**AI Behind the Wheel:**
**Work, Economics, and Preferences in the Era of Autonomous Vehicles**

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**Abstract of Dissertation**

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Autonomous vehicles (AVs) have the potential to dramatically disrupt transportation patterns and reshape cities and communities. At the core of this disruption is the substitution of a human driver with artificial intelligence (AI) technologies. Will AI-enabled vehicle automation help actualize visions of an enhanced transportation future, or will it exacerbate existing problems? The answer will ultimately depend on the capabilities of AVs and their position in our complex, sociotechnical transportation systems. While history and prior research offer lessons on how conventional automation can impact systems, less is known about the potential effects of *AI-enabled* automation, particularly when AI technologies are deployed to perform non-routine manual tasks. This dissertation unpacks several potential impacts of AVs and uses them as a case study of the potential societal effects of AI-enabled automation in the physical world.

AI advancements are changing the ways in which automation technologies can interact with and displace human labor. Unlike routine manual tasks like repetitive assembly that have undergone substantial substitution by conventional automation technologies, non-routine physical tasks have historically had limited opportunities for substitution or complementarity. AI advancements, however, are expanding automation technologies' capabilities within the non-routine task realm, demanding research into their resulting labor impacts. The first study in this dissertation uses direct observations, semi-structured interviews, and archival data to identify and map how tasks and labor roles change in response to the introduction of autonomous vehicles to a taxi work

system. This detailed analysis empirically demonstrates that introduction of AI technologies spurs the rebundling of tasks and reorganization of adjacent labor roles, and reveals three archetypal patterns of role change: *distributing*, *consolidating,* and *scaffolding*. These patterns can be used to refine labor outcome analyses and predict labor impacts at the task, role, and sector or economy level.

What motivates the substitution of a human driver with an AV system? While the promise of safer road travel is an oft cited motivation, the lure of lower operating costs is arguably the primary driver of investment in AV development. For years, Transportation Network Companies (TNCs) like Uber and Lyft, and emerging AV companies like Waymo, Cruise, and Zoox, have raised billions of dollars by promising a future of autonomous taxi fleets (robotaxis) that would eliminate the cost of a driver and pave a path to profitability. The future operating costs of robotaxi services, however, remain highly uncertain. Prior studies estimating the future costs of robotaxi services lack precision in two key areas: 1) the cost of autonomous vehicle technologies and 2) the labor costs needed to operate a robotaxi service. These two cost categories are critical as the payoff to firms for automating a particular task depends on the cost of the technology relative to the cost of the worker who performs that task.

The second study in this dissertation draws on the first study's findings about changing labor roles to develop ground-up cost models for a traditional taxi and a robotaxi service in order to compare their relative competitiveness under different operating conditions. The models reveal that labor remains a significant cost for robotaxi services but that robotaxi operating costs are still lower than those of traditional taxi services. Ultimately, utilization rates and annual mileage are the most influential factors for robotaxi competitiveness. Purported cost savings of AVs, as well as other capital-intensive AI technologies, must thus be considered in light of their remaining labor costs and intended operational contexts.

AV impacts, as well as those of other AI-enabled technologies, will ultimately depend on the extent to which people choose to adopt them. Some researchers fear that robotaxi services could compete with not only taxi and ride-hailing services, but also public transit services if vehicle automation enables significant price decreases. The third study in this dissertation uses responses from an online choice-based conjoint survey fielded in the Washington, D.C. Metropolitan Region (N = 1,694) in October 2021 to estimate discrete choice models of public preferences for different autonomous (ride-hailing, shared ride-hailing, bus) and non-autonomous (ride-hailing, shared ride-hailing, bus, rail) modes. The estimated models are then used to simulate future marketplace competition across a range of trip scenarios. On average, respondents were only willing to pay a premium for autonomous modes when a vehicle attendant was also present, suggesting that the presence of an attendant may be a critical feature for early AV adoption. Additionally, scenario analyses revealed that transit remained competitive with autonomous ride-hailing modes for trips where good transit options were available. These results suggest that fears of a mass transition away from transit to AVs may be limited by people's willingness to use AVs, at least in the short term. Moreover, these findings highlight the importance of investigating multiple design factors that might influence public adoption of emerging AI technologies.

Taken together, this dissertation examines AVs not simply as a technology, but as an element of a complex, sociotechnical system. Building on prior work, this research seeks to address gaps regarding how AI-enabled AVs are reshaping tasks and labor roles, changing the economics of existing services, and altering public preferences for different transportation modes. AI technologies and their societal impacts are not predetermined but rather emerge from a process of mutual shaping between technology and society. The aspiration with AVs is that they can help address longstanding problems with our existing transportation systems. By gaining early insights into the impacts of AVs and other AI technologies, we create the opportunity to proactively shape outcomes toward desirable futures.

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# Chapter 1: Introduction and Background

> Therefore a complex artifact…is necessarily embedded in complex systems, whose purpose is, first, to divide effort and knowledge, and second, to coordinate tasks and decisions. **As the basic artifact becomes more complex, moreover, the number of tasks and decisions that surround it will increase. To respond to these demands, the coordinating systems must themselves grow.** The coordinating systems' efficiency in dealing with higher levels of complexity in turn will have a huge effect on the **economics of the artifact**—the cost of designing, making, and using it, and the **extent to which it diffuses through human society**.
> - Baldwin and Clark, (2000) (emphasis added)

## 1.1 AI-Enabled Automation in the Physical World

We live in a time of both optimism and trepidation regarding new artificial intelligence (AI) technologies that are entering the public sphere and becoming increasingly intertwined in our lives. AI and AI-enhanced systems could complement or replace human capabilities with their capacities to process large quantities of data, recognize complex patterns, efficiently complete a variety of tasks, and learn over time. In doing so, they hold promise of not only increasing efficiency but also helping to address many of the persistent problems that plague our complex systems, including issues related to environmental sustainability, equity, and labor shortages. Yet there is also potential for AI technologies to cause exacerbate sustainability issues, spur widespread job loss, and promote an inequitable distribution of harms and benefits.

While history and prior research offer lessons on how conventional automation can impact systems, less is known about the potential effects of *AI-enabled* automation, particularly when automation technologies are deployed to perform physical tasks. Unlike routine manual tasks like repetitive assembly that have undergone substantial substitution by conventional automation technologies, non-routine physical tasks have historically had limited opportunities for substitution or complementarity (Autor et al., 2003). AI advancements, however, are expanding automation technologies' capabilities within the non-routine task realm, demanding research into their resulting system-level impacts.

Autonomous vehicles (AVs) offer an ideal domain in which to explore AI-enabled automation in the physical world. While autonomous vehicles have long been a part of public imaginations, development and deployment of AV services have only recently become possible due to AI advancements given the complex, non-routine nature of roadway driving. As they expand, AV services have the potential to dramatically disrupt transportation patterns and reshape cities and communities (Davidson & Spinoulas, 2015). Will AVs help actualize visions of an enhanced transportation future, or will they exacerbate existing problems? The answer will ultimately depend on the capabilities of AVs and their position in our complex, sociotechnical transportation systems.

This present wave of AI-enabled automation calls for investigation of the ways in which AI technologies' new capabilities for performing non-routine manual tasks might change our systems in manners that are similar to, or distinct from, prior technological transformations. This dissertation unpacks several potential impacts of AVs and uses them as a case study of the potential societal effects of AI-enabled automation in the physical world. By gaining early insights into the impacts of AVs and other AI technologies, we create the opportunity to proactively shape outcomes toward desirable futures.

## 1.2 Vehicle Automation: What is it and Where is it Occurring?

Driverless, autopilot, self-driving, autonomous, automated—multiple terms are commonly used when describing vehicle automation. While often used interchangeably, these terms actually refer to different types of vehicle automation. Many vehicles that individuals own and operate today include limited automation features such as lane-keeping assistance and automatic braking. These features represent lower levels of vehicle automation that still require a human to remain alert and operate the vehicle, and are typically classified as Advanced Driver Assistance Systems (ADAS).

At higher levels of automation, a combination of sensors, computing equipment, and software—commonly defined as an *automated driving system (ADS)*—is able to perform the driving task without assistance from the driver, under specific operational conditions (SAE, 2021). Table 1-1 presents SAE International's Levels of Driving Automation with additional details from the National Highway Traffic Safety Administration (NHTSA) (NHTSA, 2024; SAE, 2021). Per the SAE taxonomy, Levels 0-2 describe ADAS vehicle features and Levels 3-5 describe ADS-equipped vehicles. Though classified as ADS-equipped vehicles, Level 3 vehicles still require the driver to take over at times. Researchers define this type of configuration as a mixed-automation system, and many have raised concerns about safety issues that may arise from shared operational responsibility between the human driver and the automation system (Hancock et al., 2020).

**Table 1-1:** SAE Levels of Automation with additional details drawn from the National Highway and Traffic Safety Administration's Levels of Automation

| Level | | Description | Examples |
|---|---|---|---|
| **Level 0** | **No Driving Automation** | System provides momentary driving assistance, like warnings and alerts, or emergency safety interventions while driver remains fully engaged and attentive. | automatic emergency braking, blind spot warning, lane departure warning |
| **Level 1** | **Driver Assistance** | System provides continuous assistance with either acceleration/braking OR steering, while driver remains fully engaged and attentive. | lane centering OR adaptive cruise control |
| **Level 2** | **Partial Driving Automation** | System provides continuous assistance with both acceleration/braking AND steering, while driver remains fully engaged and attentive. | lane centering AND adaptive cruise control at the same time |
| **Level 3** | **Conditional Driving Automation** | System actively performs driving tasks while driver remains available to take over. | traffic jam chauffer |
| **Level 4** | **High Driving Automation** | System is fully responsible for driving tasks within limited service areas while occupants act only as passengers and do not need to be engaged. | Not currently available on today's vehicles for consumer purchase in the U.S. Available as a shuttle or robotaxi service. |
| **Level 5** | **Full Driving Automation** | System is fully responsible for driving tasks while occupants act only as passengers and do not need to be engaged. | Not currently available on today's vehicles for consumer purchase in the U.S. or as a commercial service. Would need to be able to operate everywhere, in all conditions. |

The most significant impacts, both positive and negative, resulting from vehicle automation are expected to come from Level 4 and Level 5 vehicles. This dissertation specifically examines these impacts, and uses the colloquial term *autonomous vehicle*[1] (AV) when referring to this type of system. AVs are still primarily in the testing and development phases, though Level 4 commercial services are available in a few cities. During this emergent phase, companies and cities are experimenting with multiple

[1] AV researcher Jane Lappin often jokes that using the term *autonomous* belies the true nature of the system—with an *autonomous* system, you would get into the vehicle and ask it to take you to work and it would instead decide to take you to the beach (Lappin, 2023). Nonetheless, the term autonomous vehicle has become common within both academic and public discourse and is thus used throughout this dissertation.

development models for AV deployments, both in terms of business models and the physical design of the AV (see Table 1-2 for the most common models for both passenger and goods delivery movement). Development of AV services is occurring world-wide, with the United States and China leading in terms of current and planned number of deployments. AV firms can voluntarily submit information about their ongoing AV testing projects and deployments to NHTSA's AV TEST Initiative. Figure 1-1 displays a map of reported testing projects and commercial deployments for different types of AV services (as of June 2024). Within the U.S., the states with the greatest number of deployments are Arizona, California, Florida, and Texas.

**Table 1-2:** Potential development models for autonomous vehicles.

| Development Model | Description |
|---|---|
| Private autonomous vehicle | Individuals could purchase a personal AV for use in the same manner as a traditional personal vehicle. |
| Robotaxi/<br>Shared robotaxi | Robotaxis could provide door-to-door transportation services akin to traditional taxi or Transportation Network Company (TNCs, e.g., Uber and Lyft) services. Robotaxis could be summoned on-demand and paid for via either subscription models or on a per-trip basis. In some cases, rides could be shared by multiple passengers (e.g., UberPool, shared Lyft rides). |
| Autonomous public transit | Autonomous buses could replace traditional buses. These buses could be traditional 40ft buses or custom-built shuttle buses that fit 8-10 passengers. |
| Autonomous trucks | Autonomous trucks could perform the long-haul portion of trucking routes. Multiple trucks could travel together as part of a "platooning" formation. |
| Delivery robots | Smaller autonomous vehicles would operate on sidewalks or local streets to deliver goods including packages, groceries, and prepared food. |

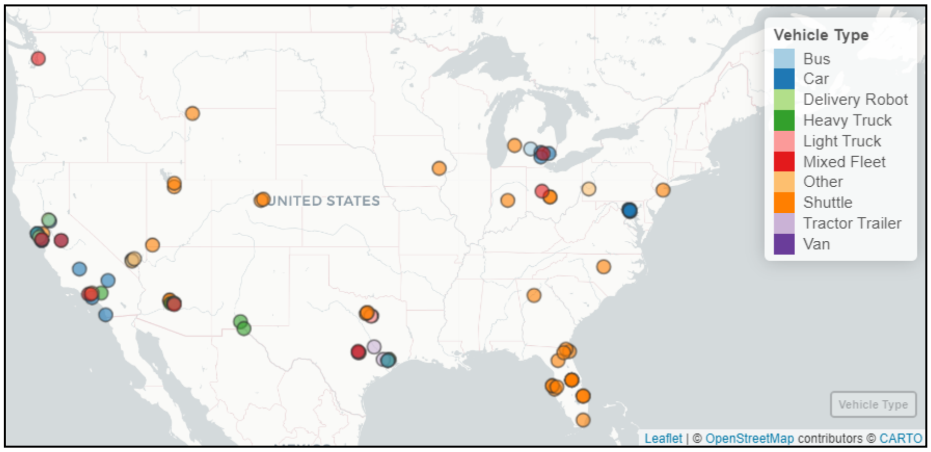



**Figure 1-1:** AV demonstration and testing projects, and commercial AV deployments. Based on data reported to the National Highway Traffic Safety Administration's AV TEST Initiative as of June 2024.

## 1.3 Potential Impacts of Autonomous Vehicles

When (or if) AVs become widespread, they are predicted to yield a variety of safety, environmental, economic, equity, and labor impacts. Uncertainty exists, however, regarding the types and extent of these impacts. Like many other AI technologies, AVs promise performance improvements. A prevailing narrative about AVs is that they will dramatically improve road safety by eliminating human error (Stilgoe, 2021). Yet some researchers note that AVs would need to be able to handle greater than 99.99% of scenarios they encounter to be comparable to an average human skilled driver, a standard beyond the current capabilities of AVs (and perhaps an impossible standard to ever achieve) (Shladover, 2018). From an environmental perspective, AVs could increase fuel efficiency via vehicle platooning, curb the need for personal car ownership, decrease traffic, and reduce the amount of space needed for parking (Williams et al., 2020a). Such benefits could be offset, however, by induced travel demand, greater urban sprawl, competition with transit, and the creation of "ghost traffic" from empty vehicles circling cities to avoid parking fees (Appleyard & Riggs, 2017; Creger et al., 2019; Milakis et al., 2018; Milakis & van Wee, 2020).

As one group of researchers asks, who might be the winners and losers in an AV future (Cohen et al., 2020)? The history of transportation in the United States, and emerging problems with AI technologies, show us that the introduction of new technologies can yield an uneven distribution of benefits and burdens. Absent equity-oriented policy interventions and design decisions, AVs may mean transportation "heaven" for some, and "hell" for others. AVs could open up new mobility pathways for low-income, car-less individuals and low-mobility populations, including elderly individuals and people with disabilities (Creger et al., 2019; Steckler et al., 2021). This promise of increased mobility, however, is contingent upon multiple design factors including avoiding financial and physical barriers that might preclude AV use by different communities (Milakis & van Wee, 2020; Steckler et al., 2021). AVs could also impact transportation equity via potential competition with transit. Transit systems have already had to reckon with competition from ride-hailing services that offer greater flexibility and convenience than many transit options (Breuer et al., 2020; Cats et al., 2022; Dong, 2020; Gehrke et al., 2019). If vehicle automation enables significant price decreases and increased availability for ride-hailing services, some fear that it could undercut public transit, which is one of the most equitable and environmentally sustainable modes of transportation (Creger et al., 2019; Williams et al., 2020b).

As with past automation technologies, potential job loss due to AVs is a key area of concern (Cohen et al., 2018; Hilgarter & Granig, 2020; Norton et al., 2021). One recent study estimated that vehicle automation could eliminate 1.3 to 2.3 million workers' jobs over the next 30 years (Groshen et al., 2018). These job losses may or may not occur alongside the creation of new jobs within the AV industry and increased employment opportunities outside of the industry via improved transportation accessibility (Farooque et al., 2021; Leonard et al., 2020; Steckler et al., 2021; Williams et al., 2020b). One cannot, however, evaluate these employment losses and gains as a one-to-one trade. Though past automation technologies have, on net, created more jobs than they have eliminated, newly created jobs were typically polarized into low and high-paying jobs (Autor, 2015; Bessen, 2016; Goos et al., 2014). In line with this trend, Viscelli (2018) found that, absent proactive policy intervention, vehicle automation will likely eliminate high- and mid-wage trucking jobs, while creating low-quality driving jobs.

Yet AI systems, like AVs, represent a new form of automation that impact not only routine—and therefore easily programmable—tasks, but also more complex, non-routine tasks. AVs thus serve as a valuable domain in which to explore how AI technologies might directly and indirectly impact the future of work. AVs could, like prior automation technologies, induce job polarization, creating a misalignment between the skillsets of individuals who lost their jobs the skill requirements for newly created roles (Steckler et al., 2021; Williams et al., 2020a). Occupations that involve driving as a secondary activity such as waste management providers or home health aides might also see their associated labor roles evolve (Beede et al., 2017). Even typical driving commuters might see work seep into their transportation routines as driving time is converted to additional working time (Milakis et al., 2018).

The full extent of AV labor impacts will unfold over time. In the meantime, U.S. robotaxi services offer an opportunity to explore how AVs are reshaping taxi work systems. The following chapter further unpacks these dynamics.

# Chapter 2: Mapping the AI-Enabled Transformation of Labor in Taxi Services by Autonomous Vehicles

In this study, we examine how the introduction of autonomous vehicles to a taxi work system reshapes tasks and frontline labor roles. This chapter is based on Kaplan et al. (2024), a conference paper accepted to the *ILR Review* "Artificial Intelligence and the Future of Work" conference.

## 2.1 Introduction

Advances in artificial intelligence (AI) are transforming how automation can interact with and change human labor. AI-enabled automation technologies can now perform more complex tasks which extend into the realm of what were previously considered uniquely human abilities. Unlike repetitive physical tasks that have undergone substantial substitution with automation technologies, non-routine manual tasks have thus far remained largely unaffected by automation. Emerging AI-enabled technologies, however, are finding success at taking on complex physical tasks, threatening the jobs of workers who currently perform them.

In light of these advancements, some voices now claim that AI will soon be able to perform all jobs and displace workers across nearly every sector. Past technological revolutions, however, have not eliminated work and workers wholesale but rather have transformed labor and work in more complex ways. Further, how technologies perform in constrained development settings is often quite different from how they exist within, shape, and are shaped by actual work systems and interaction with the physical world. This period of AI-induced change calls for careful consideration of how AI is actually transforming work and the workforce in-context. As technologies change, moreover, researchers must refine their analytical tools such that they capture the important features of these technology-induced transitions and their resultant labor outcomes.

