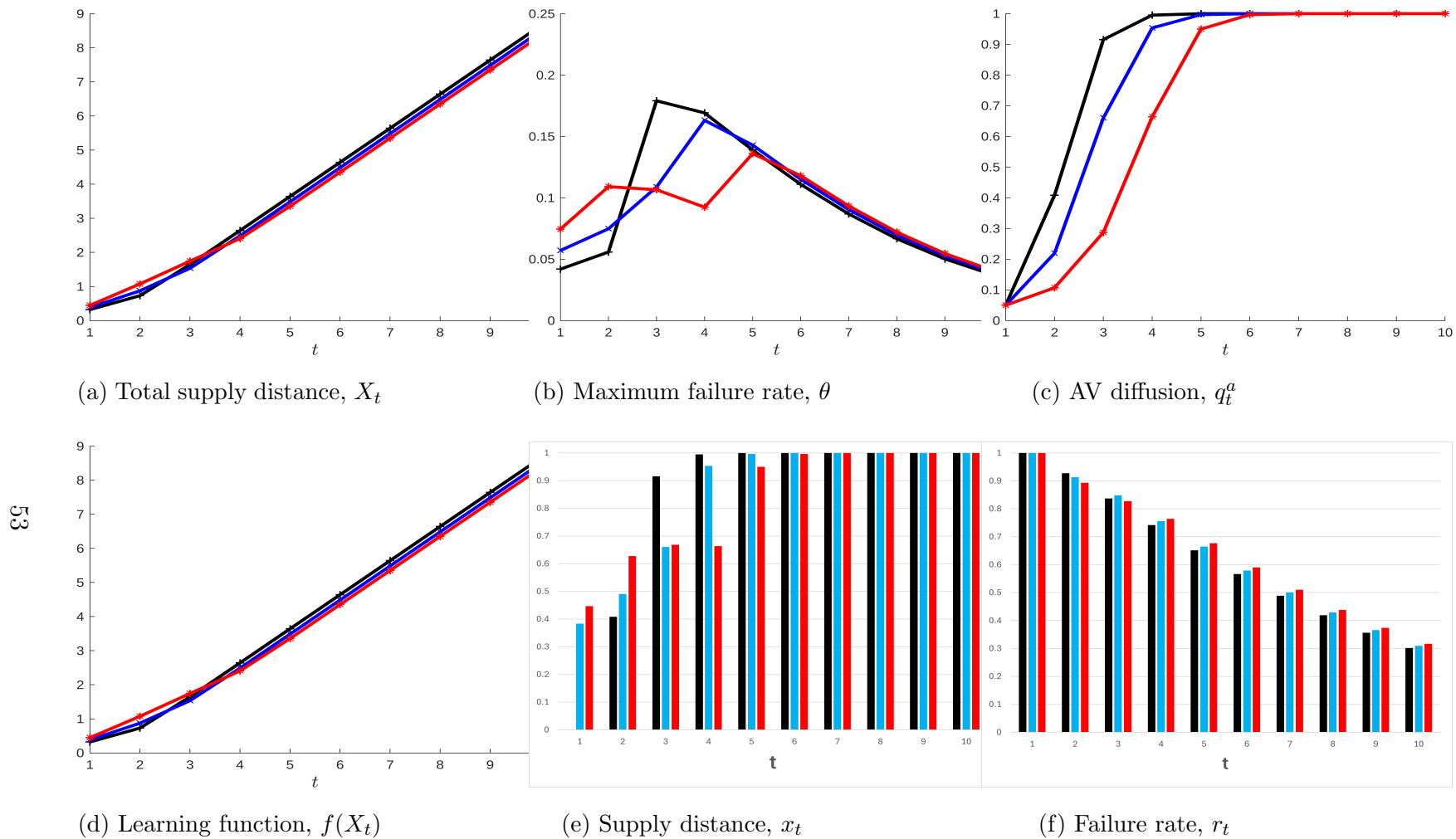


Figure 6.2: Model 1's performance by varying  $\beta$

$\beta = 1$     $\beta = 2$     $\beta = 3$

## Discount factor, $\alpha$ parameter

Adjusting the value of  $\alpha$  has a significant impact on Model 1. Generally, a decrease in  $\alpha$  (representing higher utility from AV usage) accelerates the diffusion process. Additionally, this results in more pronounced growth in the supply distance rate, which subsequently enhances the benefits derived from the learning function. An increased cumulative supply, denoted by  $X_t$ , contributes to a more substantial reduction in the failure rate. To demonstrate these key trends, comparisons of test values for the discount factor are presented in Figure 6.3.

Model 1 effectively captures these dynamics. For instance, a lower discount rate,  $\alpha = 0.65$ , which signifies greater utility for travellers, results in faster diffusion compared to cases with higher  $\alpha$  values, as shown in the diffusion graph ( $q_t^a$ ). Moreover, the lower discount factor leads to a reduced learning threshold  $fX_t$ , thereby decreasing the failure rate ( $r_t$ ) more significantly than in scenarios where  $\alpha$  provides less utility to travellers.

A key observation arises when analyzing the acceptable risk,  $\theta$ , across different  $\alpha$  values. In the early stages, the base case presents a higher  $\theta$ , which is directly linked to the elevated supply distance,  $x_t$ . This highlights the need for the social planner to account for the increased risk associated with lower  $\alpha$  values. However, a critical shift occurs later in the pilot's duration. While lower  $\alpha$  initially carries a higher risk, it ultimately results in a lower  $\theta$  compared to scenarios where AV adoption occurs later in the pilot ( $\alpha = 0.7$ ). In cases of low utility ( $\alpha = 0.75$ ), there is a reduced change in  $x_t$ , indicating that travellers may exhibit limited engagement with the pilot. This could lead the social planner to reconsider the viability of such pilots under conditions of low utility. By contrast, the other two cases reveal an advantage in early AV adoption, despite the initial higher failure risk, compared to the scenario with a larger  $\alpha$ , which displays a lower risk at the outset.

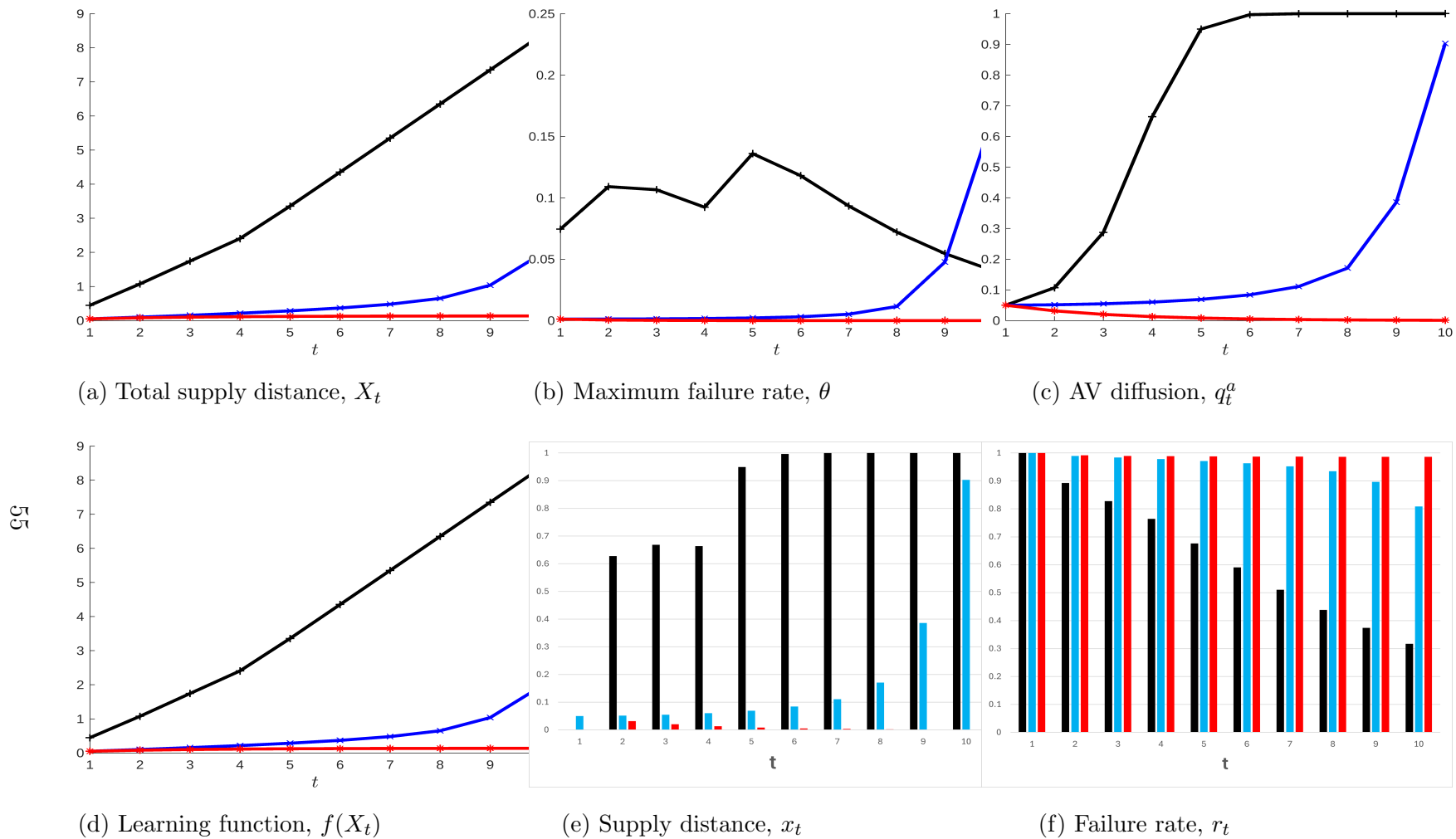


Figure 6.3: Model 1's performance by varying  $\alpha$

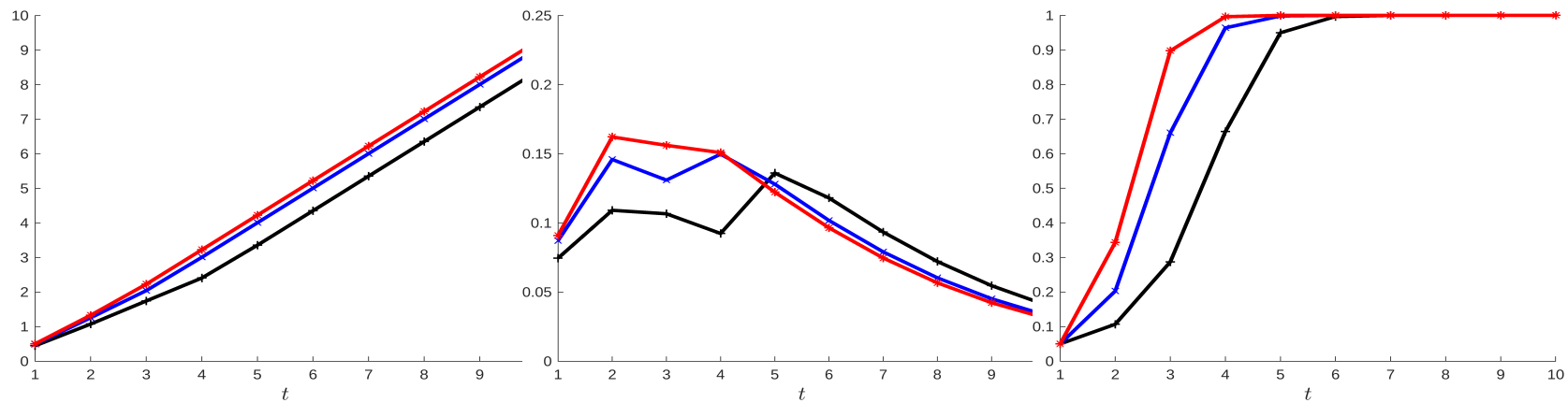
$\alpha = 0.65$     $\alpha = 0.70$     $\alpha = 0.75$