In this study, we examine how the introduction of autonomous vehicles to a taxi work system reshapes tasks and frontline labor roles. We perform an inductive, comparative analysis of taxi and robotaxi work systems, treating the two types of systems as cases of conditions prior to and following the introduction of AI technologies to a taxi work system. Drawing on government occupation data, direct observations, semi-structured interviews, and archival data, we identify tasks and labor roles for each work system and perform a granular mapping of how each of the roles and the 190 identified tasks changes. While prior studies have hypothesized about AI-induced rebundling of tasks and reorganization of adjacent labor roles, we empirically demonstrate this phenomena for a work system oriented around a non-routine manual task and add nuance to these processes, identifying three archetypal patterns of change.

Autonomous vehicles (AVs) are one of a number of emerging AI-enabled technologies being developed to perform non-routine manual tasks. Relatively few studies have examined this task category, as past automation technologies were ill-equipped to complete such tasks. Tasks like driving, which require dexterity, physical skills, mobility, and awareness of the physical context, have historically had limited opportunities for substitution or complementarity with automation technology (Autor et al., 2003; Brynjolfsson & Mitchell, 2017). Yet the promise (realized or not) of safety improvements, cost savings, and solutions to labor shortages is pushing use of AI-enabled technologies into this realm, demanding research on their labor impacts. While prior scholarship has largely focused on use of AVs in the trucking sector (Gittleman &

Monaco, 2020; Levy, 2022; Viscelli, 2018), this study is the first to investigate changes to work in the passenger transportation space, driving scholarship forward as robotaxi services expand into cities around the world, and offering insights for other types of AI technologies designed to perform non-routine manual tasks.

## 2.2 Prior Literature

Prior scholarship offers different perspectives on automation and labor based on analyses performed at the task-, role-, sector-, and economy-level. Each of these perspectives captures various elements of interest and all are sensitive to the researchers' selected boundaries of analysis.

At the task level, researchers have sought to define types of tasks in different work systems. Autor et al.'s (2003) Routine-Biased Technical Change (RBTC) theory categorized tasks across two dimensions: routine versus non-routine, and analytic or interactive versus manual. Numerous other studies have proffered revisions to these categories or proposed alternative approaches for their operationalization (see Sebastian and Biagi (2018, p. 24) for a review). In a 2020 report, Fernández-Macías and Bisello argued that task categorizations must capture not only the content of a task, but also the methods and tools of the work, features which they integrate into their taxonomy of tasks (2020, p. 8). Motivating this effort to categorize tasks is the desire to understand why substitutions of labor with capital might occur (Acemoglu & Restrepo, 2018, 2019; Autor et al., 2003; Combemale et al., 2021) or, more typical within the engineering literature, to develop guidance on what tasks *should* be performed by an automation system based on performance consequences (Fitts, 1951; Parasuraman et al., 2000). Task typologies are also commonly deployed to predict impacts of technology introduction at the role level.

Role-level analyses commonly ask whether a worker might be replaced by, or work with, a new technology. To that end, RBTC posits that automation largely substitutes for workers that perform routine tasks and complements those that perform non-routine tasks (Autor et al., 2003). Assuming that jobs with more automatable tasks are more likely to be automated, Arntz et al. (2016) estimated that 9% of jobs across 21 OECD countries were automatable. Frey and Osborne (2017) offered a significantly higher estimate that 47% of U.S. jobs were at risk of automation. AI is expected to significantly broaden the number of tasks that could be performed by automation technologies, leading some researchers to offer even more dramatic conjectures about substitution effects. Huang and Rust (2018) went so far as to assert that AI will eventually be able to perform all types of tasks and that AI technologies present a fundamental threat to human employment.

Some researchers have chosen to measure role-level impacts in terms of exposure to AI without equating that exposure to job loss. Felten et al. (2021) developed their measure of AI exposure based on the abilities on which different occupations rely. Using this measure, Felten et al. (2023) found that highly-skilled, highly-educated white-collar workers are most likely to be exposed to generative AI technologies. Eloundou et al. (2023) measured exposure based occupational tasks and estimated that approximately 80% of U.S. workers could have at least 10% of their work tasks affected by large language models. Brynjolfsson et al. (2018) similarly developed a suitability for machine learning index based on tasks and found that most occupations include at least some tasks that are suitable for substitution with machine learning, though few occupations would be fully automatable.

At the sector or economy-level, researchers have sought to predict impacts to job numbers and worker wages and skills. Acemoglu and Autor (2011) found that automation led to job polarization and shifted demand towards more educated workers in the United States and other advanced economies, though Goos et al. (2014) identified offshoring as an additional contributor to the trend. Bessen (2016) also noted that automation can decrease prices and induce demand, resulting in a net increase in jobs. Even if more jobs are created at the sector or economy level, firm-level automation can increase the probability that workers will leave their employers (e.g., via early-retirement) and experience cumulative wage loses (Bessen et al., 2019).

In addition to these more categorical approaches, a rich body of literature has examined the labor impacts of technological change through context-driven work system approaches. These studies, based out of the sociology and industry studies traditions, have offered additional insights as to how technologies and work system co-evolve (Doellgast & Wagner, 2022). A 2017 report from the National Academies of Sciences, Engineering, and Medicine noted that prior ethnographic research has demonstrated how "a variety of new technologies have altered the way work is performed, the roles that workers play in a firm's division of labor, and the way these changing roles alter the structure of organizations" (NASEM, 2017) (p80). These studies reveal that technology may impact work systems in ways other than substituting or complementing workers. Importantly, how these changes unfold can impact job quality and workers' experiences (Litwin et al., 2022; Moradi & Levy, 2020; Sheehan & Le Dantec, 2023).

As with prior technology introductions, emerging AI technologies are expected to reshape tasks performed by workers, spur reorganization of jobs, and alter production processes (Autor, 2022; Bresnahan, 2021; Brynjolfsson et al., 2018). Recent context-driven studies have begun to examine AI technology effects on work systems in multiple industries, including hospitality and tourism, retail, food retail, healthcare, transportation, and warehousing (Ivanov et al., 2017; Litwin et al., 2022; Sheehan & Le Dantec, 2023). Litwin et al.'s (2022) forum on emerging technologies identified a number of cross-cutting themes for types of impacts. Two of the themes highlight changes to work that may be missed by task and role-level analyses that are focused on individual worker-technology interactions, and by economy-level analyses that only capture net job growth or losses: 1) automation often involves substituting one worker for another, and 2) automation may offload work onto the user or customer.

As we enter into "the Era of AI uncertainty" (Autor, 2022, p. 18), researchers need to leverage context-driven work systems approaches to enhance understandings of AI technology impacts and refine their measures of these impacts at various levels of analysis. To that end, this study employs a work-systems approach to investigate AI impacts on a taxi work system, capturing changes to tasks, roles, and interactions between workers and technology.

## 2.3 Technological and Organizational Context

Forms of vehicle automation are already present in many individually-owned passenger vehicles, including features such as automatic breaking and lane departure warnings. These features represent lower levels of automation, commonly classified as Advanced Driver Assistance Systems (ADAS). The term autonomous vehicles (AVs) generally refers to vehicles at higher levels of automation, those in which an *automated driving system* consisting of sensors and computing equipment is fully responsible for the driving task, at least under specified operational conditions (SAE, 2021). A number of firms are currently developing AV systems for commercial applications with the intent to fully substitute (i.e., remove) human drivers. The most commonly discussed reason for this substitution is to improve system safety by theoretically eliminating human error (NHTSA, 2024). AV systems might also decrease operating costs by reducing labor expenditures (Bösch et al., 2018; Compostella et al., 2020; Kaplan, Nurullaeva, et al., 2024).

As with other sectors, there is significant concern that AI-enabled vehicle automation could lead to substantial job loss. Groshen et al. (2018) estimated that vehicle automation could eliminate 1.3 to 2.3 million workers' jobs over the next 30 years. Of these losses, the majority are expected to occur within the transportation and warehousing sectors (Beede et al., 2017). While startling, there is reason to suspect these estimates may be overstated. In the long-haul point-to-point trucking sector, for instance, Gittleman and Monaco (2020) found that job losses would likely be much lower than prior predictions (300,000 to 400,000 job losses compared to millions of job losses). The gap between their estimate and prior studies' estimates is largely attributable to Gittleman and Monaco's differentiation between different types of trucking work and regulatory influences within different market segments that employ truck drivers. As Viscelli (2018) notes, future regulation could play a pivotal role in what types of trucking jobs are eliminated or enhanced in an AV future.

Gittleman and Monaco (2020) also call attention to the importance of tasks that truck drivers perform besides driving. Truck drivers do more than operate their vehicle, just as bus operators perform a range of tasks as part of their role (Machek et al., 2018). Some of these tasks tie to systems of care that are embedded in our current mobility systems (Stayton & Cefkin, 2018). Replacing these additional tasks with automation technologies presents a non-trivial challenge for AV developers. Despite this challenge, AV development has continued and has recently seen the greatest momentum in the realm of robotaxi services.

Though far from the level of ubiquity promised by AV firms a few years ago, robotaxi services are commercially available in a limited number of U.S. cities and other locations around the world, allowing members of the general public to ride in these services as fare-paying customers. Alphabet-backed robotaxi firm Waymo recently expanded its robotaxi service operating area from parts of San Francisco and Phoenix to Los Angeles, with planned expansion into Austin in late 2024 (Waymo, 2024). These services operate in a similar manner as existing on-demand passenger transportation services (e.g., taking a taxi or an Uber), though are limited to specific geographic areas and, in some cases, limited service hours. Riders download a robotaxi company's app, input their desired destination, and are matched with a vehicle that transports them to their destination (within the service area).

For each city in which they operate, robotaxi firms have a depot in which the AVs are stored and receive general maintenance services. Some depots include equipment like that of an automotive mechanic shop so that the firms' mechanics can perform vehicle repairs in-house (Hawkins, 2018). Robotaxi firms also have central command centers that oversee operations of their fleets across multiple cities. These command centers house workers that monitor and assist the AVs in a manner similar to air traffic controllers (Ohnsman, 2019, 2020). Researchers have speculated about what other new roles may arise to support robotaxi services, with the bulk of discourse focusing on the interactions between AVs and remote monitors (Cesafsky et al., 2019; Leonard et al., 2020; Mutzenich et al., 2021).

Little is known about other types of workers who directly support these services, and how the overall taxi work system might be changing. In this study we ask, how does the introduction of autonomous vehicles to a taxi work system reshape tasks and frontline labor roles? In doing so, we contribute to theory on how the introduction of AI-enabled technologies that can perform non-routine manual tasks can change tasks and roles in a work system.

## 2.4 Methodology

To investigate AI-induced labor changes to a taxi system, we perform an inductive, comparative analysis of taxi and robotaxi services in the United States, pursuing an inductive approach as inductive studies are better suited for emergent phenomena that are poorly understood (Eisenhardt & Graebner, 2007; Szajnfarber & Gralla, 2017). Robotaxi services are still developing and our current mixed transportation system, which includes both human-driven and AI-driven taxi-type services, offers a valuable opportunity to compare two work systems oriented around the same type of service. These systems may come to represent distinct eras in our transportation system: one primarily human-driven state and another dominated by AI-driven vehicles.

We select taxi services as our basis of comparison as both taxi and robotaxi services provide on-demand, public-serving, point-to-point transportation services. Another similar type of service is ride-hailing (e.g., Uber, Lyft). While fairly equivalent from a rider-perspective, the work systems of robotaxi firms and Transportation Network Companies (TNCs) like Uber that support ride-hailing services differ quite significantly. Robotaxi firms provide *transportation* as a service, whereas TNCs provide *technology* as a service and classify themselves as technology companies (Dubal, 2017). TNCs' work systems are oriented around developing and maintaining their software platforms rather than fleet maintenance and operations. Though consideration of ride-hailing jobs is important for understanding the overall labor impacts of robotaxis, ride-hailing work systems are not suitable as a direct comparison with robotaxi work systems. We thus adopt taxis services as our basis of comparison.

We investigate changes that occur to a taxi work system due to AV introduction through the lens of tasks and roles. In essence, these are the key constructs around which we seek to organize our data (Eisenhardt, 1989). Variation exists both between taxi firms and robotaxi firms, and amongst different taxi and robotaxi firms. To isolate our concept of interest—the allocation of tasks to roles—and compare taxis and robotaxis as distinct work system paradigms, we perform our comparative analysis on representative versions of the two systems. These representative versions capture the dominant task-role architectures for each type of system. By using these representative systems, we control for factors like company culture and individual worker characteristics that could influence work system organization and task allocation.

To develop these representations, we first establish definitions for tasks and roles. The U.S. Department of Labor's O*NET database offers standardized definitions for tasks and roles, as well as detailed information for nearly 1,000 occupations (O*NET, 2024). O*NET is the United States' primary source of occupational information and its data have been used in numerous studies to examine the potential impacts of other AI technologies on tasks and occupations (Beede et al., 2017; Brynjolfsson et al., 2018; Brynjolfsson & Mitchell, 2017; Eloundou et al., 2023; E. Felten et al., 2021; E. W. Felten et al., 2023). O*NET organizes role information by general occupations that cover multiple related job titles (e.g., Taxi Driver = Cab Driver, Taxi Cab Driver, and Taxi Driver) and defines tasks as "specific work activities that can be unique for each occupation" (O*NET, 2024).

O*NET's occupation data come from questionnaires fielded amongst workers performing that job or from occupation-specific experts (O*NET, 2017). Though this approach may work well for established occupations, we are not yet ready to survey workers in emergent robotaxi occupations as the relevant survey questions and target survey population is yet unknown. To build an equivalent set of standardized occupation-specific information for the robotaxi system, we conduct direct observations, semi-structured interviews, and analysis of archival documents.

Taxi occupations are well-established and both O*NET and academic literature offer detailed descriptions of taxi system tasks and roles on which we can draw. We thus use a mix of primary and secondary data sources to develop our representative taxi and robotaxi systems, reconciling differences between the sources via an iterative analysis process that we detail below (see Table 2-1 for a summary of our data sources, additional details provided in Appendices A.1, A.2, and A.3).

We bound our analysis to include only those tasks and roles directly involved in providing the taxi service for a rider, excluding labor involved in robotaxi technology development and early algorithm training of AV vision systems (e.g., image labeling). As we identify tasks and roles for one case, we iteratively determine whether those tasks and roles are equivalent between the cases, or whether they undergo changes. This iterative within-case and between-case analysis also helps ensure that we capture all relevant tasks and roles. Finally, we map how tasks move between roles after the AV technology is introduced, and work to identify and describe patterns of change that occur. Figure 2-1 provides a visual depiction of our data collection and analysis process. We further describe this process in the following sections.

**Table 2-1:** Summary of data sources.

<table>
<tr><td rowspan="9">O*NET Data & Archival Documents</td><td colspan="2">Document Type</td><td>Number of Items</td><td>Total # of Pages</td></tr>
<tr><td colspan="2">O*NET Occupation Information</td><td>4</td><td>4</td></tr>
<tr><td colspan="2">U.S. Bureau of Labor Statistics Data on Occupations</td><td>3</td><td>3</td></tr>
<tr><td colspan="2">News Articles Mentioning Frontline Robotaxi Roles</td><td>7</td><td>64</td></tr>
<tr><td colspan="2">AV Firm Public Reports and Petitions</td><td>5</td><td>168</td></tr>
<tr><td colspan="2">Job Postings for Frontline Robotaxi Roles</td><td>24</td><td>50</td></tr>
<tr><td colspan="2">Reports about AV Regulations</td><td>4</td><td>271</td></tr>
<tr><td colspan="2">Supplementary Responses and Documents from Interviewees</td><td>4</td><td>17</td></tr>
<tr><td colspan="2">Total:</td><td>51</td><td>577</td></tr>
<tr><td rowspan="5">Observations</td><td colspan="2">Observation Type</td><td>Number of Observations</td><td>Total Duration (min)</td></tr>
<tr><td colspan="2">Robotaxi rides</td><td>13</td><td>237</td></tr>
<tr><td colspan="2">Observations of robotaxi command center</td><td>1</td><td>360</td></tr>
<tr><td colspan="2">Observations of robotaxi fleet maintenance depot</td><td>1</td><td>120</td></tr>
<tr><td colspan="2">Total:</td><td>15</td><td>717</td></tr>
<tr><td rowspan="10">Semi-Structured Interviews</td><td>General Role of Interviewee</td><td>Type of AV Deployment</td><td>Number of Unique Interviewees</td><td>Total Length of Interview(s) (min)</td></tr>
<tr><td>Frontline Worker</td><td rowspan="3">Commercial Operations</td><td>6</td><td>280*</td></tr>
<tr><td>Mid-level Manager</td><td>5</td><td>166</td></tr>
<tr><td>Senior Manager</td><td>5</td><td>209</td></tr>
<tr><td>Operations Manager</td><td rowspan="2">Pilot Program or Government-Run Deployment</td><td>3</td><td>182**</td></tr>
<tr><td>Policy/Communication Manager</td><td>2</td><td>278</td></tr>
<tr><td>AV Operations Expert</td><td rowspan="3">External Perspective</td><td>3</td><td>131</td></tr>
<tr><td>AV/Taxi Regulations Expert</td><td>3</td><td>357</td></tr>
<tr><td>Taxi Manager</td><td>1</td><td>30</td></tr>
<tr><td colspan="2">Total:</td><td>28</td><td>1633</td></tr>
<tr><td rowspan="4">Conferences</td><td colspan="2">Type</td><td>Number of Events</td><td>Event Length (hrs)</td></tr>
<tr><td colspan="2">Academic, industry, and regulatory conferences about AVs</td><td>2</td><td>44</td></tr>
<tr><td colspan="2">Conference sessions about AVs at academic and regulatory conferences</td><td>2</td><td>16</td></tr>
<tr><td colspan="2">Total:</td><td>4</td><td>60</td></tr>
</table>

*One 30min interview included a Frontline Worker and a Mid-Level Manager. Interview length counted here.