## Travel time / financial cost parameter, $c$

The cost parameter,  $c$ , plays a significant role in shaping the dynamics of Model 1. An increase in  $c$  indicates a rise in the cost associated with using HVs, while the cost equation for AVs (refer to Equation 4.4) benefits from a reduction through the discount factor,  $\alpha$ . This creates scenarios where the cost of AVs may either exceed or fall below that of HVs. However, in positive use cases, AVs generally provide a net benefit. To demonstrate this, three cases are examined where AVs offer comparative advantages. Although the numerical values are not precisely calibrated due to model sensitivity, the general trend for this single parameter adjustment is illustrated in Figure 6.4.

The behaviour observed mirrors that of the discount factor scenario, where an increase in cost—moderated by  $\alpha$  in the AV cost equation—results in a higher initial maximum  $\theta$ , which decreases substantially as the pilot progresses. This case also shows an increased supply distance,  $x_t$ , early in the pilot. While it may seem counterintuitive that both the cost and the number of users increase, it is crucial to recognize that this cost pertains to HVs, and the AV cost equation, reduced by  $\alpha$ , generally favours the base case—assuming AVs provide sufficient utility. Hence, an increase in  $c$  reduces the relative attractiveness of HVs in a scenario where  $\alpha < 1$ . If the sensitivity parameter,  $\beta$ , were adjusted, there could be cases where AVs no longer present a clear advantage.

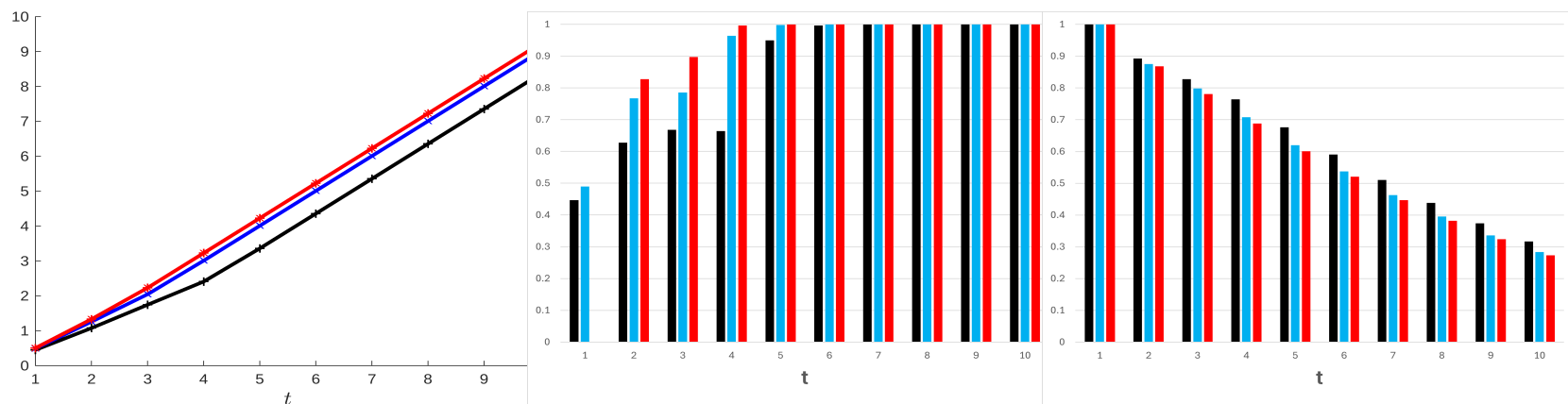
Even in the scenario of lower  $c$ , there remains a significant difference in the acceptable risk level,  $\theta$ , when compared to the base case. The higher-cost scenario consistently exhibits a greater  $\theta$  early on, but, over time, the learning function results in improved outcomes, reducing risk. Furthermore, the high-cost case demonstrates a larger supply distance and a lower failure rate,  $r_t$ , by the pilot's later stages compared to the other cases.



(a) Total supply distance,  $X_t$

(b) Maximum failure rate,  $\theta$

(c) AV diffusion,  $q_t^a$



(d) Learning function,  $f(X_t)$

(e) Supply distance,  $x_t$

(f) Failure rate,  $r_t$

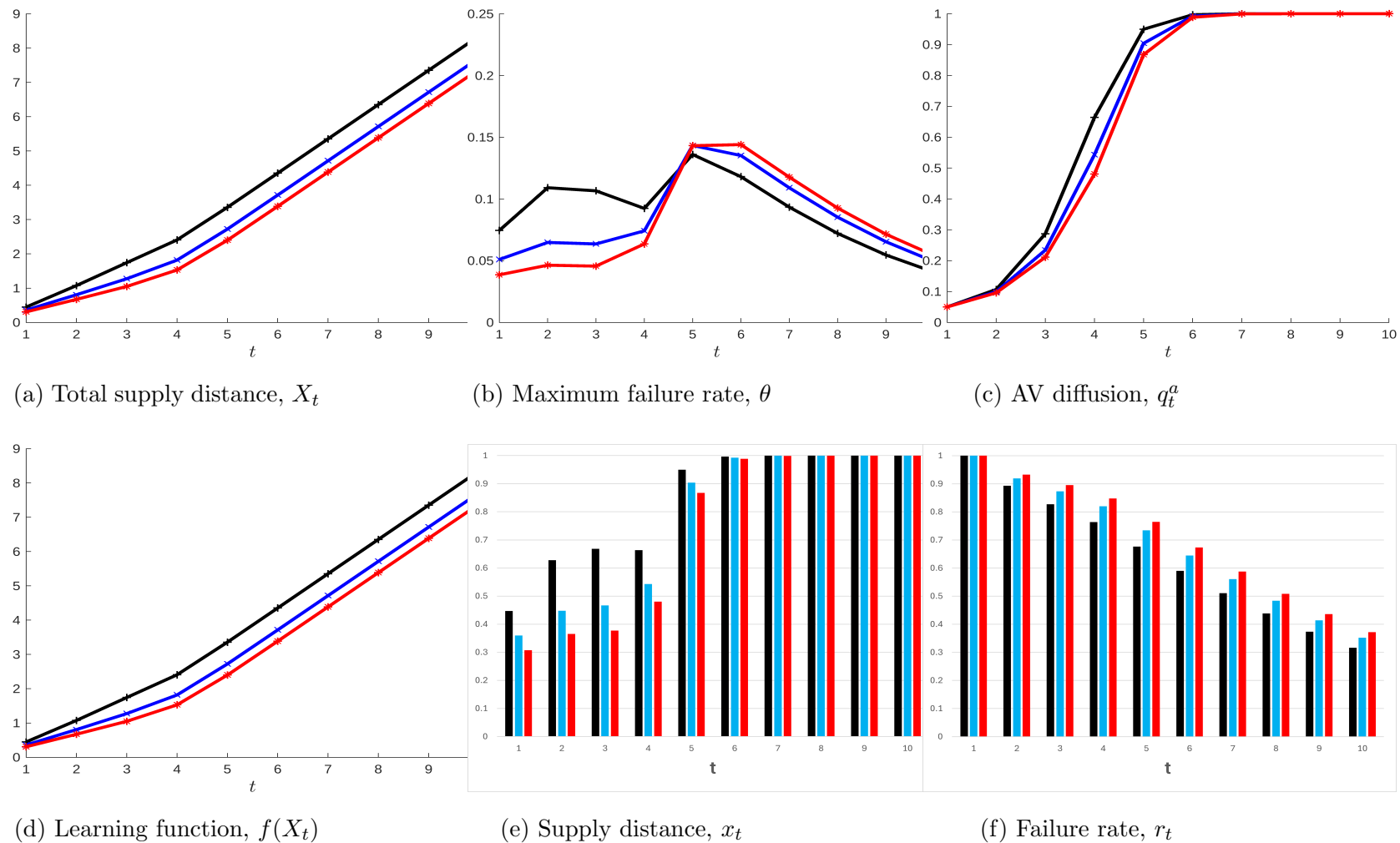
Figure 6.4: Model 1's performance by varying  $c$

$c = 10$   $c = 12$   $c = 14$

## Social cost parameter, $C$

The parameter  $C$  directly influences the objective function of Model 1. An increase in  $C$  signifies a higher social cost associated with AV usage, which is linked to  $\theta$  within the objective function. This scenario reflects situations where the social planner faces limited flexibility in conducting tests, as failures carry significant repercussions for the pilot. On the other hand, a decrease in  $C$  implies that the social planner is more tolerant of potential societal issues, indicating a higher acceptance of risk within the pilot framework. Thus, three comparative cases will be analysed, though the numerical values are not precisely calibrated due to model sensitivity. The general trend for this parameter variation is depicted in Figure 6.5.