**One 64min interview included an Operations Manager and a Policy/Communication Manager. Interview length counted here.

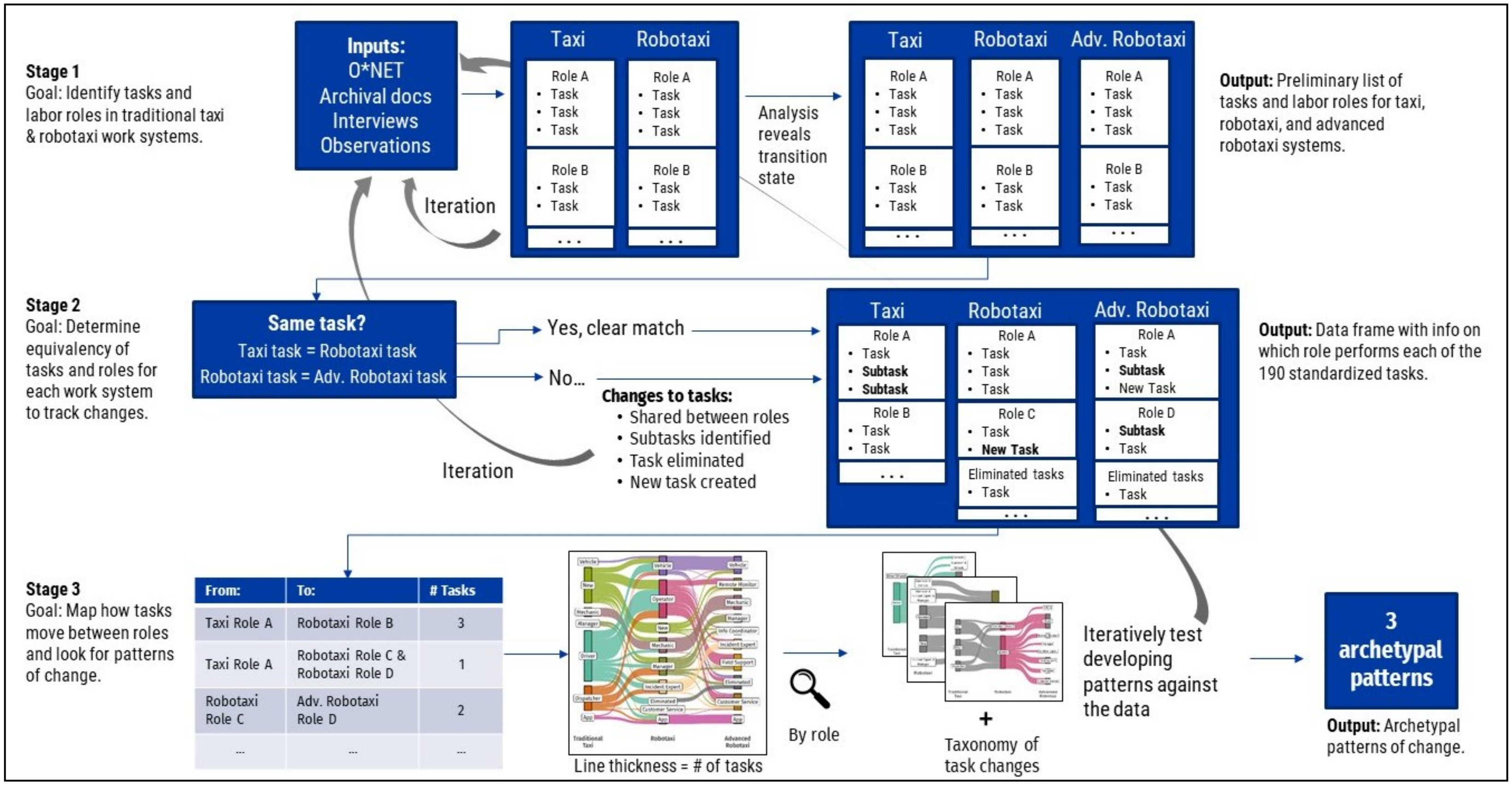



**Figure 2-1:** Data collection and analysis process.

### 2.4.1 *Stage 1*: Constructing a Comprehensive Dataset of Tasks and Roles

To construct our representative systems for comparison, we collect data on robotaxi and taxi system tasks and roles. At present, less than half a dozen[2] firms are developing and deploying robotaxi services in the U.S. Key elements of robotaxi fleet operations are fleet maintenance, remote forms of passenger and vehicle support, and the in-vehicle rider experience. As we collect our data, we aim to conduct in-depth probes of each of these elements, though doing so at a single robotaxi firm is not possible. We instead split our more in-depth probes and data collection efforts amongst multiple firms, taking care to make sure our takeaways are representative of the general robotaxi firm population.

O*NET data and prior academic research has already largely characterized tasks and roles for taxi systems. We leverage these data as sources of in-depth information for our taxi system representation. As we learn more about robotaxi services, we collect additional data on taxi services to refine our taxi representation and to capture details that are of particular relevance for our comparison. We include more details on task and role identification in the following sections.

#### 2.4.1.1 Robotaxi System Tasks and Roles

To identify tasks and labor roles involved in robotaxi system operations, the lead researcher in the study took thirteen rides in a commercially-available robotaxi service (twelve rides in one firm's service and one ride in a different firm's service), conducted

[2] At the time of writing this chapter, four companies in the U.S. were either currently offering or had previously offered robotaxi services to members of the public as part of early-rider programs or publicly-available commercial services.

six hours of observation of one firm's robotaxi central command center, and performed two hours of observation of the same firm's fleet depot between 2022 and 2023. To fill in the gaps of potentially missed roles, collect additional task information for identified roles, and check for representativeness, the researcher conducted semi-structured interviews with AV technical and operational experts (N = 26 semi-structured interviews with 27 unique interviewees), each lasting between 30 to 80 minutes. Observations and interviews were conducted with approval from George Washington University's Institutional Review Board. Thirteen interviews were conducted in-person, with the remainder conducted over Zoom. All interviews for which consent to record was given were recorded and transcribed.

Over half of the interviewees were either current or prior employees of a robotaxi company and were able to provide detailed descriptions of their roles and the associated tasks. Ten interviewees came from the same firm. Interviewees were selected via purposive sampling to capture the different types of frontline roles involved in robotaxi services and cover different perspectives (Eisenhardt & Graebner, 2007). Interviews were conducted until theoretical saturation was reached for each type of role (i.e., new interviewees did not mention any new tasks or labor roles) (Eisenhardt, 1989; Szajnfarber & Gralla, 2017).

In addition to semi-structured interviews and observations, the researcher attended academic, regulatory, and industry conferences about autonomous vehicle deployment. At some of these conferences, robotaxi firms had their autonomous vehicles on display for participants, along with frontline workers from the firm who were available to answer general questions, thus offering additional informal opportunities to engage with frontline robotaxi workers. These conversations were not recorded but the researcher took notes during the discussions and typed these as additional field notes.

We triangulate our findings (Yin, 2018) using the observations, interviews and archival documents which include job postings, public reports from AV firms detailing elements of their operations for regulators, and written responses from AV firms that were not directly interviewed. These sources confirm the existence or planned development of similar types of roles at the other commercially-available or in-development (i.e., testing on public roads but not available for public commercial use) robotaxi firms in the U.S. and provide additional task information. Interview transcriptions, observation field notes, and archival documents are entered into the NVivo software for coding analysis.

We use our collected data to construct standardized task and role entries akin to those in O*NET for the robotaxi roles[3]. To do so, we open-code the interview transcriptions, observational notes, and archival documents to generate a list of standardized roles and their associated tasks for robotaxi operations. Table 2-2 includes one example of this translation process. This process also reveals that a transition point exists that significantly impacts what roles exist in the robotaxi system and what tasks they perform. This transition points occurs when the technological capabilities of the AVs improves such that the onboard operator (i.e., safety driver) can be removed. We consequently split our comparison into three representative systems: 1) pre-AI technology introduction –*Taxi*, 2) AI technologies introduced with limited capabilities –

[3] We also check how well seemingly related O*NET occupations compare to our identified robotaxi roles and find that O*NET entries for jobs such as "Air Traffic Controllers" and "Remote Sensing Scientists and Technologists," the latter of which includes Unmanned Systems Operators and Drone Operator, descriptions do not align with the information from our observations and interviews.

*Robotaxi*, and 3) AI technology capabilities expanded – *Advanced Robotaxi*.

#### 2.4.1.2 Taxi System Tasks and Roles

Social, economic, and regulatory forces have changed the structures of taxi firms over time (Dubal, 2017; Mundy, 2022). The current landscape of U.S. taxi firms includes a variety of organizational structures; some firms have centralized structures and classify drivers as employees, whereas other firms have decentralized structures and instead lease vehicles to drivers who operate as independent contractors (Cooper et al., 2016; Mundy, 2011). We assume a centralized taxi firm structure since robotaxi firm structures more closely mirror those of a centralized firm. Dubal's (2017) ethnographic analysis of the taxi industry in San Francisco and Cooper et al.'s (2016) book on taxi firm structures, roles, and technologies provide detailed information about roles associated with a taxi system.

We leverage the O*NET occupation-specific task[4] information for "Taxi Drivers," "Dispatchers, Except Police, Fire, and Ambulance," and "Automotive Service Technicians and Mechanics" to define tasks for the driver, dispatcher, and mechanic roles, excluding tasks that do not pertain to the taxi system (e.g., excluded the task "Ensure timely and efficient movement of trains, according to train orders and schedules" for the dispatcher role). We include a manager role as part of assuming a centralized taxi firm structure and include an app role since many modern taxi firms incorporate digital technologies to enhance their operations (Cooper et al., 2016). O*NET does not have data for taxi-specific managers, nor does it specify tasks performed by technologies. We

[4] An alternative approach would be to use O*NET's Detailed Work Activities (DWA). DWAs describe tasks in a more general manner so that they can be compared across occupations. We feel that these more general descriptions mask important details for taxi work system change, and indeed find during our analysis that these details are valuable for characterizing role changes.

instead used archival data and a supplementary interview with a manager of a taxi firm to identify the tasks performed by taxi managers and apps. We note that the work of managers can vary significantly between firms, between types of managers, and by level of management. We focus specifically on managerial tasks related to coordinating work with frontline employees, managing worker performance, and developing standard operating procedures, tasks which we find are reallocated to emergent specialized roles in the robotaxi system.

As we learn about roles and roles for the robotaxi system, we check whether these roles exist within a typical taxi service[5] and revise our taxi system representation accordingly. We also leverage supplemental data sources to highlight the differences in roles that might exist for both the taxi and robotaxi systems. Differences between taxi and robotaxi mechanics are derived, in-part, via comparison of course requirements for a traditional vehicle mechanic training program with those of an AV mechanic training program (De Anza College, 2024). Distinctions between the functions of a non-autonomous vehicle and a robotaxi vehicle are extracted from a technical document detailing differences in vehicles with varying levels of automation (SAE, 2021).

### 2.4.2 *Stage 2*: Determining equivalency of tasks and roles to track changes

We further reconcile our task and role lists for our taxi and robotaxi systems through an additional analysis step, matching up tasks and roles between our constructed lists. During this matching process, we find that some of the O*NET taxi tasks

[5] We do not claim that roles excluded from the taxi system that appear in the robotaxi system do not exist at *any* taxi firm, but rather the role may not be common for a taxi service.

correspond with multiple tasks from our developed robotaxi list. In some cases, we combine our robotaxi tasks to align with the O*NET task generality. For certain instances, however, we find that the additional granularity for the robotaxi tasks is necessary in order to properly reallocate tasks between roles or because the granularity captures a fundamental difference in the way a role might perform a given task (e.g., a human versus an AI system driving). For eight of the "Taxi Drivers" O*NET tasks, we split the task into two separate tasks, finding that the O*NET task captures distinct tasks that are performed by different roles in the robotaxi system or that a portion of the task is eliminated in the robotaxi system. We check all matches that are unclear against our data and discuss them amongst the research team until consensus is reached.

The matching process also surfaces tasks that are not included in the O*NET data. We conduct an additional interview with a Senior Manager at a taxi firm to verify the existence, or lack thereof, of those tasks in the taxi system, and check some of the task-role pairings for which the research team is uncertain. If the task exists for the current taxi system, we add it to our list of taxi tasks. If the task does not exist, we consider it a new task. We also check a subset of the robotaxi tasks with prior interviewees from robotaxi firms to ensure proper task-role allocation. Through this iterative checking and refining process, we develop a data frame of 190 tasks with information on which role or roles performs each of the tasks in the taxi, robotaxi, and advanced robotaxi systems. Table 2-2 presents examples of research decisions made during the matching process. Though the cases incorporate different data sources, our process leverages the strengths of O*NET data while using additional sources to develop a more comprehensive picture of the work systems for our cases. Moreover, the iterative nature of our process converges the cases into an equivalent basis of comparison to support the remainder of our analysis.

### 2.4.3 *Stage 3*: Mapping how tasks move between roles and identifying patterns

We use the R programming language (R Core Team, 2024) and the *ggsankey* package (Sjoberg, 2021) to create Sankey diagrams that visually map task movement between roles across the three work systems. These diagrams show roles as nodes and tasks as flows. An initial Sankey diagram of the overall work system (Figure 2-2) is chaotic and difficult to interpret. To improve interpretability, we analyze changes at the role level.

By constructing Sankey diagrams for individual roles, we identify preliminary patterns and group roles accordingly: 1) flows branching out from a single role, 2) flows converging into a single role, 3) flows moving in and out of a role (further subdivided into sub-groups), and 4) roles with minimal flows. We then investigate why tasks shift between roles and why some roles appear unchanged, which could indicate either minimal between-system changes or missing task information.

To explore these patterns, we open-code each task movement (331 total) to develop a typology of task changes and categorize changes to each role's tasks (e.g., "reassignment and sharing" describes a task moving from one role to multiple roles that share the task, as occurs for the task "interacts with first responders."). Using the detailed task-level analysis and individual Sankey diagrams, we write memos on each role's changes. Our guiding questions include:

- From which role(s) do most of its tasks originate?
- To which role(s) does it distribute its tasks?
- Does the role mostly retain or redistribute its tasks?
- Does it share any tasks and does that change?
- When tasks are redistributed, how similar is the absorbing role to the original role?

This analysis helps us determine whether visually similar Sankey diagrams reflect similar patterns of change and if visually dissimilar diagrams mask similar underlying changes, signaling a special case of a general pattern. The most challenging patterns to disentangle are those involving branching in and out of a role. We experiment with different groupings and test them against our data to see if they can be described parsimoniously. Groupings that do not meet this standard are dissolved. Through iterative memo writing, role sorting, and author discussions, we refine our patterns, constantly comparing them with our data to ensure a close fit (Eisenhardt, 1989).

In the following section, we present the visual maps that depict how the introduction of autonomous vehicles to a taxi work system reshapes tasks and labor roles, and how this rebundling occurs via identifiable patterns. We also discuss the general function of frontline roles in the robotaxi system offer preliminary insights into the sociodemographic makeup of the emerging frontline robotaxi workforce.

**Table 2-2:** Examples of data analysis processes.

| Process | O*NET Task | Open-coding Task(s) | Quotes | Firm | Role |
|---|---|---|---|---|---|
| Task and role identification from data.<br><br>Task performed by different role in Robotaxi and Advanced Robotaxi systems.<br><br>Matching O*NET task to open-coding task. | Vacuum and clean interiors and wash and polish exteriors of automobiles. (O*NET, Taxi Driver) | Perform vehicle cleaning and detailing | "We'll clean the cars every day. Yeah, I mean, the driverless ones...we'll clean the cars every day inside and out. Use a, you know, the gen-seven disinfectant on anything inside of the car..." (Interview with Frontline Worker, August 10, 2023) | Firm A | Field Support |
| | | | "Yeah, so they [the AVs] were cleaned every day. Because they're being cleaned every day, it's kind of minimal work, because not too much ever accumulates in the cars. Maybe once a month they do like a vacuum clean, and that was always done by the [operators] themselves." (Interview with Mid-Level Manager, January 3, 2023) | Firm B | Operator |
| | | | "The [operator] is also responsible for cleaning the vehicle. They don't do a big cleaning everyday but more as-needed. They check the vehicle cleanliness as part of their daily checks." (Interview notes for interview with Frontline Worker, October 26, 2022 10/26/22, no consent to record) | Firm F | Operator |
| Matching multiple open-coding tasks to one O*NET task.<br><br>Dividing O*NET task (task split at ellipses).<br><br>Identifying a task that is eliminated. | Pick up passengers at prearranged locations… | Confirm identity of rider | "So it's [the vehicle] sort of built for autonomy and for mobility as a service...there's an integrated tablet in the back so that you can, you know, scan your QR code to make sure it's the right person getting in the right vehicle." (Interview Operations Management Official, October 18, 2022) | Public sector | Vehicle |
| | | Alert passenger of arrived vehicle location | "The Waymo app also allows riders to prompt their Waymo AV to emit a distinctive chime sound or to honk the vehicle's horn...This functionality helps riders identify and find their way to their vehicle using sound." (Waymo Passenger Safety Plan, January 2024) | Waymo* | Vehicle & App |
| | ...at taxi stands, or by cruising streets in high traffic areas. | N/A (robotaxis are hailed via apps) | "Ready to move with May Mobility? You're almost there—just download the May Mobility app on the Apple App Store or Google Play and the app's prompts will guide you through the rest." (May Mobility Website, 2024) | May Mobility* | Eliminated Task |

| Table 2-2 (cont.) | | | | | |
|---|---|---|---|---|---|
| **Process** | **O*NET Task** | **Open-coding Task(s)** | **Quotes** | **Firm** | **Role** |
| Identifying new task. | N/A | Perform pre- and post-trip systems checks | "They [field support agents] have a checklist, as simple as you can think of where they're walking around the vehicle, making sure the quality of vehicle—we don't want to send a car out that has a massive dent or a broken mirror, you know, from a brand perspective and safety perspective. But they're looking at the physical aspects of the vehicle. And then there's a number of technical things they are checking…" (Interview with Senior Manager, August 10, 2023) | Firm A | Field Support |
| | | | "…we had another team that handled like, setting up the cars for us. So they would like in the mornings, they [field support agents] would start up the cars, because it has to go through some procedure, like software, like when you turn on your computer…they have to turn it on, they have to like run tests, they have to make sure there's no issues." (Interview with Frontline Worker, September 30, 2023) | Firm B | Field Support |
| | | | "…the [operators] are responsible for like kind of pre and post service vehicle checks. You know, so like before they take their vehicle out, they run through a checklist of things to make sure that it's ready to go." (Interview with Operations Management Expert, October 18, 2022) | Firm F | Operator |

*Firm names provided because sources are public and the quotes are easily searchable. Adding the anonymized name would thus risk de-anonymizing the other data.

## 2.5 Mapping the Impact of AVs on Tasks and Roles

Figure 2-2 depicts how the 190 identified tasks move between labor roles as the work system transitions from *Taxi* to *Robotaxi*, and finally to *Advanced Robotaxi*. Sankey diagrams often depict the movement of materials between processes. In Figure 2-2, rectangular nodes represent roles and flows depict the movement of tasks between roles (line thickness proportional to the number of tasks). To better interpret the figure, consider the task “test vehicle equipment.” This task is performed by drivers in the *Taxi* system, operators in the *Robotaxi* system, and field support agents in the *Advanced Robotaxi* system. This task thus represents one portion of the teal line that flows from driver to operator and a portion of the pink line that flows from operator to field support.

Less intuitive are the “new tasks” and “eliminated tasks” nodes on the diagram. New tasks indicates tasks that are introduced in the following state. Consider the task “offload vehicle data.” Traditional taxi vehicles do not need to have data from sensors manually offloaded but operators must perform this task for robotaxi vehicles. When the operator role is eliminated, field support agents perform this task. Thus, the task represents a portion of the gray line flowing from new tasks to operator, and a portion of the pink line flowing from operator to field support. Similarly, the node labeled eliminated tasks absorbs tasks that were performed in the previous state but are no longer performed by one of the roles. For example, drivers perform the task “collect vouchers from passengers and make change” in the *Taxi* phase, but no roles in the *Robotaxi* or *Advanced Robotaxi* systems perform this task. That task is captured by a portion of the teal line flowing from driver to eliminated task, and a portion of the gray line that flows from eliminated tasks to eliminated tasks (i.e., remains eliminated).

Interpreting these role changes is difficult absent an understanding of the general purpose of each of the frontline roles. We assume a general level of familiarity with taxi system roles and describe the emergent frontline robotaxi roles in the following section, drawing comparisons between the taxi and robotaxi roles when relevant.