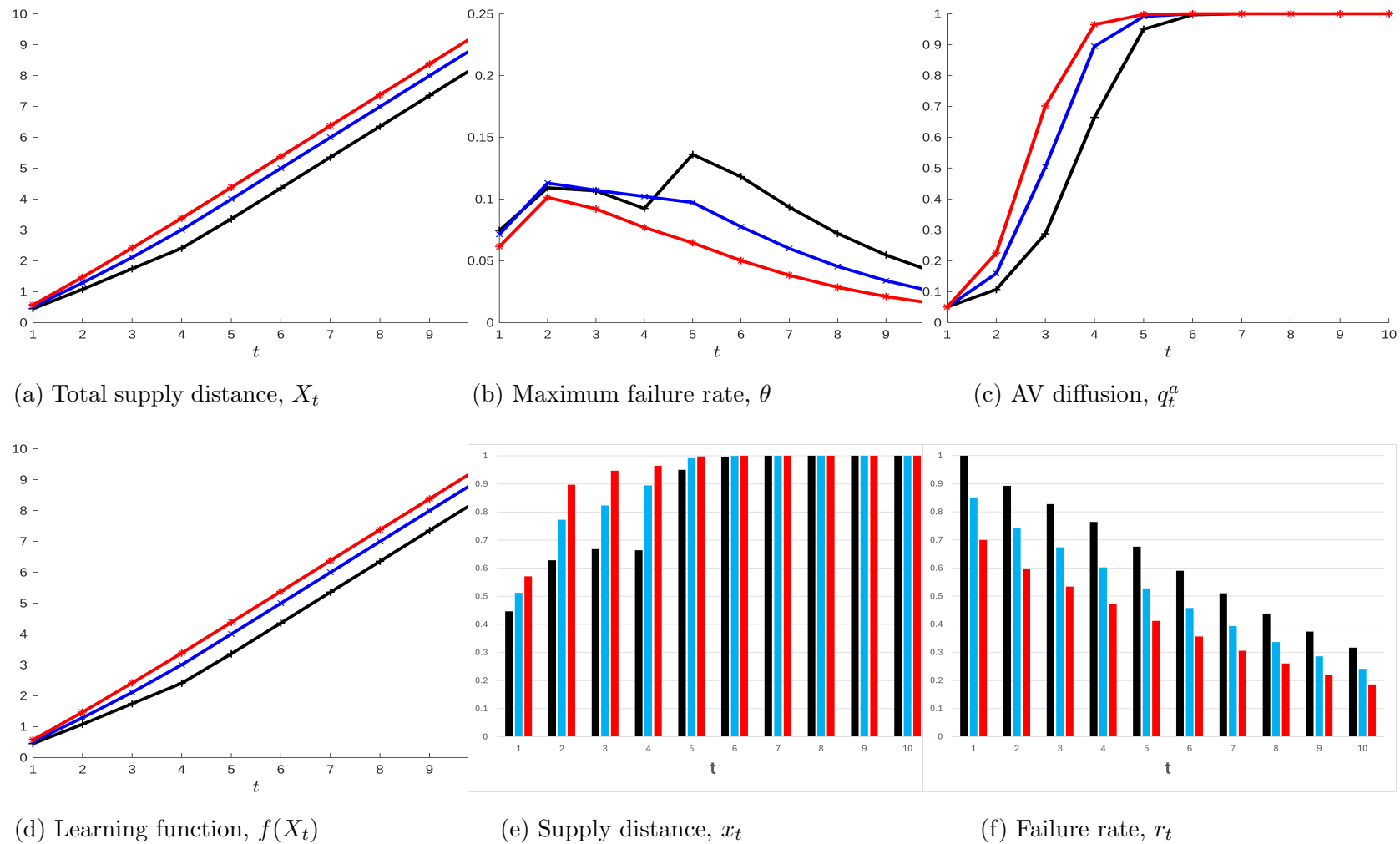
Generally, a lower social cost,  $C$ , corresponds with a reduced cumulative supply distance,  $X_t$ , throughout the pilot. In this context, the lower  $C$  results in a higher maximum acceptable failure rate,  $\theta$ , initially, which then trends down to a lower  $\theta$  by the pilot's conclusion. This initial higher  $\theta$  indicates a greater risk acceptance from the social planner, while the eventual reduction in  $\theta$  suggests effective risk management strategies that come into play as the pilot progresses. This relationship may appear unintuitive, as one might expect that lower social costs would naturally lead to more rapid diffusion; however, the results reveal a more complex interaction. The higher social cost, while introducing additional risk, still remains below the threshold constraint, allowing for aggressive risk management strategies that effectively mitigate long-term risks. Consequently, this may result in a faster diffusion despite the initial risk. Thus, further sensitivity analysis may be warranted to fully understand the dynamics at play and explore how variations in social cost impact risk and diffusion outcomes.

Figure 6.5: Model 1's performance by varying  $C$  $C = 20$  $C = 25$  $C = 30$

## Initial failure rate, $R$

The importance of the initial failure rate,  $R$ , is particularly significant at the onset of a pilot. Depending on the learning and risk functions, the benefits gained may not meet the social planner's standards if they are either excessively high or too low. In the general model utilized in this study,  $R$  is evaluated during the first month of the pilot, which can determine its successful deployment. The general expectation is that high-risk pilots necessitate a higher threshold of acceptable risk from the social planner and may require additional time to begin realizing benefits from usage. Figure 6.6 illustrates the general trend associated with changes in the  $R$  parameter.

This expected trend is consistent within Model 1. A higher  $R$  corresponds to a lower cumulative supply distance,  $X_t$ , indicating that the function  $f(X_t)$  yields fewer benefits initially, resulting in a higher failure rate,  $r_t$ , compared to other scenarios. The diffusion pattern also aligns with this trend, with the lower  $R$  leading to quicker adoption. Moreover, the maximum failure rates become more pronounced with variations in this parameter, providing social planners with a clearer understanding of the significance of the initial failure rate in decisions regarding pilot implementation. The benefits derived from learning are contingent upon effectively reducing the failure rate over time.

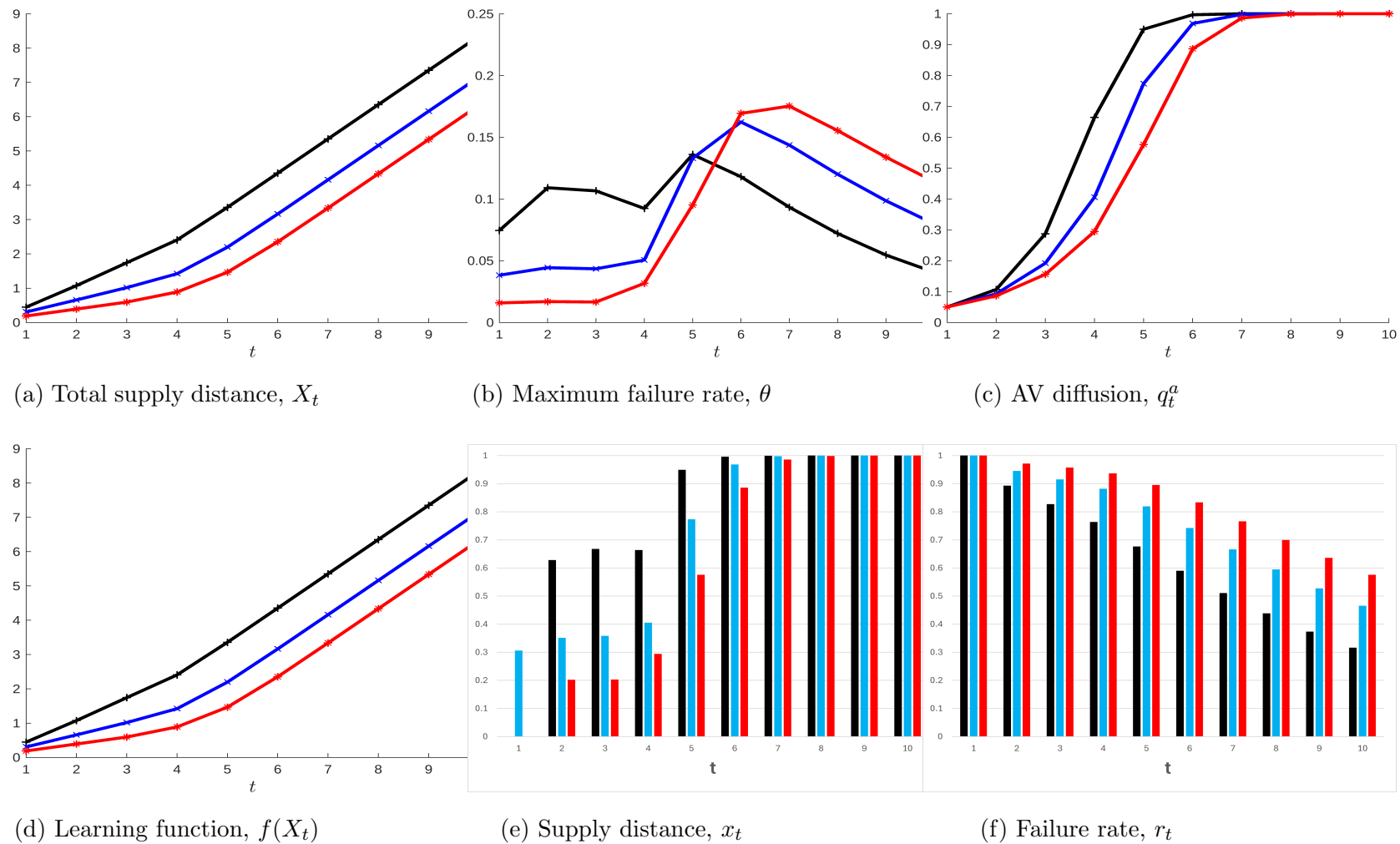
Figure 6.6: Model 1's performance by varying  $R$ 

$R = 1$ 
 $R = 0.85$ 
 $R = 0.70$

## Rate of improvement of the learning function, $A$

Some simple tests can represent scenarios where benefits are likely to be gained, demonstrating how the rate of improvement in the learning function,  $A$ , affects the model. When  $A$  is decreased, the learning function becomes smaller. Based on previous trends involving the failure rate and the learning function, smaller  $f(x_t)$  corresponds to a reduced  $r_t$ . Figure 6.7 shows a general trend for the initial failure rate parameter change.

The general trend holds for this parameter as well. When  $A$  is small, there is a greater cumulative distance, which leads to a smaller  $f(x_t)$  and a lower  $r_t$ . The diffusion in this case also occurs more rapidly. However, the  $\theta$  for the social planner starts higher than in other cases before the benefits from the supply distance ultimately lower it.

Figure 6.7: Model 1's performance by varying  $A$ 

$A = 5$     $A = 6$     $A = 7$

# Chapter 7

## Discussion

This section explains the implications derived from the outcomes of the models. It seeks to correlate these findings with the overarching question of when the implementation of AVs should be pursued, with the underlying objective of preventing the problem of perfection from being the enemy of the good.

### 7.1 Social planner implications and adaptability

The mathematical framework presented in a general format is designed for versatility by accommodating various diffusion models through different representations. While the models discussed in Section 4 provide specific formulations, the general framework's format allows for the exploration of diverse diffusion models. This flexibility fosters opportunities to utilize cases such as the general model (Model 1) or the simplified diffusion model (Model 3), thereby addressing Objective 1 and 2 by utilizing and defining essential concepts within the context of an AV pilot.

The adaptability of the mathematical framework emerges as a key strength in its design. Social planners can select between simplicity or complexity, tailoring the initial framework to meet their specific needs. The case study outlined within this study illustrates a general scenario and provides insights into model application, aligning with Objective 3 and 4. However, it also highlights potential challenges associated with interpretation. The framework endeavors to predict multiple variables based on the parameters chosen by the social planner, aiming to minimize traveller costs and maximize social welfare within the AV pilot context. Nonetheless, certain values, such as social costs ( $C$ ) and monetary or

travel time costs ( $c$ ), require precise definition and calibration, posing challenges for effective implementation. Additionally, measures such as VMT and disengagement rates have gained prominence relatively recently, leading to variability in their availability. These limitations associated with prediction modelling, combined with the necessity for well-defined parameters, complicate the social planner’s task.

Furthermore, the introduction of concepts such as diffusion and learning, though challenging to quantify precisely, expands the framework’s scope. While measuring gains in utility from conducting pilots may not be straightforward, the framework serves as a foundational baseline that can be modified and adjusted based on nuanced knowledge of pilot factors. This adaptability allows the framework to evolve alongside changing contexts and scenarios, addressing Objective 5 by assessing the balance between perfection and timely implementation, and suggesting areas for potential improvements.

Adjustments to the mathematical models yield diverse results tailored to the social planner’s objectives. If the social planner perceives the reduced failure rate due to learning as overly optimistic based on pilot experiences, the learning function can be calibrated accordingly. For instance, connecting the learning function to the failure rate through variables such as travel efficiency can enhance the model’s adaptability. The framework’s simplicity facilitates use in basic scenarios while allowing for adjustments to meet evolving needs. Model 3, which presents a simplified diffusion model, illustrates how different equations can yield varying results, demonstrating the social planner’s ability to customize the framework to better align with specific objectives and constraints. This flexibility can also extend to considerations of social costs, enabling deeper links between travel efficiency, safety, and other relevant factors.

Context proves crucial in dealing with the mathematical framework, as illustrated by ideas of perception, possible backlash, and the incorporation of factors controllable or observable by the social planner. Concepts like social cost and maximum acceptable risk offer a means of gauging external factors, addressing limitations noted in previous reports such as the RAND study [6].

Additionally, the framework acknowledges the challenge of measuring diffusion and learning, recognizing that gaining a set amount of utility from each stage of testing may not be accurate. While the framework provides a baseline, adjustments and calibrations are likely possible with adequate background knowledge.