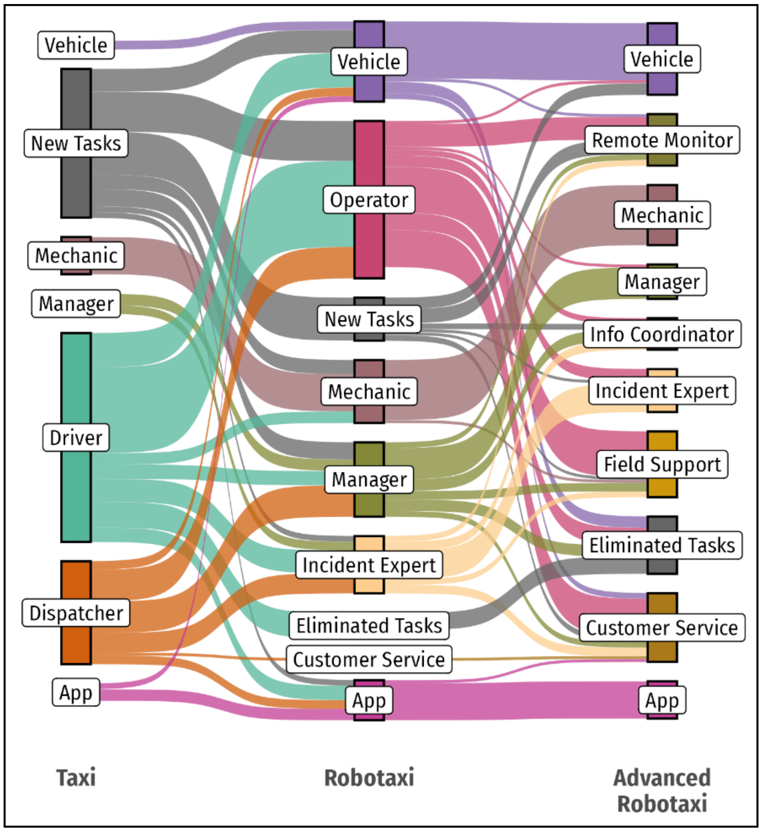



**Figure 2-2:** Tracing flow of tasks between roles.

## 2.6 Frontline Labor Roles in Robotaxi and Advanced Robotaxi Systems

What are these frontline roles and who fills them? Many of the robotaxi frontline roles do not exist in typical taxi systems, and those that do have changed to varying degrees. We describe these roles below and provide preliminary insights regarding the types of individuals filling these roles, their training requirements, and their compensation levels[6].

[6] These descriptions are based on our limited sampling of the current industry. We encourage further

### 2.6.1 Mechanic

Robotaxi mechanics, like traditional taxi mechanics, perform vehicle repairs and maintenance. They also need expertise in software and computing systems for the AV technologies. Some AV firms have partnered with community colleges to develop AV-specific mechanic training programs (De Anza College, 2024), and robotaxi mechanics typically receive in-house training on their company's technologies. A Senior Robotaxi Maintenance Department Manager equated this training to specialized trainings that mechanics at dealerships might receive:

> …there's a process that they go through as they would with any other shop, whether they were becoming like a Master Technician at a Honda dealership, you know. We have our own process for how we train them and how we certify them and how they grow within the company (Interview, August 10, 2023).

The same manager explained that, in some cases, AV firms have recruited individuals from software engineering backgrounds and trained them on traditional vehicle repair procedures. The vehicle mechanic industry has historically been male-dominated, though women are increasingly entering the field (Data USA, 2021). Currently, the emerging AV mechanic industry reflects a similar makeup.

### 2.6.2 Manager

Like taxi managers, robotaxi managers develop standard operating procedures, coordinate information and responsibilities, and evaluate workers. Some of this evaluation focuses on how workers interface with the AVs. Managers provide guidance, for instance, on when onboard operators should takeover and manually navigate the

investigation into the demographics of workers filling these roles, their compensation levels, and their individual experiences.

vehicle through a situation versus allow the vehicle to handle the situation independently. One former operator described this evaluation experience:

> Another aspect of it is you have one-on-ones, with your manager. So during those one-on-one meetings…you would go over like your dash cams. And you would go over your takeovers, if you were…driving in autonomous, auto, we call it. If your takeover was a good takeover, or if you should have just let the car play out that situation. (Interview, September 30, 2022)

Some robotaxi managers collect feedback on the AVs' software performance from the operators and convey this information to the engineers developing the AV systems. As with traditional taxi managers, robotaxi managers bring several years of experience into their roles, and most have at least a Bachelor's degree (Job postings). Robotaxi firms recruit individuals with extensive experience in operations, fleet management, logistics, and transportation management for these positions, suggesting that similar types of individuals are filling managerial roles in both taxi and robotaxi systems.

### 2.6.3 General Profile & Compensation: Operator, Remote Monitor, Customer Service, Field Support

No single profile appears to exist for the operator[7], remote monitor, customer service, or field support roles. One Senior Manager who estimated having been involved in hiring around 3,000 employees for his robotaxi firm describes the frontline workforce as follows:

> …the background and the profile of people that have come through these roles is quite varied. I mean, we have like very early career people, we have students, we have, you know, middle career, late career. We've actually had folks that, it's probably not the norm, but folks that had been retired and they're like, you know, early retirement and they're like, "hey, this stuff is amazing. Like I just want to come get involved." So it's really hard to put a finger on it. (Interview, December 27, 2022)

[7] Early in the industry, some robotaxi firms hired professional drivers as operators (Interview with Former Operator, November 8, 2022).

Observed and interviewed frontline workers varied in terms of age, gender, and racial background, and described having prior employment in sales, retail, food service, and "Corporate America" as well as gig work as ride-hailing drivers (Interviews on October 18, 19, 26, 2022; Observations on July 7, October 25, 2022, August 9, 2023). These roles require a high school diploma or equivalent, and roles that interface with the vehicle directly or indirectly require a valid driver's license, a minimum of three years of driving experience, and a clean driving record (Job postings). Many robotaxi companies use contractor firms to hire and directly manage these workers as a contingent labor force, with some firms offering the opportunity to convert to employee status over time (Interviews November 8, 2022, December 27, and August 9, 2023). These roles earn slightly higher wages than current taxi drivers and dispatchers who earn mean hourly wages of $16.88/hr and $17.05/hr, respectively (Bureau of Labor Statistics, 2023b, 2023a). Job postings for the robotaxi roles list hourly wage ranging from between $18-$26/hour, with one firm even offering a wage of $34/hour for an operator role in California (Job postings).

### 2.6.4 Operator

Operators serve as backup or safety drivers in case of failures with the AV, and their presence required for robotaxi testing or deployment in some cities (Written Interview Supplement from AV Regulatory Expert, February 15, 2023). Operators do more than simply fulfill a regulatory requirement; they carry out many of the vehicle-support tasks previously performed by taxi drivers like refilling the gas. Depending on the firm, some operators receive customer service training including "customer service techniques, how to answer questions, [and] how to talk about the software without…breaking your confidentiality agreement" (Interview with Frontline Worker, September 30, 2022). At other firms, operators are instructed not to speak to passengers in order to simulate the "driverless experience" (Observation and Informal Conversation with Operator, July 8, 2022). By instructing operators to remain silent, firms are working to shift the relational practices previously performed by drivers (L. D. Cameron, 2022) to remote roles.

Operators also play an active role in evaluating AVs' performance, taking notes on their areas of failure. Early on in the technology development process, firms typically have two operators onboard each AV to manage operator fatigue and facilitate data collection efforts (Interview with Senior Manager, August 10, 2023). Some firms' appreciation of operator feedback has increased over time. One firm changed the name of its operator role to highlight the active, rather than passive nature of the role:

> [Operators] used to be called Fleet Attendants. We changed the role name in line with responsibilities added to the position to help us get a better understanding of what is happening on the roads. [Operators] are more technical and able to help guide potential autonomy improvements. (Written supplement from AV firm, December 1, 2023)

Operators receive both in-classroom training and multiple weeks of shadowing training for their role.

### 2.6.5 Remote Monitor

Remote monitors perform real-time (though not continuous) monitoring of the autonomous vehicles. These roles do not remotely drive the vehicles but instead provide secondary verifications for the AVs and can perform a limited number of vehicle maneuvers remotely. One Senior Manager explained:

> …when the car gets into a situation where it's, say, maybe less familiar, or wants to double check something, a human behind a terminal can take a look at what the car is seeing, and sort of answer some questions for it to let it continue to operate...[the] expectation is to have these calls answered within like, a couple seconds. So basically, instantly, the scene comes up on the terminal in front of the [remote monitor]. These are central roles. They have access to all the cameras that are functioning in the car plus an overlay of LiDAR[8] data. They have really strong situational awareness, and they'll help confirm the scene for the car, basically, and then the car is still driving itself, it continues on through the situation. (Interview, December 27, 2022)

Many of the remote monitors started as operators and understand the functionality of the AVs. As robotaxi firms have expanded their fleets, they have exhausted their ability to recruit from their operator worker supplies and have begun to directly hire for the remote monitor role. Firms perform internal trainings for remote monitors, built around their bespoke technologies. These trainings include in-classroom instruction and multiple weeks of shadowing, both of which include regular testing and knowledge-checks. Through these trainings, remote monitors develop the technical skills to navigate "customized tools that they [the firms] build to interact with the AVs" (Interview with Mid-level Manager, September 26, 2023). New remote monitors are limited in the types of maneuvers they are allowed to perform with the AVs, and gain increasing responsibilities and abilities to perform more complex maneuvers over time.

### 2.6.6 Customer Service

Customer service agents have adopted many service tasks that were previously performed by taxi drivers and dispatchers. These tasks include answering rider questions,

[8] LiDAR is a type of vehicle sensor that helps to create a three-dimensional detailed map of the AV's surroundings.

issuing safety reminders (e.g., buckle your seatbelt), and managing rider behavior. This role serves as a critical interface between the passengers and the AV technology, helping to explain seemingly irregular vehicle behavior to riders and checking on passenger wellbeing. One AV firm's Passenger Safety Plan explains:

> Waymo anticipates that a rider may experience a medical event (e.g. intoxication that renders a rider unresponsive or other health issue). If [the customer service agent] is alerted to the event either through the in-car screen or mobile app buttons, or observes an apparent medical event occurring with a rider, agents are trained to quickly assist and assess the rider's needs, including to contact 911 to dispatch emergency services to the location of the Waymo vehicle. (Waymo Passenger Safety Plan, January, 2024)

Similar to remote monitors, customer service agents were initially recruited from the pool of operators but more recently, robotaxi firms have directly hired for this role. This role does not require a post-secondary degree but job postings call for prior experience in a call center (Job postings). Customer services agents must respond to a range of types of calls from safety-critical calls akin to those handled by emergency service operators to lower-stakes technology support calls. These agents receive in-classroom and on-the-floor training to acquaint them with AV technology and their firm's specialized tooling systems.

### 2.6.7 Field Support

If the AV is involved in an accident or is otherwise unable to continue on its journey (e.g., vehicle gets a flat tire), field support agents provide the necessary in-person response. These agents assist passengers with getting a new ride and can move the robotaxi vehicle or call for a tow, as needed. This role adopts many of the general service functions like vehicle cleaning and refueling that were previously performed by the taxi driver. These tasks take on additional importance in the robotaxi system, as one Mid-level Manager explained:

> …it's not just for the superficial aspect, there's actually a functionality to it with the sensors and the camera and stuff like that. If it's dirty, it's just not going to work so that's why cleanliness is a pretty big priority. (Interview, August 10, 2023)

Field support agents also need to perform additional preparatory work, as one Senior Manager of a fleet depot described:

> In the trunk of the car is where the brain or the machine of the car lives. All of our computers, they're [field support agents] actually using their computer to connect to that vehicle to…fire up of all of the systems in the car, like a pre systems check…Think like an airplane. Before you have to send it out to fly or with NASA [going] into space, they're doing all these pre-safety checks. (Interview, August 10, 2023)

Field support agents receive in-classroom and on-the-floor training, including shadowing other agents. They follow strict, pre-established protocols for how to clean and prepare each vehicle before it can be deployed into the field.

### 2.6.8 Incident Expert

As their title implies, incident experts manage both real-time and post-hoc incident responses. These individuals help develop response protocols, advise other roles on how to respond in case of an incident, and collect information for mandatory data reporting requirements. As one incident expert described:

> We deal with everything from assaults to car crashes to media exposure to service outages, anything that can have a tangible effect on the brand or the operations of the fleet (Interview, August 9, 2023).

In a typical taxi firm, dispatchers and managers perform these functions. Robotaxi firms are also subject to a number of reporting requirements at both the federal and, in many cases, the state and local levels. Incident experts ensure that the required data are collected and reported to not only meet these external requirements but also to support internal organizational learning. One Mid-level Manager explained that incident experts:

> …handle the situation after. Once the dust settles, once everything's handled, [an incident expert's] job is to backtrack. Let's go backwards. Let's figure out what happened. Where [were] we located exactly? What speed were we going? [Were] airbags deployed? Were seatbelts buckled? They go through all the little nitty gritty stuff. (Interview, September 26, 2023)

AV firms can adjust their technology designs and operational protocols based on these detailed analyses. The incident expert role is not an entry-level position. Incident experts come from other high-stakes domains such as the military, the airline industry, and government intelligence agencies (Interview with Frontline Worker, August 9, 2023). They receive training on the technology systems and protocols for their firm but largely rely on their past experiences managing high-stakes situations to prepare them for the role. Unlike many of the other frontline roles, incident experts are employees and earn between $78,000-$115,000 (Job postings).

### 2.6.9 Information Coordinator

The creation of multiple new distinct but interconnected roles introduces greater complexity and information processing requirements into the robotaxi system. As Tushman and Nadler (1978) describe, the more that a subunit's tasks rely on the tasks of another subunit, the greater the need for coordination, continual monitoring, and feedback. Some of this collaboration occurs through use of technology systems, but technology alone has proven insufficient to meet AV firms' information processing needs, prompting the creation of the information coordinator role. Information coordinators monitor operations in the central command center and track any incidents or issues that occur, synthesizing this information into regular reports that support organizational learning. Additionally, information coordinators act as a general support system for other roles. As one information coordinator described:

> When I first got here, it was a very siloed position focused on just writing a very specific summary, where we really kind of expanded into being a support system for every single team" (Interview, August 9, 2023).

In effect, these roles serve as coordinating mechanisms, which Baldwin and Clark (2000) define as "channel[ing] effort and knowledge toward useful, attainable, and consistent goals."

Information coordinators are also not an entry-level positions. These workers have pivoted from other fields, bringing prior experience with vehicle fleet maintenance companies, warehouse or logistics operations centers, emergency medical services, or the military (Two separate Interviews Frontline Workers, August 9, 2023; Job postings). Information coordinators receive training on AV technologies, and learn the specific operations of their firm primarily by shadowing other information coordinators, as well as remote monitors and customer service agents. These shadowing experiences expose information coordinators to the other roles' duties so they can perform their coordinating role more effectively.

## 2.7 Patterns of Change: How roles respond to the introduction of AI

Armed with a clearer understanding of robotaxi frontline labor roles, readers may now redirect their attention to Figure 2-2. This figure makes evident a phenomenon which prior studies have hypothesized: the introduction of AI technologies spurs a rebundling of tasks and reorganization of adjacent labor roles. Through our analysis, we find that these processes occur via archetypal patterns (Figure 2-3). As the taxi work system transitions from a traditional to a robotaxi system, its roles exhibit one of the following three patterns of change:

1. *Distributing* its tasks to other roles in the system,
2. *Consolidating* tasks from other roles into one (often new) role, or
3. *Scaffolding* other roles by absorbing tasks temporarily or on a semi-permanent basis to support the transition between phases.

We note that these pattern names describe the type of change that occur and are not meant to imply decision-making on the part of a particular role, nor are they meant promote the idea of technological determinism. Rather, these changes arise from firms' decisions on how to allocate work between capital and labor. Robotaxi firms could keep drivers onboard the AV[9] to perform all remaining non-driving tasks but instead choose to eliminate this role, presumably because higher vehicle-to-worker ratios could yield significant cost savings (Kaplan, Nurullaeva, et al., 2024; Nunes & Hernandez, 2020). We thus emphasize that these patterns of change emerge as a result of technological, social, and economic forces. The following sections further describe these patterns.

[9] Prior research finds that this type of role, often referred to as an "in-vehicle attendant," could be an important feature for public acceptance of AVs, in particular for early adoption (Dong et al., 2019; Kaplan & Helveston, 2023a; Kyriakidis et al., 2020).

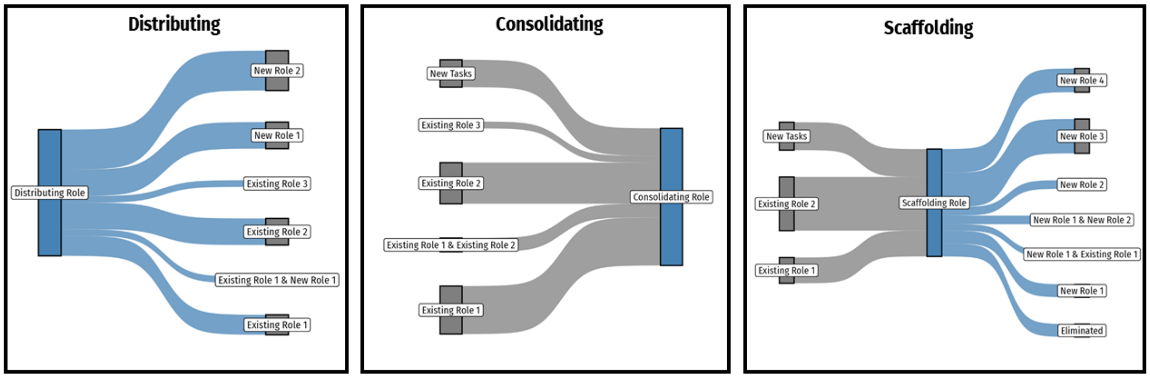


**Figure 2-3:** The three archetypal patterns of change.

### 2.7.1 Distributing

*Distributing* of tasks occurs when a role is eliminated from the system. Role elimination is preceded by the substitution of one or more of the role's core tasks with an AI technology. During the distribution process, some tasks are distributed to a single role, while others are distributed to multiple roles that must then coordinate with one another. Tasks are not evenly distributed; some roles receive a greater portion redistributed tasks, yet no role receives a large enough portion that it could be considered a redefinition of the eliminated role. Distribution of tasks may, in some cases, require the identification of subtasks, a process which bears resemblance to Baldwin and Clark (2000)'s *inverting* operator which takes previously-hidden information and makes it visible.

Some distributed tasks may be offloaded to the user, a trend also identified by Litwin et al. (2022), or excluded from the capabilities of the system. Offloading of tasks is distinct from outsourcing a task beyond the firm's boundary. Our approach does not distinguish between whether a role exists within or beyond the boundaries of the firm. Rather, we establish our system boundary in terms of tasks that a firm must complete as part of its service and the associated task-role assignments. Indeed, some robotaxi firms use contractors or have partnerships with traditional fleet maintenance companies to fill certain roles or perform specific tasks (Cruise, 2023a; Perez, 2018). Even if a firm outsources a role, those tasks are still performed by a worker and should be captured when mapping changes to labor roles. We acknowledge, however, that workers' classifications and offshoring of labor have important implications for both worker and economy-level outcomes (NASEM, 2017).