In Section 6, the concept of weighting variables was introduced in the discussion of varying the discomfort factor in the Model 1. This raises the possibility of employing multi-objective optimization within the framework, which would allow social planners to balance trade-offs among several competing objectives, such as minimizing costs, maximiz-

ing safety, and more. In contrast to the single-objective framework utilized in this thesis, which focuses on optimizing social welfare by minimizing costs, a multi-objective approach introduces greater complexity by enabling the planner to prioritize different outcomes based on their relative importance. For instance, while the current framework simplifies decision-making by honing in on a singular objective, a multi-objective optimization model would allow for more nuanced evaluations, accommodating varying stakeholder preferences and emphasizing certain metrics—such as safety over travel time costs—according to the social planner’s goals. This potential for variable weighting and multi-objective optimization further underscores the adaptability of the framework, inviting more informed and tailored responses to the complexities of AV pilot implementations.

In conclusion, the mathematical framework’s inherent adaptability, foundational representation, and capacity for customization establish it as a significant tool for social planners in the context of AV pilot programs. This framework not only accommodates diverse diffusion models but also allows for adjustments based on specific objectives and constraints, thereby enhancing its relevance in practical applications. While challenges in measurement and potential biases in interpretation remain—such as subjective assessments of parameters, the influence of varying stakeholder perspectives, and the potential for over-optimism regarding learning outcomes—the framework serves as a robust starting point for planners to build upon. By integrating concepts such as multi-objective optimization and variable weighting, social planners can navigate the complexities of competing objectives—balancing safety, cost, and efficiency—more effectively. This adaptability invites ongoing refinement and calibration, ultimately fostering informed decision-making tailored to the evolving landscape of AV pilot designs.

## **7.2 Representations of the concepts within the models**

The mathematical framework, presented in a general format and exemplified by specific representations in Section 4, serves as a versatile expression of this adaptability, addressing Objectives 1 and 2 by defining essential concepts relevant to AV pilots. The selected representations capture common phenomena, including S-curve diffusion and the benefits of learning, applicable across various contexts beyond transportation. This adaptability is particularly evident in the comparative analysis of the models examined within this study.

The strength of the framework lies in its flexibility, enabling social planners to choose between simplicity and complexity according to their specific requirements. The case study

illustrates a general case while underscoring the challenges associated with interpretation. Although the framework aims to predict variables, such as minimizing traveller costs, the definition and calibration of critical values—including social costs ( $C$ ) and monetary or travel time costs ( $c$ )—pose significant challenges. Nonetheless, the framework serves as a foundational tool for social planners, acknowledging common issues in predictive modelling. Concerns regarding data quality, particularly for newer parameters like the discount factor, social cost, and discomfort factors, further complicate the analysis. Additionally, measures such as VMT and disengagement rates, may not be readily accessible from vendors.

Furthermore, the framework incorporates concepts such as diffusion and learning, which, while beneficial, present challenges in precise measurement. Assuming a fixed utility gain from each testing phase oversimplifies the complexities involved. By integrating these considerations, the framework establishes a foundation that is adaptable to nuanced variables, contingent upon a comprehensive understanding of the factors influencing AV pilot outcomes.

Adjusting the mathematical framework yields varied results, providing flexibility for different scenarios. For instance, sustainability concerns related to AV emissions could be addressed by introducing a social cost linked to broader environmental impacts. This approach allows for the integration of environmental factors into the decision-making process, aligning with contemporary objectives of minimizing overall societal costs. It may also be utilize the relationship between VMT and emissions. The concepts must be defined before usage and the current framework would need an update for this.

The three models derived from the framework each offer unique interpretations and results, contributing to a more nuanced evaluation of AV implementation, thereby addressing Objective 4. Model 1, with its S-curve properties, provides a comprehensive representation of diffusion that captures the complexities of adoption over time. Conversely, Model 3 serves as a “simplified case” with linear diffusion, which may be beneficial in scenarios where the diffusion process does not require intricate modelling. The selection of the most appropriate model ultimately rests with the social planner, who must assess the specific context and objectives of their project.

In summary, the mathematical framework is versatile and adaptable, serving as a foundational tool for social planners. It navigates challenges in predictive modelling while providing a basis for adjustments and expansions. The simplified diffusion case underscores the framework’s flexibility, highlighting the social planner’s pivotal role in determining the most suitable model for their unique circumstances.

## 7.3 Contextual limitations of the model

The related literature emphasizes the significance of contextual considerations when engaging with the mathematical framework. Previous discussions have explored perceptions and potential backlash, leading to a strategic incorporation of factors that fall under the social planner’s influence. Concepts such as social cost and maximum acceptable risk, introduced to address limitations identified in the RAND report [6], offer a means to evaluate external factors within the framework and models.

Quantifying aspects such as social costs within the mathematical framework remains challenging but establishes a foundation for further development. Social costs, as exemplified in ongoing research, indicate the framework’s potential for expansion. While contextual considerations that extend beyond the framework’s current scope cannot be precisely assessed with the existing results, the inclusion of social costs allows for a more comprehensive evaluation of factors impacting decision-making. For instance, decisions like increasing the maximum acceptable failure rate carry societal implications that may not be fully captured by the quantitative metrics presented in this paper. The introduction of social cost aims to gauge these dimensions, necessitating the social planner’s discretion in assigning appropriate values and interpreting the results.

Moreover, variables such as the discount factor ( $\alpha$ ) and the discomfort factor ( $\beta$ ) do not possess universally fixed values; they require case-by-case evaluations tailored to specific pilot programs. These values, influenced by the social planner’s interpretation and the characteristics of diverse communities, may vary significantly. For example, more risk-averse communities that have experienced accidents in the past may assign higher values to  $\beta$ . This variability enhances the framework’s adaptability and relevance, allowing social planners to customize it according to their specific contexts. While the framework acknowledges the potential for uncertainties, future enhancements could incorporate sensitivity analysis or stochastic modelling to better address these challenges. The results remain contingent on the social planner’s discernment, reinforcing the framework’s role as a valuable tool for informed decision-making in autonomous vehicle pilot programs.