Figure 2-4 illustrates the *distributing* pattern of change for the driver and dispatcher roles. During the distribution process, the operator role receives the greatest number of tasks from the driver, with fewer tasks redistributed to the app, incident expert, manager, and mechanic roles, and some tasks eliminated. *Distributing* of driver tasks also spurs sharing of tasks between the app and vehicle, the incident expert and manager, and the operator and vehicle.

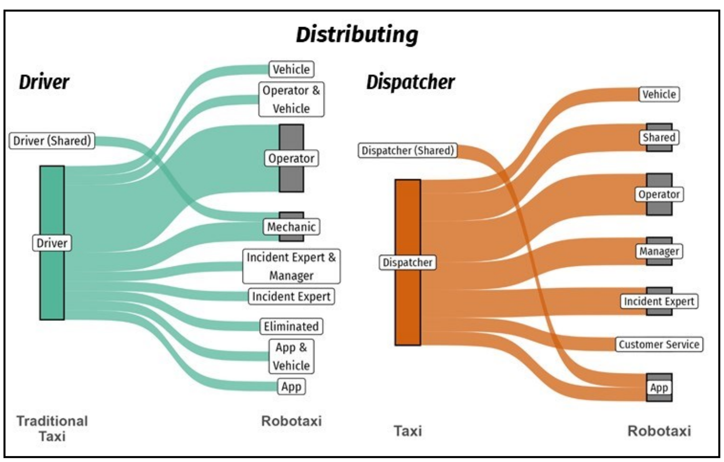



**Figure 2-4:** The *distributing* pattern.

### 2.7.2 Consolidating

*Consolidating* describes the rebundling of tasks into a role. Human workers are generally flexible in terms of their ability to perform a variety of tasks (Autor, 2015), giving firms greater latitude to experiment with different task-bundling approaches and role designs. Eventually, *consolidating* codifies task allocation into end-state roles. These roles do not exist in the initial system but rather come into being as firms gain an understanding of the types of roles required to support their new system designs. *Consolidating* involves allocation of both existing and newly-created tasks to roles. These new tasks emerge as part of a reinstatement effect wherein the introduction of automation technology generates new tasks that are better performed by labor than capital (Acemoglu & Restrepo, 2019).

Figure 2-5 depicts the *consolidating* pattern for the field support, information coordinator, remote monitor, and customer service roles. The remote monitor's core functions primarily derive from the operator role and new tasks. As a result of *consolidating*, the remote monitor also becomes involved in shared tasks with the vehicle, incident expert, field support, customer service, information coordinator, and manager.

When the intended purpose of a role is well-known, *consolidating* can happen immediately following the introduction of the AI technology. We note this special case as a form of *early consolidating*, as occurs with the app, mechanic, and vehicle roles (Figure 2-5). Since the purpose of a technology is typically prescribed in advance as part of its design process, *early consolidating* may be more common for technology roles. Though taxi firms use apps, *consolidating* transforms the app role by integrating tasks from the driver and dispatcher, along with new tasks. In the robotaxi and advanced robotaxi states, the app also shares tasks with the vehicle and operator. These changes create a distinctly new app role.

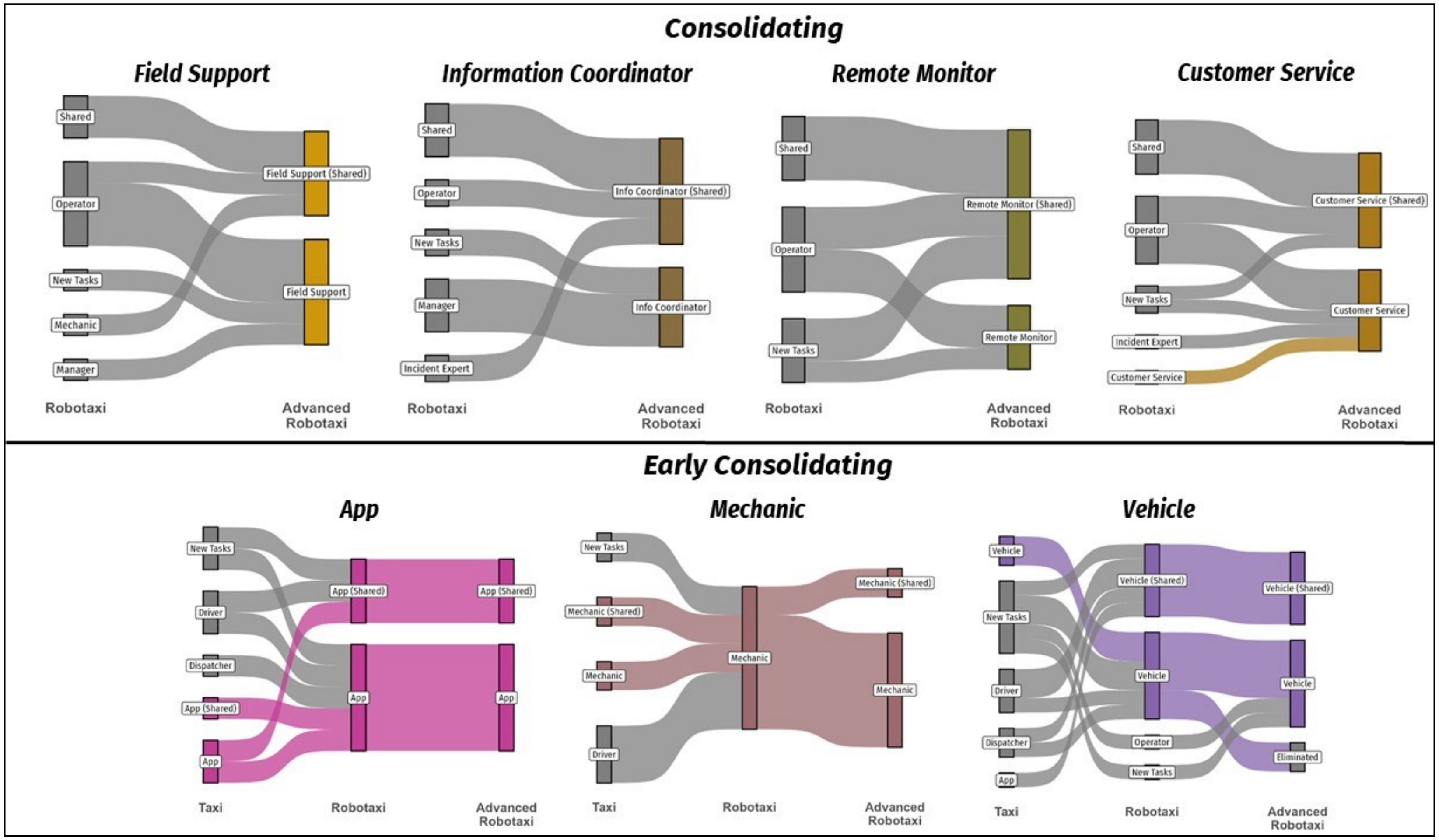



**Figure 2-5:** The *consolidating* and *early consolidating* patterns.

### 2.7.3 Scaffolding

Firms introducing AI technologies to their work systems may undergo transitional phases during which they further develop their technologies and experience organizational learning, both of which impact role design. During these transition states, tasks may be temporarily assigned to *scaffolding* roles that absorb tasks from roles in one phase and redistribute or share them in a later phase. Some *scaffolding* roles exist only during the transition phase, whereas others remain as part of the mature system. Though *scaffolding* roles may absorb large portions of existing roles, they are not redefinitions of those roles because their composition and purpose are substantially different from the original roles.

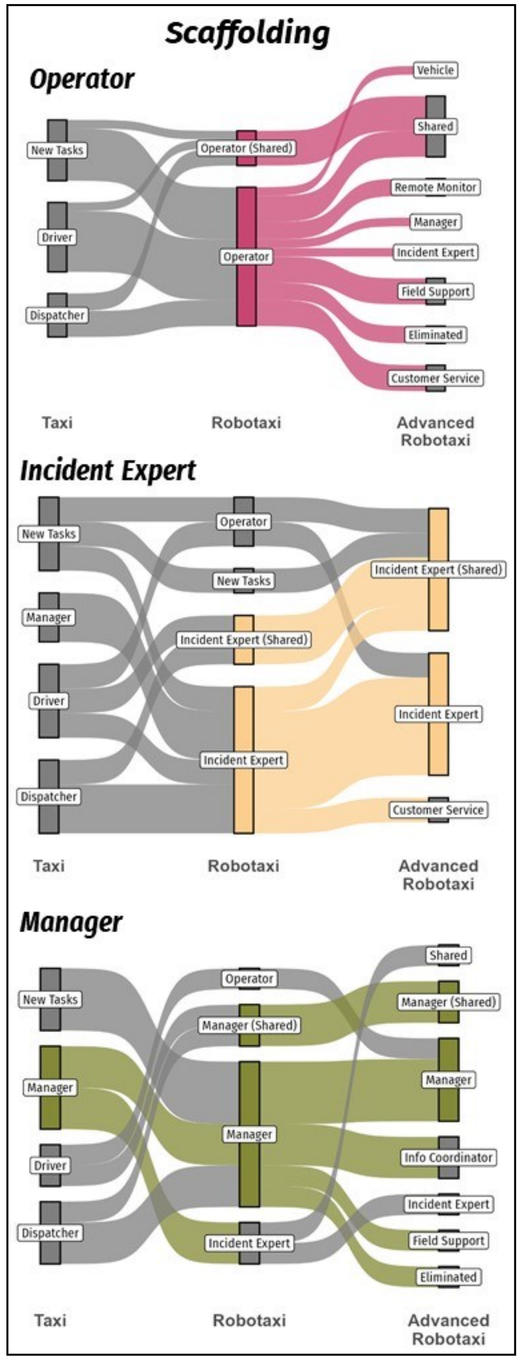



**Figure 2-6:** The scaffolding pattern.

Figure 2-6 illustrates the *scaffolding* pattern for the operator, incident expert, and manager roles. As an example, the operator absorbs tasks from the driver and dispatcher and gains multiple new tasks. Some of these new tasks are only relevant to the transition state and are eliminated in the following state (e.g., taking notes on AV performance). The operator role is not intended to remain in the robotaxi system and is ultimately eliminated; when this occurs, its absorbed tasks are redistributed to other roles. Some *scaffolding* roles, like the incident expert, remain in the advanced robotaxi system. In this later state, the incident expert reassigns some tasks to the customer service role and shares tasks with the manager, field support, information coordinator, and remote monitor roles. One could imagine the gradual phasing out and eventual elimination of the incident expert role if technology improvements result in fewer incidents and robotaxi firms' reporting requirements decrease, reducing the importance of having a separate role to perform these functions. Over a longer timescale, the incident expert's diagram may converge to look like the operator's diagram.

### 2.8 Using the Identified Patterns to Refine Analyses of AI Labor Impacts

The results of this study demonstrate that altering the system boundary of analysis by taking a work-systems approach can reveal additional information about how AI-enabled technologies are changing work. The identified patterns not only offer insights into how tasks and roles are being reshaped for a taxi system, but suggest adjustments for how scholars might refine their analyses of AI and labor at the task, role, sector, and economy-levels. Each of these levels of analysis deepens our understanding of changes that are occurring; by broadening the system boundary at which these analyses occur and leveraging our identified patterns, scholars can capture additional nuances that may alter the outcomes of their analyses, and may influence how practitioners plan for the introduction of AI technologies.

### 2.8.1 Task Level

Our process of tracing tasks between roles reveals that additional task information emerges when trying to reallocate tasks from workers to technologies. In particular, reallocation may require identification of subtasks, some of which may still require human labor. The work required to identify and reallocate subtasks could introduce additional friction, manifesting as a cost penalty, when reallocating tasks to AI technologies. This friction may be more pronounced if firms need to establish collaborative relationships between human workers and AI technologies to perform certain subtasks. In their study of task automatability in the context of manufacturing, Combemale et al. (2021) identify “task separability,” defined as the feasibility, or cost, of having two tasks assigned to different performers, as a mediating factor influencing automatability. Our analysis suggests that subtask *identifiability* as a precursor to *separability* might also influence automatability, especially in work contexts where processes may be less well defined. Future models of technology change and labor impacts should incorporate these interacting effects.

At the task level, there are also streams of literature which aim to characterize types of tasks so that different task types may be evaluated in terms of potential exposure to emerging technologies. While we do not measure task characteristics in this study, our identified patterns: 1) highlight that task characteristics are not fixed and can change as a result of technology introduction, and 2) suggest a directionality of change for certain task characteristics in established taxonomies. For example, Fernández Macías and Bisello’s (2020, p. 8) task taxonomy includes *teamwork*, defined as the extent to which the worker has to collaborate and coordinate her actions with other workers, as a measurable attribute of a task. In all three of our patterns*,* we find that previously unshared tasks can become shared following AI introduction, suggesting an increase in *teamwork* required for many tasks. Based on Tolan et al.'s (2021) study of AI impacts based on task types, this would indicate that roles created after AI introduction could subsequently have lower AI exposure than the roles from which they were created. Using our identified patterns and existing task typologies, researchers could refine their predictions regarding how AI may reshape the workforce.

### 2.8.2 Role Level

Our identified patterns also allow researchers to refine their categorization of AI impacts to focus less on end-states and more on the processes by which changes are occurring. Referring to a role as substituted implies that the AI technology is performing all of that role's tasks. In reality, the *distributing* pattern reveals that many of that role's tasks are redistributed to multiple labor roles. This helps explain why "automating away" payrolls has largely been an aspiration goal for firms rather than an achievable outcome (Litwin et al., 2022). Similarly, the *consolidating* patterns demonstrates that multiple roles can emerge from the introduction of AI, some of which do not directly interface with the technology.

Labor roles exhibiting the *distributing* and *consolidating* patterns may have different wages, education requirements, training needs, etc. depending on how those processes unfold. When researchers focus on the end-states of roles, they miss many of the important decisions that shape work system design during that process of change. Our identified patterns draw attention to these decision points. Previously, researchers may have asked:

- Does a firm choose to adopt a technology to perform a task?
- Does a firm choose to eliminate the role associated with that task (substituting) or use the technology to help perform that task (complementing)?

By leveraging our patterns, researchers could open up investigation of:

- How does the firm choose to bundle the eliminated role's tasks (i.e., how does *consolidating* take place)? Do workers have higher skill levels and wages as a result of *distributing* or *consolidating*? Do they hold more power?
- Does a firm exhibit *scaffolding*, suggesting the existence of a transition state? If so, what happens to *scaffolding* roles during and following these transition states? Might *scaffolding* roles be desirable but lack long term stability?

The *scaffolding* pattern in particular draws attention to transition states that may take place as part of AI deployment. Depending on the timescale of analysis, current categorization schemes might be labeling *scaffolding* roles as either substituted or complemented, or these roles might be missed entirely if looking only at the beginning and end state of a system. By looking for evidence of the *scaffolding* pattern, researchers can more systematically identify this type of role and start tracking its labor outcomes. As part of those analyses, they could evaluate how these types of roles are initially created and later changed or eliminated, and whether those decisions play a critical role in the performance of that work system.

In their 2022 paper, Doellgast and Wagner urge scholars to consider the political and institutional factors that shape how technologies are deployed and their impacts on workers (Doellgast & Wagner, 2022). Researchers performing these types of comparative studies could use our identified patterns as grounding points of comparison between contexts. For instance, they could compare how workers and worker representatives influence *consolidating* processes. Beyond retrospective analyses, identifying patterns of change using our categories may create opportunities to be intentional about shaping role-level outcomes. Just as workers and society could have a greater say in what technologies are introduced into the workplace (D. E. Bailey, 2022), workers could take part in discussions regarding how tasks and roles are reorganized to promote positive outcomes.

### 2.8.3 Sector/Economy Level

Finally, our patterns suggest that sector-level estimates of AI impacts on labor may be miscounting the number of affected occupations—undercounting impacts in some respects and over-counting impacts in others. Researchers have undercounted impacts by focusing on the primary roles associated with an "automatable" task. Sector-level estimates about AVs, for instance, have bounded their analyses to occupations whose primary responsibility is driving, occupations associated with personal driving, and occupations that require driving as a skill (Beede et al., 2017; Groshen et al., 2018). Our analysis reveals that occupations that interact with those primary roles (e.g., dispatchers) are also impacted by the introduction of AI technologies. These impacts to secondary occupations may emerge from process reconfigurations that prompt *distributing* of secondary occupations' tasks. Researchers may therefore need to increase their estimates of workers who may be exposed to AI. One way to do this would be to look through O*NET data (or data from other work survey instruments) for mention of connected roles. For example, O*NET tasks for "Taxi Drivers" include "communicate with dispatchers by radio, telephone, or computer to exchange information and receive requests for passenger service" and "notify dispatchers or company mechanics of vehicle problems" (Bureau of Labor Statistics, 2023b). These tasks call out the involvement of other roles which should be considered in impact analyses.

While researchers may be undercounting impacts to some degree, our patterns demonstrate the erroneous nature of evaluating a role through the narrow lens of a particular automatable task. We reaffirm Gittleman and Monaco's (2020, p. 1,4) finding that "drivers do more than drive." In the general passenger transportation sector, AV firms are choosing to eliminate the driver role and redistribute its tasks to other roles. In other market segments, however, the importance of the non-driving tasks might outweigh the value-added of automating the driving task. For example, taxi drivers have become more involved in non-emergency medical transport, a sector for which the in-person support tasks are more essential (Interview with AV Regulation Expert, February 15, 2023). Taxi drivers that are involved in that sector may be less affected by AVs. Sector-level analyses of job impacts should incorporate regulatory requirements and consider the relative importance of automatable versus non-automatable tasks within that specific context to better predict how many jobs might realistically be impacted. Ultimately, the remaining tasks not performed by AI technologies may determine whether the technologies are introduced at all.

### 2.9 Conclusion

In this study, we find and empirically demonstrate that the introduction of AI-enabled technologies can spur the rebundling of tasks and labor roles in a work system.

For the robotaxi work system, the introduction of autonomous vehicles leads to the redistribution of tasks between multiple new and existing labor roles. This seemingly chaotic redistribution process occurs via archetypal patterns which we identify and characterize. *Distributing* roles reallocate their tasks to other roles in the system. *Consolidating* roles absorb tasks from other roles into their, often newly created, role. Work system changes may also involve transition states. During these transition states, *scaffolding* roles absorb tasks temporarily or on a semi-permanent basis to support the transition. These patterns provide a structured way to examine and predict how labor changes and resultant labor impacts might unfold in response to a new AI technologies' introduction and suggest changes for how researchers should refine their labor impact analyses at the task, role, and sector levels. Finally, by characterizing role changes as processes, these patterns empower members of the public, workers, and practitioners to actively shape desirable labor outcomes.

# Chapter 3: The Economics of Robotaxi Services

The objective of this study is to compare the relative competitiveness of traditional taxi and robotaxi services. This research draws on findings from the first study regarding what labor roles currently exist in robotaxi firms and which ones are likely to persist in the future. This chapter is based on Kaplan et al. (2024), a conference paper accepted to the 2024 Bridging Transportation Research Conference.

## 3.1 Introduction

Autonomous vehicle (AV) companies are rolling out driverless taxi-type services (robotaxis) in cities around the world, including in multiple cities in the United States. These firms have attracted billions of dollars of investment, with financial backers betting on a future in which vehicle automation could cut labor costs and increase profitability via removal of the driver (Shetty, 2020). Indeed, labor is one of the main cost expenditures for current taxi operators (Daus, 2023).

Investors are not the only group eager for an AV future. Many cities are looking to AVs to make their transportation systems cheaper, safer, less congested, and more accessible (McAslan et al., 2021). Prior studies find that robotaxis could improve road safety (Blumenthal et al., 2020), enhance fuel efficiency via more efficient driving and braking (Williams et al., 2020a), and offer new mobility pathways for low-income and low-mobility populations if designed appropriately (Creger et al., 2019; Steckler et al., 2021).

Balanced against these hopes is significant concern for the impact of AVs on labor (Cohen et al., 2018; Hilgarter & Granig, 2020; Norton et al., 2021). One recent study estimated that vehicle automation could eliminate 1.3 to 2.3 million workers' jobs over the next 30 years (Groshen et al., 2018). While many of the at-risk jobs are in the trucking sector, AVs still pose a potential threat to taxi and ride-hailing drivers' jobs. In the United States, there are an estimated 395,700 taxi drivers, shuttle drivers, and chauffeurs, and over 830,000 jobs in the broader door-to-door passenger transportation service sector (Bureau of Labor Statistics, 2023c; L. Cameron, 2020). Critically, many of these driver roles are filled by immigrants who may face greater challenges recovering from job displacement (Dubal, 2017).

In this study, we investigate potential competition between traditional taxi and robotaxi services with the aim of contributing to discussions on potential AV labor impacts. We develop ground-up cost models for both types of services, and are the first study to ground our labor assumptions in data on the operations of currently-deployed robotaxi services in the U.S. We exclude direct analysis of autonomous ride-hailing services, as the structure of existing robotaxi firms more closely mirrors that of a centralized taxi company rather than a decentralized (with regard to frontline workers) Transportation Network Company (TNC, e.g., Uber). Moreover, Negro et al. (2021) find that vehicle automation largely does not impact TNCs' operating costs. While competition from robotaxis could still impact the jobs of ride-hailing drivers, the cost dynamics by which that competition may arise are beyond the scope of this study. To further unpack potential labor impacts, this study also offers estimates regarding the number of frontline workers required to support traditional taxi and robotaxi services and their associated wage distributions.

### 3.2 Prior Literature on Robotaxi Costs

Multiple prior studies have modeled the costs of different AV services (Table 3-1). Burns et al. (2012) proposed one of the earliest estimates, investigating costs for three different types of AV operational scenarios and concluding that a system of shared robotaxis in Manhattan could provide transportation services at a cost of \$0.40/mi or \$0.80 per trip (compared to \$7.80 per trip for conventional taxis). Additional cost model studies have similarly estimated that autonomous taxi and ride-hailing services would outcompete their non-autonomous counterparts (Compostella et al., 2020; Greenblatt & Saxena, 2015; Wadud, 2017). Fulton et al. (2017) described how a combination of two potential transportation revolutions—electrification and automation—could decrease system operational costs by 40%. From the consumer perspective, a report from UBS Global Research (2017) posited that cost savings from robotaxi operations could decrease fares by as much as 80%, dramatically shifting mode preferences.

Though cost estimates have become more detailed over time, they still lack precision in two key areas: 1) the capital cost for autonomous vehicle technology, and 2) the labor costs to operate an AV service. Critically, these two forms of fixed asset expenditures account for the majority of costs in conventional modes (Negro et al., 2021).

The capital cost of AV technology is highly uncertain, with prior estimates ranging from \$2,700 to \$50,000 per vehicle (Burns et al., 2012; Fagnant & Kockelman, 2016; Greenblatt & Saxena, 2015; Stephens et al., 2016). Many studies either provided no details regarding this assumed cost or generally discussed high upfront investment costs that will decrease over time (Arbib & Seba, 2017; B. Johnson, 2015; UBS Global Research, 2017). The majority of studies used an automation cost value of around

$10,000 per vehicle, which originates from a 2015 Boston Consulting Group report and is based on Tesla's original proposed cost for its "full self-driving" sensor suite (Bauer et al., 2018; BCG, 2015; Bösch et al., 2018; Compostella et al., 2020; Fulton et al., 2017; Hazan et al., 2016; C. Johnson & Walker, 2016; Nunes & Hernandez, 2020; Sperling et al., 2018; Stephens et al., 2016; Wadud, 2017). Notably, Tesla's sensor suite does not include LiDAR sensors, which many experts believe are essential for safe AV operations and are used in all commercially-available robotaxi services (Bauchwitz & Cummings, 2022; Cruise, 2023c; Waymo, 2023; ZF, 2023). While LiDAR costs have decreased significantly over the past decade, and will undoubtedly continue to decline, top-of-range LiDAR sensors still cost approximately $5,000 each (Korosec, 2019). Current robotaxis rely on multiple LiDAR sensors and dozens of other sensors to achieve critical autonomy and mapping functions, and require additional on-board compute equipment (Rodnitzky, 2022). It is unclear when, or if, AV capital costs might actually reach prices akin to prior studies' assumptions. In this study, we utilize AV prices that reflect current AV capital costs in order to look at nearer-term competition, and consider lower technology costs as part of our scenario analysis.

A second common assumption is that vehicle automation will "zero out" labor costs by removing the driver (Arbib & Seba, 2017; Compostella et al., 2020; Fulton et al., 2017; Greenblatt & Saxena, 2015; C. Johnson & Walker, 2016; Sperling et al., 2018; UBS Global Research, 2017). This assumption not only appears in AV cost models, but also in microsimulation studies of AV impacts (Brownell & Kornhauser, 2014; Wigand et al., 2020; Zhu et al., 2021). More recent cost model studies have begun factoring in labor costs for AV services. Wadud (2017) and Wadud & Mattioli (2021) accounted for some labor expenditures by decreasing former driver costs by 60% for AV services to capture other roles that may arise (e.g., back office infrastructure, ensuring safety) and Bauer et al. (2018) similarly included a $2.50 per vehicle-day general administrative overhead expense. Bösch et al. (2018) and Becker et al. (2020) noted that labor expenses for robotaxis will shift from drivers to higher cleaning costs as customers may sully or damage vehicles more often absent social pressure from a driver. Nunes and Hernandez (2020) were the first to consider emerging labor roles in their model, adding in costs for AV safety oversight monitors (Heineke et al. (2022) also mentioned workers based in an AV control center but provided no cost details). Negro et al. (2021) offered the most detailed inclusion of labor to date, including safety oversight monitors, general fleet maintenance personnel, and administrative staff members. Their model, however, still relies on assumptions about required labor roles rather than actual operational practice.

In this study, we improve the precision around labor cost estimates with an up-to-date understanding of the labor roles needed to support robotaxi services. We are the first study to ground our model in actual robotaxi operations, basing our input values on direct observations of commercial robotaxi services operating in U.S. cities, semi-structured interviews with AV operational and regulatory experts, and published reports from AV firms. Adding detail to the labor roles not only offers a clearer idea of the actual labor costs for robotaxi services and how they might compete in the transportation marketplace, but also suggests what labor ratios companies may push for in order to become more competitive. Ultimately, the labor ratios robotaxi firms adopt will yield important safety and labor-displacement impacts.

**Table 3-1:** Summary of prior cost estimates, including assumed technology costs and labor considerations. VMT = vehicle miles traveled, PMT = passenger miles traveled.

| Paper | Units | Cost | Tech estimate | Labor Considerations |
|---|---|---|---|---|
| Burns et al. (2012) | $/VMT | $0.40 | $6,935* | NA |
| Johnson (2015) | $/VMT | $0.12-0.29 | NA | NA |
| Greenblatt and Saxena (2015) | $/VMT | $0.30-0.50 | $5,000 (2030) | Eliminate driver costs for AVs |
| Boston Consulting Group (2015) | NA | NA | $10,000 | NA |
| Stephens et al. (2016) | $/PMT | $0.28-$0.55 | $2,700-$10,000 | NA |
| Fagnant and Kockelman (2016) | NA | NA | $50,000 | NA |
| Johnson and Walker (2016) | $/VMT | $0.08 | $2,700 (2035) - $10,000 (2025) | Eliminate driver costs for AVs |
| Hazan et al. (2016) | $/PMT | $0.15 | $10,000 | NA |
| Arbib and Seba (2017) | $/VMT | $0.06-0.24 | NA | Eliminate driver costs for AVs |
| Wadud (2017) | $/VMT | $1.01 | $16,000 | Decreases driver costs by 60% for AVs to account for other roles (e.g., back office infrastructure, ensuring safety) - max scenario decreases labor costs by 80% |
| Fulton et al. (2017) | $/PMT | $0.68 | $10,000 (2030)- $5,000 (2040) | Eliminate driver costs for AVs but include overhead costs of operating a ride-hailing service for the shared AV/EV fleet |
| UBS Global Research (2017) | NA | NA | NA | Eliminate driver costs for AVs |
| Bösch et al. (2018) | $/PMT | $0.66 | $7,000** | Costs for autonomous taxis will shift from paying drivers to higher cleaning costs |
| Bridges (2018) | $/VMT | $0.06-0.24 | NA | NA |
| Sperling (2018) | $/PMT | $0.10-0.20 | $10,000 | Eliminate driver costs for AVs |
| Bauer et al. (2018) | $/VMT | $0.29-$0.61 | $10,000 | $2.50 per vehicle-day ("administrative overhead") |
| Becker et al. (2020) | $/PMT | $0.10-$0.71 | $5,000 | Include cleaning and fixed overhead costs |
| Compostella et al. (2020) | $/VMT | $0.36-0.41 | $10,000*** | Eliminate driver costs for AVs |
| Nunes and Hernandez (2020) | $/VMT | $1.58-$6.01 | $15,000 | Include safety oversight for robotaxis at varying vehicle to worker ratios |
| Negro et al. (2021) | $/VMT | $0.76-$0.84 | $40,000 | Include safety oversight for robotaxis, fleet maintenance personnel, and administrative staff |
| Wadud and Mattioli (2021) | $/VMT | $0.68-$0.83 | ~$3,800**** | Based on Wadud (2017) taxi labor costs |
| Heineke et al. (2022) | NA | NA | NA | Discuss vehicle control center, no cost provided |
| Litman (2023) | $/VMT | $0.50-$1.00 | NA | Discusses potential need for other types of onboard workers, not included in cost comparison |

NA indicates that info about the given variable not provided.; *Assuming cost of $19 per day; **Automation increases vehicle price by 20% (midsize vehicle)
***Assuming $30,000 for high-cost scenario.; ****Converted from British pounds

## 3.3 Methods

We develop ground-up cost models for a non-AV taxi service and a robotaxi service, grounding our analysis in data on current robotaxi operations in U.S. cities and existing taxi operations. Though some studies hypothesize that AVs could induce higher transportation demand (Harper et al., 2016; Wadud et al., 2016), AV companies need to develop business models in the short term that align with current mobility demands. We therefore leverage existing taxi operational data when possible and test assumptions regarding operations of robotaxi services via a baseline and four alternative scenarios (*AV Advanced Technology*, *AV High Usage*, *AV Medallion System*, and *AV Lower Density Region*). We use Monte Carlo simulation to account for both uncertainty and variation in our model inputs (e.g., differences in demand based on time of day or time of year). All models are built in the R programming language (R Core Team, 2024) and all code is publicly available at https://github.com/lkaplan25/av_labor_cost_2024.

### 3.3.1 Identifying Labor Roles

Although the majority of AV firms are still in testing and development phases, a limited number of AV firms are operating commercial robotaxi services in select cities. We investigate firms operating robotaxi services in the U.S. to gain early insights into the "frontline" labor roles (i.e., those that directly support the service rather than those involved in the technology design and development) necessary to support these services and the current wages for those roles. In doing so, we adopt the same system boundary for labor as was used in Study 1 (Chapter 2).

Rather than include all of the identified taxi and robotaxi frontline labor role expenses as part of a single labor cost category, we divide the labor costs across a few different cost categories (further detailed in the next section) to better leverage existing data and research on taxi operational costs. We include the Manager role as part of general and administrative (G&A) costs and the Mechanic role as part of vehicle maintenance costs. We also combine the Incident Expert and Information Coordinator roles into one "Coordinator" labor role since there are relatively few of each type of worker and both roles earn similar wages. The remaining taxi and robotaxi frontline roles are included in the labor cost category for their respective models.

We use multiple data sources to triangulate information about current labor roles, including direct observations, interviews, and a variety of archival data sources (Table 3-2). In doing so, this study is the first to base robotaxi labor assumptions on actual operational practices.

One of the authors conducted direct observations of two different firms' commercially-available robotaxi services in the U.S. (N = 13 rides), as well as six hours of observation of a robotaxi command center and two hours of observation of a robotaxi fleet maintenance depot between July 2022 and August 2023. Five of the robotaxi rides included a human safety driver onboard while the remainder did not. Over the course of the rides, the researcher interacted with customer-facing employees of the service, including forms of human remote support.

To supplement these observations, the same researcher conducted 26 semi-structured interviews with AV operational and regulatory experts (27 unique interviewees in total, two interviews included two individuals, and one interviewee was interviewed twice). Interviewees were recruited via purposive sampling (Eisenhardt & Graebner, 2007). Over half of the interviewees were either current or prior employees of a commercial robotaxi company. Five of the interviewees were involved in robotaxi pilot programs or government-run robotaxi deployments. The remaining interviewees had expertise on additional operational and regulatory considerations for AV labor roles. The interviewees were primarily familiar with U.S.-based deployments, though one participant also had expertise in AV operations occurring in the European Union.

Interviews were conducted until theoretical saturation was achieved (i.e., new interviewees did not mention any new labor roles, and previously observed roles were mentioned multiple times across different interviewees). Consistency across interviewees provided us with confidence that additional interviews would not yield new information about additional labor roles. All interviews for which consent to record was given were recorded and transcribed via auto-transcription software within 24 hours of the interview. All transcripts were edited by the researcher who conducted the interviews within 48 hours.

We triangulated information from these interviews with archival data provided by the interviewees and identified by the researchers, including safety cases published by AV companies that further detail their operations, job postings for frontline roles at AV firms, and news articles that mention frontline labor roles for different robotaxi services (Eisenhardt, 1989). These sources confirmed the existence of equivalent roles across multiple robotaxi firms. We used the information from the observations, interviews, and archival documents to generate a list of frontline labor roles for robotaxi operations which we then incorporate into our cost model. We summarize these labor roles in the following section.

Although vehicle automation may eliminate drivers, analysis of our observations, interviews, and archival documents reveals that AV firms still require human labor for numerous other roles, many of which are *new* labor roles that do not exist in traditional taxi or TNC services. These roles include not only cleaners and safety oversight monitors (or "remote monitors") included in prior studies, but also field support agents, customer service agents, and coordinators. Table 3-3 compares how traditional and robotaxi services use a combination of technology and human labor to fulfill necessary functions of a taxi-type service, including brief descriptions of each of these functions.

**Table 3-2:** Summary of data sources used to identify labor roles in robotaxi services.

| | | | | |
|---|---|---|---|---|
| **Interviews** | **Category** | **Position** | **Number of Unique Interviewees** | **Total Length of Interview(s) (min)** |
| | Commercial Operations | Frontline Worker | 6 | 280* |
| | | Mid-level Manager | 5 | 166 |
| | | Senior Manager | 5 | 209 |
| | Pilot Program or Government-Run Deployment | Operations Manager | 3 | 182** |
| | | Policy/Communication Manager | 2 | 278 |
| | External Perspective | AV Operations Expert | 3 | 131 |
| | | AV Regulations Expert | 3 | 357 |
| | | **Total:** | **27** | **1603** |
| **Observations** | **Observation Type** | | **Number of Observations** | **Total Duration (min)** |
| | Robotaxi rides | | 13 | 237 |
| | Observations of robotaxi command center | | 1 | 360 |
| | Observations of robotaxi fleet maintenance depot | | 1 | 120 |
| | | **Total:** | **15** | **717** |
| **Archival Documents** | **Document Type** | | **Number of Items** | **Total Number of Pages** |
| | News Articles Mentioning Frontline Robotaxi Roles | | 7 | 64 |
| | AV Firm Public Reports and Petitions | | 5 | 168 |
| | Job Postings for Frontline Robotaxi Roles | | 20 | 39 |
| | Reports about AV Regulations | | 4 | 271 |
| | Supplementary Responses and Documents from Interviewees | | 4 | 17 |
| | | **Total:** | **40** | **559** |

*One 30min interview included a Frontline Worker and a Mid-Level Manager. Interview length counted here.
**One 64min interview included an Operations Manager and a Policy/Communication Manager. Interview length counted here.

Field support agents are responsible for providing in-person response in case of incidents ranging from minor problems that inhibit the vehicle's progress, such as a flat tire, to more severe issues like a collision. These workers also assist with general vehicle service tasks like vehicle cleaning and refueling. Customer service agents answer rider questions, issue safety reminders, and manage rider behavior. Coordinators facilitate the sharing of information both within and beyond the AV firm. Their primary responsibilities include managing communication with key stakeholders in case of incidents, collecting and reporting data in support of mandatory reporting requirements, and facilitating collaboration across different teams (see chapter 2 for more detailed descriptions of the aforementioned roles and their responsibilities).

Some AV firms also include an in-vehicle attendant as an additional layer of technology and passenger support or to comply with existing regulations requiring a safety driver. We choose to exclude this role in our cost model as most robotaxi firms have either already removed or plan to eliminate this role in the future. We bound our analysis to the steady-state operations of robotaxi services and exclude labor involved in training the AV systems (e.g., roles often called AV Test Drivers or AV Operators).

**Table 3-3:** Comparing labor and technology roles in traditional and robotaxi services.

| Function | Function description | Taxi Service | Robotaxi Service |
|---|---|---|---|
| **Vehicle general service** | Vehicle cleaning, refueling, start-up procedures ("Pre-flight checks") | Driver | Field Support Agent |
| **In-vehicle passenger support** | Assisting ADA riders, providing entertainment, managing conflict between riders | Driver | In-Vehicle Attendant or Vehicle Design |
| **Customer service** | Answering questions about the service, managing rider behavior | Driver & Dispatcher | Customer Service Agent |
| **Driving** | Operation of the vehicle | Driver | Automated Driving System |
| **Incident response** | Assisting riders, speaking with Emergency Management Services (e.g., in case of accident) | Driver | Field Support Agent + Coordinator |
| **Fare collection** | Collecting payment for ride | Driver/App | App |
| **Dispatch** | Matching vehicle to riders, allocating vehicles in service area | Dispatcher (+ Computerized dispatch technology) | Dispatch algorithm |
| **Vehicle maintenance** | Repairs to vehicle (and sensors), oil changes, tire rotations | Mechanic | |
| **Remote monitoring** | Providing remote assistance to the vehicle as needed | N/A | Remote Monitor |
| **Information Processing** | Coordinating communication between roles, documenting processes, collecting information for mandatory reporting | N/A | Coordinator |

### 3.3.2 Cost Model

We develop cost models to compare the fare per mile values of traditional taxi and robotaxi services. We base our cost models on Nunes and Hernandez’s (2020) framework, but separate out labor as its own cost category and include financing of the automation technology (i.e., sensors and computing equipment) as a separate expense for the robotaxi calculation (Equation 3.1). We summarize each component of the cost model below and provide detailed descriptions of each individual input calculation in Appendix B. For robotaxis, we compute fare per mile values for a baseline scenario as well as four alternative scenarios described in the Scenario Analysis section below.