The preliminary outcomes of the case study underscore the necessity for comprehensive examination, echoing insights from the RAND report [6, 31]. While the RAND report suggests avenues for future research into social costs, this thesis attempts to model these costs within its framework. The long-term perspective emphasized in the RAND report may be less applicable to short-term pilot programs. In contrast, the framework developed herein is specifically designed for short-term pilots, allowing for rapid comparisons of results against real-world outcomes. This adaptability enables potential recalibration of the model

on a monthly basis or at specified time intervals, which would not be feasible for projections extending 15 years or more into the future. Consequently, the framework provides a more pragmatic approach for evaluating the implications of social costs in the context of AV pilots.

# Chapter 8

## Conclusion

This thesis set out to achieve several key objectives in the context of AV pilots:

- **Objective 1:** Utilize and define concepts essential for the framework within the context of an AV pilot. Core concepts such as diffusion, learning dynamics, AV safety, and risk will be emphasized.
- **Objective 2:** Develop the framework to minimize the risk within an AV pilot, with the minimization representing the optimal scenario for this study.
- **Objective 3:** Demonstrate the adaptability of the framework by testing a case study with models derived from the framework.
- **Objective 4:** Evaluate the effectiveness of the framework and the results produced by the models.
- **Objective 5:** Assess whether the framework addresses the balance between perfection and timely implementation, and propose potential improvements.

Navigating the balance between “perfection being the enemy of the good” is critical when considering AV implementation through pilot programs. This thesis directly addresses Objective 1 by utilizing and defining key concepts such as safety, learning, and diffusion within the context of AV pilots. Additionally, it satisfies Objective 2 by optimizing the timing of AV pilot introductions, aiming to minimize risk and enhance social welfare through the framework developed in this study.

Key parameters, including VMT, disengagement rates, and societal costs of failures, are incorporated, with some inputs based on assumptions. This allows the social planner to adapt parameters according to the specific deployment context. The case study demonstrates the adaptability of the framework, fulfilling Objective 3 by showcasing how it can be applied through different models and varied key parameters of Model 1. An example of this would be adjusting the learning function reshapes modelled risks, offering flexibility to depict scenarios with varied rates of improvement. This enables a comprehensive evaluation of which models best capture the dynamics of future pilot programs.

The effectiveness of the framework, as outlined in Objective 4, is evaluated through observation of results and discussion of potential limitations in Section 7. For instance, the case study results illustrate how disengagement rates, though initially high, can decrease over time with improvements in AV technology. This reduction in disengagements reflects the potential trade-off between initial risks and long-term rewards, where early-stage risk is balanced by the expected gains in safety and efficiency over time, making the case for iterative learning within AV pilots.

While the Poisson distribution for disengagement rates is utilized for its simplicity, it presents an opportunity for further enhancement by switching to more complex diffusion models, such as piecewise diffusion or Bass diffusion and adapting them for AVs. These alternatives could provide a more nuanced understanding of adoption and disengagement dynamics, allowing for richer insights into pilot performance. Although they introduce additional layers of complexity, exploring these models may be beneficial in future iterations of the framework. The current use of the Poisson distribution facilitates straightforward integration and comparison across scenarios, making it well-suited for the early stages of AV pilot testing, while also laying the groundwork for potential advancements in model sophistication.

Furthermore, this framework facilitates the iterative improvement of pilot designs, addressing Objective 5 by offering flexibility for updates based on real-world data. Rather than striving for unattainable perfection, the framework supports timely implementation, with the ability to recalibrate as new information becomes available. This iterative approach ensures that social planners can refine the model over time, contributing to the continuous improvement of AV pilot programs.

While the framework is adaptable, it has limitations. Beyond the simplicity of the Poisson distribution, challenges remain in accurately quantifying social costs and community reactions to failures, as these factors are difficult to model precisely. Additionally, the current model does not incorporate weighted variables, which could allow for a more flexible representation of different factors such as safety or cost across time. Acknowledging

these limitations is critical for informed decision-making. Future refinements, including the introduction of variable weighting and the integration of insights from emerging literature and new data, will help ensure the model remains practical, adaptable, and robust for future applications.

The mathematical framework developed in this thesis supports social planners in navigating the balance between pursuing perfection and achieving practical, short-term AV pilot deployment. By minimizing risk while incorporating key concepts like learning, safety, and diffusion, it provides a robust starting point for decision-making. As data becomes available and alternative functions emerge, the framework can be iteratively updated to reflect these changes, with parameters adjusted over time—potentially at each time step. This adaptability offers a practical approach for improving pilot designs in real-time, rather than waiting for long-term projections to materialize.

While this framework addresses shorter-term scenarios, with a deployment timeline assumed to be under two years, a longer-term outlook would necessitate recalibrating parameters to account for evolving factors, such as technological advancements or broader shifts in transportation infrastructure. Comprehensive AV adoption models could benefit from more complex diffusion models or extended time horizons that reflect a full-scale transition from HVs to AVs. However, the current framework’s focus on short-term applications allows for recalibration as new data is gathered, making it adaptable to the immediate needs of pilot programs while laying the foundation for future refinement.

Challenges remain in modelling external social factors, but the introduction of social cost elements allows planners to better account for community-specific concerns. The framework remains flexible and can be tailored to various deployment contexts, ensuring that it does not fall victim to overcomplexity or perfectionism. As pilot programs evolve, this framework provides a foundational tool for social planners to refine AV designs, strike a balance between perfection and practicality, and adapt pilot projects to better reflect real-world dynamics.

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