*Fare per mile =*
*(Vehicle Financing + Technology Financing + Licensing + Insurance + Maintenance + Cleaning + Fuel + Profit + Labor + G&A) / Capacity Utilization Rate* (3.1)

Prior cost model studies used annual mileage values ranging from approximately 36,000 to 100,000 miles per year (Bösch et al., 2018; Compostella et al., 2020; Fagnant & Kockelman, 2016; Greenblatt & Saxena, 2015; Nunes & Hernandez, 2020; Sperling et al., 2018). We assume an annual mileage of 65,000 miles per year for our baseline taxi and robotaxi models based on the average annual mileage for a taxi in New York City (Schaller Consulting, 2006) and test additional annual mileage values in the robotaxi scenarios.

*Capacity Utilization Rate* is defined in this study as the number of passenger miles traveled divided by the total miles traveled (passenger miles + unoccupied miles). Cramer and Krueger (2016) calculated taxi and UberX utilization rates for five U.S. cities and found utilization rates between 32.0-54.9%. We assume a utilization rate of 50% in our baseline models in alignment with Nunes and Hernandez's (2020) utilization rate of 52% for their San Francisco-based model and explore alternative utilization rates in the robotaxi scenarios.

*Vehicle Financing* covers costs associated with the fixed expense of the vehicle. Following prior studies, our baseline models assume no down payment, an annual fixed interest rate of 7%, a 3-year loan payment period, and a 5-year vehicle lifespan (Compostella et al., 2020; Nunes & Hernandez, 2020). We use the mean price for a hybrid electric vehicle (as developed in Compostella et al. (2020)'s ground-up cost model). While some AV companies like Cruise are using battery electric vehicles, the majority of current companies use hybrid vehicles for their commercial or pilot-scale AV deployments. For this reason, we also use hybrid vehicles in our robotaxi scenarios. Some robotaxi companies are developing vehicles that are purpose-built for autonomy that lack features present in other vehicles, such as a steering wheel and brake pedals (Ammann, 2020). The current cost of such purpose-built vehicles is not publicly available, but the potential cost savings due to removing redundant parts is tested in one of the robotaxi scenarios.

*Technology Financing* provides an estimate for automation capital costs, including sensors, computing equipment, and data storage expenditures. We assume the same interest rate, loan payment period, and technology lifespan as for the vehicle financing calculation. In a 2021 interview, the CEO of the robotaxi firm Waymo asserted that their vehicles cost approximately the same as a moderately equipped Mercedes S-Class (in the mid-$100,000 range) (Moreno, 2021). Public reporting also estimated the cost of Cruise's autonomous Chevrolet Bolt between $150,000 to $200,000 (Mickle et al., 2023). Eight of our interviewees offered estimated costs of over $100,000 per AV, with five interviewees estimating a cost of over $250,000 per AV (the remaining interviewees did not provide estimates). Deducting the cost of the base vehicle, these estimates suggest that automation costs could still exceed $100,000. We assume a technology cost of $150,000, which we exclude from the traditional taxi model.

*Licensing* accounts for fees levied on for-hire vehicles. In Chicago, taxicabs must pay a per-vehicle license fee ($500 per 2-year term), a ground transportation tax ($98/month), a taxi accessible fund fee ($22/month), and an advertising fee ($100/year)[10]

[10] This fee is required prior to displaying interior or exterior advertising. The advertising fee is included since it is assumed that robotaxi companies will leverage advertising as an additional revenue source

(BACP, 2020). Taxi chauffeurs must also pay a nominal chauffeur license fee ($5 per 2-year term) which was excluded from the analysis as the model adopts the perspective of the operator rather than the chauffeur and the nominal fee was not expected to significantly change results. Though this study adopts the term "robotaxi" to refer to fully-automated, on-demand passenger transportation services, the regulatory status of these types of services is yet undetermined in the United States[11]. Future robotaxi services could fall under either existing taxi regulatory structures or those for TNCs. These two regulatory structures involve different licensing fees. In Chicago, TNCs must pay a license and administration fee ($10,000/year for each company + $0.02/trip), a ground transportation tax ($0.53 to $7.88 per trip), an accessibility fund fee ($0.10/trip), and a per-vehicle advertising fee ($100/year).

We test both types of fee structures for future robotaxi operations and find that our model is not highly sensitive to either fee structure. We therefore adopt a taxi fee structure for the baseline models. We note that in some cities (including New York) licensing occurs through a medallion system which can impose an additional high cost on taxi operators. We explore the effects of a medallion system in one of the scenarios.

*Insurance* covers the monthly cost to insure the vehicles. A monthly insurance premium of $682 is assumed in our baseline scenario based on the average monthly taxi insurance rates for fleets of greater than 100 vehicles (Bodine & Walker, 2023). Prior studies have proposed that vehicle automation will alter maintenance, fuel, and insurance

(Gonzalez, 2021), though advertising revenue is not included in the model. We found that the model is not sensitive to this input so excluding this fee would not change the study's findings.

[11] Taxi regulation typically occurs at the city-level, though TNC regulation has primarily occurred at the state level. The California Public Utilities Commission has issued the only service regulation for robotaxi services thus far, and used TNC regulations as the underlying framework, suggesting other states may employ a similar approach.

costs. We include these effects in some of our robotaxi scenarios given their uncertain nature.

*Maintenance* covers routine vehicle maintenance and repair. Two studies evaluating the operational expenses of TNC drivers in Seattle and New York find that maintenance expenses average approximately 5 to 7 cents per mile (Parrott & Reich, 2018; Reich & Parrott, 2020). Usage of vehicles for taxi and ride-hailing purposes is presumed to be equivalent, and a value of 6 cents per mile is assumed for the baseline models.

*Cleaning* accounts for the cost of cleaning the interior and exterior of the vehicle. We assume that taxi drivers clean the interiors of their vehicles every other day using $6 do-it-yourself cleaning supplies and clean the exterior of their vehicles using a $10 automatic car wash once per week (Rainstorm Car Wash, 2023). Given the sensitive nature of their sensors, robotaxi vehicles must be cleaned by hand by field support agents. We thus account for the robotaxi cleaning costs as part of the field support agent labor cost, assuming that the cost of the worker is greater than the marginal cost of the cleaning supplies required to perform the cleaning task.

*Fuel* estimates the gasoline costs for operating robotaxi services. We use current estimated gas prices (AAA, 2023) and fuel efficiencies for hybrid vehicles (EPA, 2021).

*Profit* accounts for the firm's profit margin. We assume that robotaxi firms will aim to achieve at least the same profit margin as current taxi firms and adopt Nunes and Hernandez's (2020) assumption of $0.27/mile.

*Labor* covers the cost of frontline workers for traditional and robotaxi services. For traditional taxi services, we include costs for taxi drivers and dispatchers. We assume wages of $15.82/hour for drivers and $17.05/hour for dispatchers based on the mean hourly wages for those roles in the U.S. Taxi and Limousine Service industry (Bureau of Labor Statistics, 2023b, 2023a). We assume that for 24/7 operations a taxi firm would require two driver shifts and three dispatcher shifts. Each dispatcher would be responsible for 20 vehicles (Nunes & Hernandez, 2020).

Based on our data collection regarding current robotaxi operations, we include the following labor roles for robotaxi services: remote monitors, field support agents, customer service agents, and coordinators. For 24/7 operations, we assume three eight-hour shifts for each role. We use recent job postings by AV companies on contractor websites and on general job sites such as Indeed for equivalent positions to set hourly wages for the roles: $19/hour for customer service agents and remote monitors, $24/hour for field support agents, and $29/hour for coordinators (Adecco, 2023; Cruise, 2023a; ICONMA, 2023; Indeed, 2023). We assume an overhead rate of 1.59 that applies to one full-time worker per shift (Nunes & Hernandez, 2020).

A 2023 statement from the robotaxi firm Cruise's CEO described how the firm's remote monitors typically manage between 15-20 vehicles each (Kolodny, 2023). We assume a 1:16 worker to vehicle ratio for both the remote monitors and the customer service agents in the *AV Baseline* model. As described in Table 3-3, field support agents are responsible for cleaning and preparing the robotaxi vehicles prior to their use. One field support agent can prepare a vehicle in approximately 20 minutes (Interview 22), meaning 24 vehicles could be prepared per 8-hour shift if one worker is always preparing a vehicle. In addition to preparing vehicles, field support agents must also be stationed in the deployment area in order to quickly respond to incidents. We assume a 1:6 ratio for field support agents to vehicles to account for their responsibilities both within the vehicle depot and out in the field. Coordinators are a more specialized role that help manage communication between the other labor roles. We assume a 1:5 ratio between the coordinators and the remote monitors, which translates to a 1:80 coordinator to vehicle ratio.

*General and Administration (G&A)* accounts for additional administrative costs. We assume that the traditional and robotaxi firms are similarly structured centralized firms and have similar G&A costs. We adopt Nunes and Hernandez's (2020) assumption of $0.05/mile.

### 3.3.3 Monte Carlo Simulation

Prior studies have accounted for variation in service usage by considering multiple spatial and temporal utilization scenarios and location-specific input values (H. Becker et al., 2020; Bösch et al., 2018). For each scenario, we conduct a Monte Carlo simulation to account for variation and uncertainty in a broader number of model inputs. In the Monte Carlo simulations, inputs are modeled as distributions rather than point estimates, which are passed through the model by taking random draws (N = 10,000) of the assumed distributions. We compute the fare per mile for each set of draws across all random inputs, resulting in a distribution for the fare per mile value rather than a point estimate. For the miles per trip input, as well as one mileage-based licensing fee, we assume log-normal distributions to match the distributions of public datasets on taxi operations from the City of Chicago (City of Chicago, 2023) and the City of New York (New York City Taxi & Limousine Commission, 2023a). For all other inputs, we assume normal distributions with mean values equal to our assumed baseline scenario values and standard deviations selected based on a combination of real-world data and assumptions such that the resulting distributions fell within defined boundaries (see Appendix B for specific assumptions for each input).

### 3.3.4 Scenario Analysis

Cost per mile values for robotaxi services will depend on a number of operational factors that will vary by location and by time (e.g. future technological conditions). To account for these possibilities, we explore four alternative scenarios to our baseline robotaxi scenario and compare the fare per mile value for each: *AV Advanced Technology*, *AV High Usage*, *AV Medallion System*, and *AV Lower Density Region*. Table 3-4 details the changes to specific model inputs for each scenario.

***AV Advanced Technology*****:** This scenario captures operational improvements that may occur as the performance of the AV technology improves. Stephens et al. (2016) propose a 40%-80% reduction in insurance premiums for fully-automated vehicles due to lower potential accident rates. Fagnant and Kockelman (2016) assume reduced maintenance requirements for AVs due to smoother operation. Greenblatt and Saxena (2015) posit fuel savings of 80% due to more efficient fuel usage. For this scenario, we assume insurance reductions of 50%, fuel reductions of 20%, and maintenance reductions of 10%. We also assume that technology improvements reduce the demands on different workers, allowing robotaxi operators to increase the number of vehicles handled by each worker. Finally, we assume that the price of the AV technology decreases to the $10,000 value used in prior studies.

***AV High Usage*:** AVs are predicted to induce greater travel demand by opening up new mobility options for individuals (Appleyard & Riggs, 2017; Milakis & van Wee, 2020; Wadud et al., 2016; Williams et al., 2020b). Higher utilization might also occur via greater sharing of rides which would reduce the number of unoccupied vehicle miles. Multiple AV companies are exploring business models that involve dual-use of their fleets for both passenger and goods delivery services which could further increase vehicle utilization and annual mileage (Cruise, 2023b; Perez, 2018). In this scenario, we increase annual mileage to 80,000 miles/year and the capacity utilization rate to 70%. We assume that higher vehicle use would increase maintenance costs by 20% due to greater wear on the vehicles and would also shorten the lifespans of the vehicle and the AV technology to 4 years.

***AV Medallion System*:** Some U.S. cities such as New York and San Francisco regulate the number of taxis in operation by issuing a limited number of permits, typically called medallions. Over time, the value of these medallions in some cities has risen significantly. In 2019, the median price of a medallion in New York was approximately $225,000 (New York City Taxi & Limousine Commission, 2023b). Given their high price, medallions are often financed in a similar manner as a vehicle. As described in the *Licensing* section above, the regulatory scheme for robotaxis is not yet determined. Mo et al. (2021) propose limiting the number of licenses available for robotaxis to avoid overcrowding of the transportation network with these vehicles. In this scenario, we explore the impact of a medallion-based regulatory structure for robotaxi services, adopting the medallion financing scheme assumed by Nunes and Hernandez (2020).

***AV Lower Density City*: ** Private AV companies will only deploy commercial services in regions in which they can achieve profitability. This scenario investigates the economics of robotaxi deployment in a lower density city. We assume that in a lower density city, more individuals will own personal vehicles and that demand for robotaxi services will be lower, decreasing both the annual mileage and the capacity utilization rate. We assume an annual mileage of 64,000 and a utilization rate of 43.6%, approximate values for taxi-type services in Seattle (Cramer & Krueger, 2016; UITP, 2020). The population density of Seattle is approximately 8,791.8 people/mi$^2$ compared to Chicago's density of 12,059.8 people/mi$^2$ (US Census Bureau, 2020). Moreover, we assume that decreased usage will reduce the wear on the AV, increasing the vehicle and AV technology lifespans to 6 years.

**Table 3-4:** Changes to input values for each scenario.

| Scenario | Scenario Description | Scenario Value (change to means only) |
|---|---|---|
| **Advanced AV Technology** | Maintenance | Reduced by 10% |
| | Insurance | Reduced by 50% |
| | Fuel | Reduced by 20% |
| | Remote Monitor | Worker-to-vehicle ratio increased to 1:30 |
| | Customer Support | Worker-to-vehicle ratio increased to 1:30 |
| | Field Support | Worker-to-vehicle ratio increased to 1:8 |
| | Coordinator | Worker-to-vehicle ratio increased to 1:150 |
| | AV Tech Price | Decreased to $10,000 |
| **High Usage** | Annual Mileage | Increased to 80,000 mi/year |
| | Maintenance | Increased by 20% |
| | Capacity Utilization Rate | Increased to 70% |
| | Vehicle Lifespan | Decreased to 4 years |
| | AV Tech Lifespan | Decreased to 4 years |
| **Medallion System** | Medallion price | $225,000 |
| | Down payment percent | 20% |
| | Percent of down payment paid upfront | 25% |
| | Financing period for down payment | 7 years |
| | Financing period for remaining medallion cost | 5 years |
| | Medallion interest rate | 5.4% |
| | Medallion lifespan | 20 years |
| **Lower Density Region** | Annual Mileage | Decreased to 64,000 mi/year |
| | Vehicle Lifespan | Increased to 6 years |
| | AV Tech Lifespan | Increased to 6 years |
| | Capacity Utilization Rate | Decreased to 43.6% |

## 3.4 Results

### 3.4.1 Cost by Category and Fare per Mile Estimates

Our simulation results reveal that while all AV robotaxi scenarios can achieve lower per-mile costs than non-AV taxi services, labor still remains a key operational cost for robotaxi services (Figure 3-1). The labor costs alone for the AV scenarios already exceed the total cost per mile estimates from most prior studies ($0.76-$1.04 /mile for this study, see Table 3-1 for estimates from prior studies). Technology advancements that allow for fewer workers to manage a greater number of vehicles could, however, significantly reduce labor expenditures and allow for the low (<$1.50/mile) total operational costs predicted by prior studies (Table 3-5, *AV Advanced Tech* scenario). The *AV Medallion System* scenario has the highest operational cost per mile amongst the AV scenarios due to the added expense of the medallion, highlighting regulatory decisions that could impact the economic competitiveness of AV services.

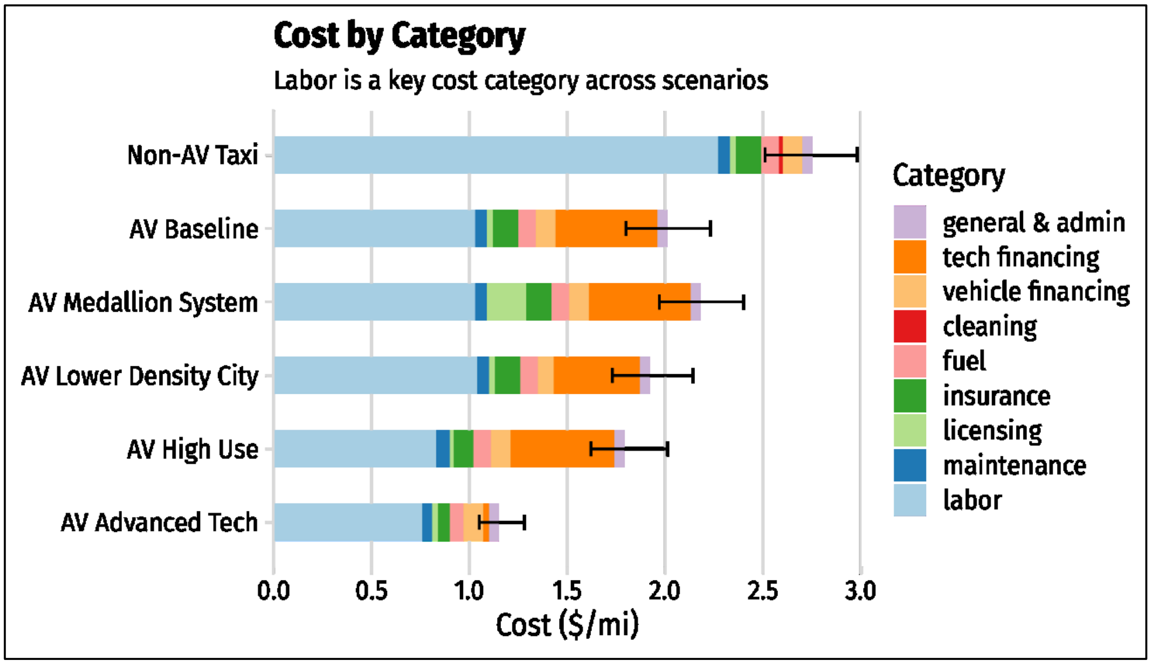



**Figure 3-1:** Operating costs by category for each scenario with 95% quantile bars from the Monte Carlo simulations of the total cost across all categories.

Even with the additional labor roles, the labor costs for the AV scenarios remain significantly lower than those of the non-AV taxi service. Even with the added technology expense and substantial labor cost, the mean cost for the *AV Baseline* scenario is $1.99/mi compared to $2.74/mi for the *Non-AV Taxi* scenario. Assuming similar utilization rates and profit margins for all scenarios, these lower costs translate to lower fares (Figure 3-2). The mean estimated fare per mile for the *Non-AV Taxi* scenario is $6.03/mile compared to $4.52/mile for the *AV Baseline* scenario (Table 3-5), suggesting that robotaxi providers could out-compete human-driven taxi services on price. Though the *AV Medallion System* scenario is the highest cost AV scenario, the lower utilization rate in the *Lower Density City* scenario results in a higher fare per mile value. We discuss the importance of utilization rates in the following section.

**Table 3-5:** Mean total cost and mean cost by category estimates from the Monte Carlo simulations.

| | Non-AV Taxi | AV Baseline | AV Medallion System | AV Lower Density City | AV High Use | AV Advanced Tech |
|---|---|---|---|---|---|---|
| **Cost ($/mi)** | | | | | | |
| Labor | 2.27 | 1.02 | 1.02 | 1.04 | 0.83 | 0.76 |
| Cleaning | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Fuel | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.07 |
| General & Admin | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Insurance | 0.13 | 0.13 | 0.13 | 0.13 | 0.10 | 0.06 |
| Licensing | 0.03 | 0.03 | 0.20 | 0.03 | 0.02 | 0.03 |
| Maintenance | 0.06 | 0.06 | 0.06 | 0.06 | 0.07 | 0.05 |
| Tech Financing | 0.00 | 0.52 | 0.52 | 0.44 | 0.53 | 0.03 |
| Vehicle Financing | 0.10 | 0.10 | 0.10 | 0.08 | 0.10 | 0.10 |
| **Total Cost ($/mi)** | | | | | | |
| **Mean:** | 2.74 | 1.99 | 2.16 | 1.91 | 1.79 | 1.15 |
| **Std. Dev:** | 0.14 | 0.13 | 0.14 | 0.13 | 0.12 | 0.07 |
| Fare ($/mi) | | | | | | |
| **Mean:** | 6.03 | 4.52 | 4.87 | 5.01 | 2.95 | 2.84 |
| **Std. Dev:** | 0.31 | 0.28 | 0.29 | 0.31 | 0.18 | 0.15 |

To evaluate our findings in light of current taxi operations, we compare our estimated fare per mile values to existing fare data from two public datasets on taxi operations from the City of Chicago (City of Chicago, 2023) and the City of New York (New York City Taxi & Limousine Commission, 2023a). We use data from the year 2019 to capture market conditions prior to the COVID-19 pandemic but during a period when taxis faced competition with established Transportation Network Company (TNC) services such as Uber and Lyft. We find that our mean non-AV taxi fare is similar to those of Chicago and New York City, suggesting that our model is fairly reflective of current operational practice (Chicago: \$5.70/mi, New York: \$5.69/mi).

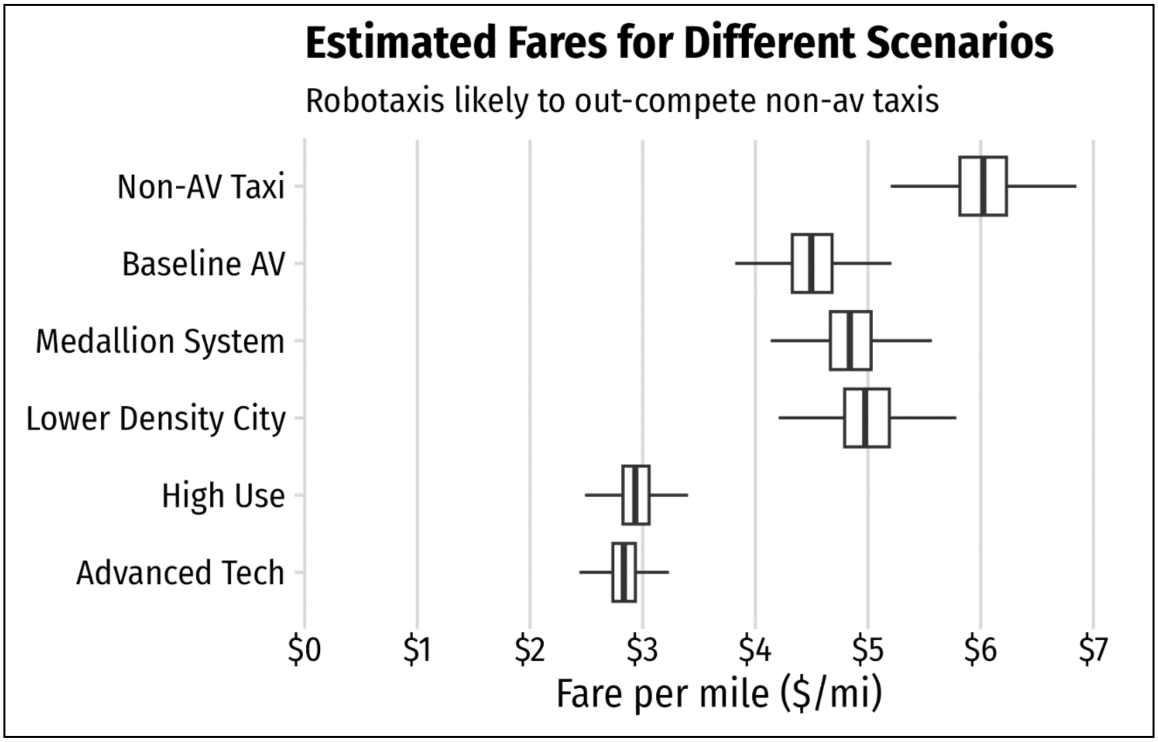



**Figure 3-2:** Distribution of per-vehicle fare per mile estimates for each scenario from Monte Carlo simulations.

### 3.4.2 Investigating Sensitive Inputs

We perform two systematic sensitivity checks, one on the taxi-specific model inputs and one on the AV-specific model inputs, testing values 50% higher and 50% lower than the assumed values in the baseline scenario. We exclude model input values for which changes to the assumed value would not make logical sense (e.g., time conversion variables, number of days per year). We find that both models are most sensitive to capacity utilization rate and annual mileage (Figure 3-3). This sensitivity suggests that operational features may play a larger role than labor in determining the cost of future robotaxi services.

The *AV Baseline* model is also sensitive to the price and lifespan of the AV technology. Given that the technology price is expected to decrease over time, the *AV Baseline* results may be interpreted as a conservative estimate for how traditional taxis and robotaxis might compete with one another. The *AV Advanced Technology* scenario offers a more bullish picture of a future in which technology prices decline significantly. Even as technology costs decline, operational factors could impact the technology lifespan and subsequent technology financing costs. As one interviewee noted, "*How many times does an AV need to get damaged such that, in the cost equation, it would not be profitable anymore?*" (Interview 15). AV firms will need develop vehicle designs that can maintain or increase their vehicles' lifespans and the lifespans of their AV technology suites to remain competitive. While perhaps not as influential as utilization-related inputs, both models are also sensitive to the wages and labor ratios for their associated labor roles.

To further investigate the most sensitive inputs, we compute how fares vary based on changes to the three most sensitive model inputs: *capacity utilization rate*, *annual vehicle miles traveled*, and *labor ratios*. Figure 3-4 shows these results for the *Non-AV Taxi*, *AV Baseline*, and *AV Advanced Technology* scenarios, with the bands reflecting 95% quantile outputs from the Monte Carlo simulation results. The curves show how the fare changes with changes to each input, holding all other inputs constant. We select these three scenarios to capture status quo non-AV taxi operations, current robotaxi operations, and an optimistic scenario for future robotaxi services where the technology improves to achieve greater performance at lower cost. The points on each curve denote the assumed value used for each scenario.

The exponentially decreasing nature of these input parameters emphasizes the importance of robotaxi firms' ability to achieve utilization rates equivalent to or higher than those of existing taxi services. If their usage falls relative to that of non-AV taxi services, they could lose their competitive edge in terms of lower fare per mile rates. Operational and technology advancements characteristic of the *AV Advanced Technology* scenario would give robotaxi firms greater leeway with such operational pressures and could allow them to expand into regions that have historically had lower taxi utilization.

As Figure 3-4 demonstrates, fare per mile is also highly sensitive to high labor ratios (i.e., more workers required), but firms reach economies of scale relatively quickly. This sensitivity explains the notable difference in labor costs between the non-AV and robotaxi services shown in Figure 3-1. Though robotaxi firms may employ a greater number of types of frontline workers, the worker-to-vehicle ratios for those roles are lower than those for non-AV taxi roles. Taxi firms can—and presumably do—optimize their dispatcher-to-vehicle ratios but are limited by their need to always have a driver operating each vehicle. In contrast, robotaxi firms can have remote monitors and customer service agents manage greater numbers of vehicles at a time.

At a labor ratio of approximately three vehicles per worker (e.g., per remote monitor), the mean fare per mile for the *AV Baseline* scenario reaches approximately \$6, the estimated mean value for the *Non-AV Taxi* scenario. One interviewee with experience in the airline industry noted that flight dispatchers—a role which the interviewee described as more equivalent to the remote monitor position than an air traffic controller—typically work at around a 1:5 worker-to-aircraft ratio (Interview 25). A 1:5

ratio would raise the mean estimated fare per mile value to over $5 for the *AV Baseline* model, which is still lower than that of a non-AV taxi service. While we did not use this ratio in our baseline scenario, we note that regulation that limits how many vehicles each worker can monitor could result in higher costs for robotaxi firms and limit their competitiveness against existing services.

Striving for the lowest possible number of workers, however, may not be necessary either. After an initial steep decline, fare per mile values are relatively similar for labor ratios of 1:15 or higher. Some prior studies have assumed ratios of one remote monitor for 80 vehicles (Negro et al., 2021). Striving for such a high number of vehicles per monitor might not only impose cognitive overload challenges for the monitor (Mutzenich et al., 2021), but it may offer fairly marginal cost reductions. In the future, AV firms will have to weigh these marginal reductions against impacts to service quality for their passengers, as well as performance consequences for their employees (e.g., mental workload, situational awareness).

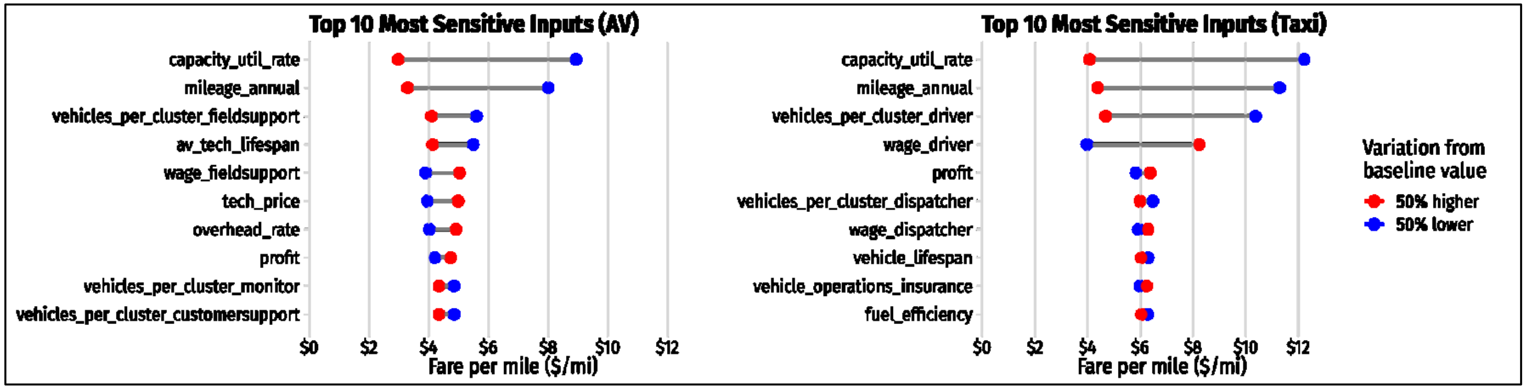



**Figure 3-3:** Top ten most sensitive model inputs for the AV Baseline and Non-AV Taxi models.
Input values were varied 50% higher and 50% lower than the assumed values

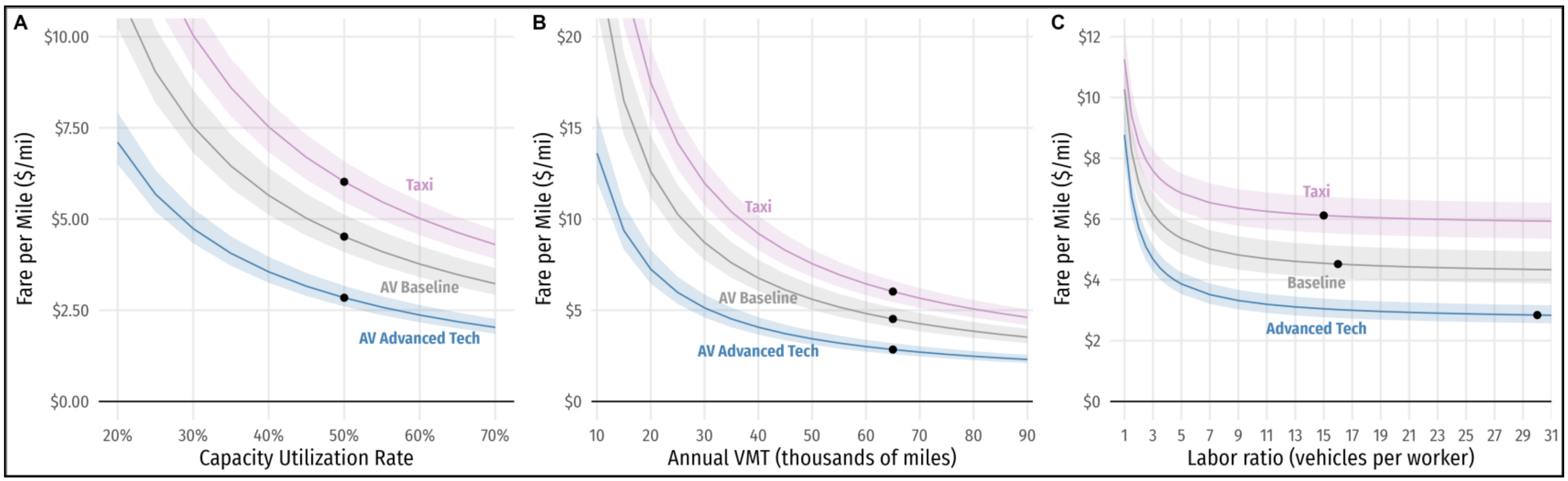



**Figure 3-4**: Estimated mean fare per mile values across a range of A) capacity utilization rates, B) annual vehicle miles traveled values, and C) labor ratios.
Colored bands indicate 95% quantile bands from the Monte Carlo simulations. Black points mark the assumed values used to the scenarios.

### 3.4.3 Wage Outcomes

We now turn to an examination of the differences in wages between frontline workers in the taxi and robotaxi systems. Based on the roles examined in this study, we find that wages would shift higher for frontline workers in an AV service (Figure 3-5), but the total number of workers would decrease by approximately 57% for the *AV Baseline* scenario (from 216 to 93 workers to service a 100-vehicle fleet). In the *Advanced AV Technology* scenario, the total number of workers decreases by approximately 76% due to increases in the number of vehicles managed by the labor roles, but the distribution of the wages remains similar to that of the *AV Baseline* scenario. For the AV scenarios, wages follow a bimodal distribution, with the limited number of coordinator roles earning higher wages than the field support, customer service, and remote monitor roles, which make up most of the labor force. We emphasize that these distributions do not capture other labor roles and job numbers that may be created to support AV services for the development and production of AVs, their distribution, and roles involved in a potentially expanded upgrades and repairs industry (Chamber of Progress, 2024).

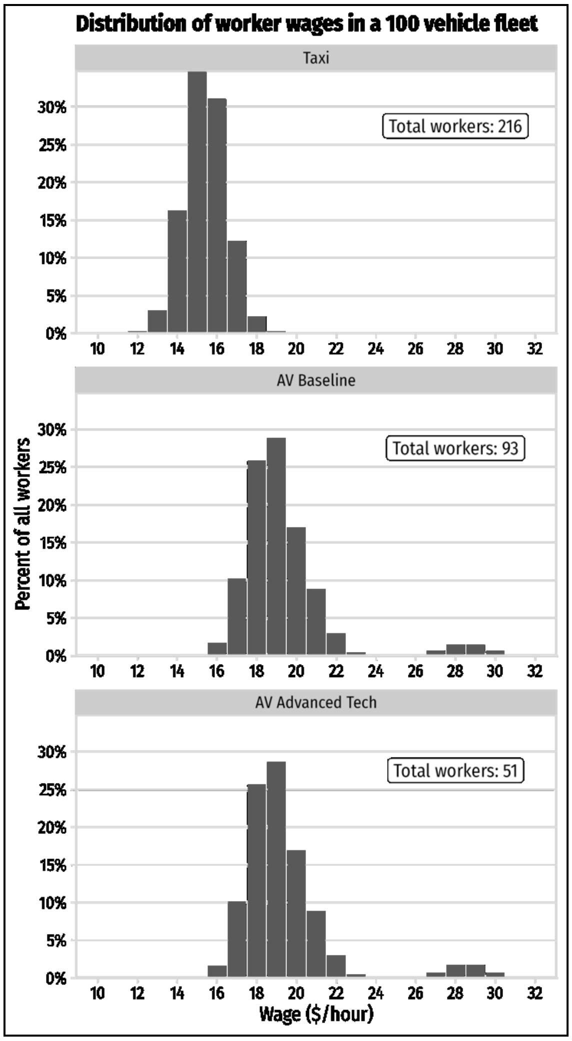



**Figure 3-3:** Estimated percent of workers that would fall within a given wage range for the Non-AV Taxi, AV Baseline, and AV Advanced Technology scenarios.
Plotted values depict the mean values from the Monte Carlo simulations (i.e., mean value for estimated total workers and mean values for estimated percent of workers within each wage bin).

### 3.5 Discussion

In this study, we provide the first model and analysis of robotaxi services with labor assumptions that are grounded in currently deployed robotaxi services in the U.S. Our estimated labor cost of **$1.02/mi** is higher than nearly every prior estimate: **$0.01-0.19/mi** (depending on the country) (H. Becker et al., 2020), **$0.21/mi** (Bösch et al., 2018), **$0.22-0.23/mi** (depending on utilization) (Negro et al., 2021), and **$0.34/mi** (Wadud, 2017; Wadud & Mattioli, 2021). Only Nunes and Hernandez (2020) suggest the potential for a higher labor cost than our estimate, offering an estimate ranging from **$0.10-$2.40/mi** for cleaning and safety oversight services. The high end of their estimate range assumes a remote monitor to vehicle ratio of 1:5, which would significantly drive up the labor cost (a finding mirrored in our sensitivity analysis); however, using our *AV Baseline* assumption of 1:16 for the remote monitor to vehicle ratio, their labor cost estimate drops to approximately **$0.15/mi**, aligning with the low estimates from prior studies. Our inclusion of additional labor roles that are a part of current robotaxi services reveals that robotaxi labor costs are substantially higher than previously expected.

Nonetheless, even after accounting for higher labor expenditures and for technology costs that are more representative of the current state of technology, our results still align with prior findings that robotaxi services could out-compete traditional taxi services on price and that utilization rates and annual mileage remain the most influential factors affecting robotaxi competitiveness (Negro et al., 2021; Nunes & Hernandez, 2020). If regulation or technological limitations result in higher worker-to-vehicle ratios, however, labor costs could grow to levels that limit robotaxi competitiveness.

Our results from the *AV Advanced Technology* scenario also align with prior studies' findings that even with low labor costs, robotaxi services are unlikely to achieve lower costs than personal vehicle ownership (Kuhnimhof & Eisenmann, 2023; Nunes & Hernandez, 2020; Wadud & Mattioli, 2021). For example, Kuhnimhof and Eisenmann (2023) find that mobility on demand prices—a category of services which includes robotaxis—would need to drop to around $0.52/mile to notably impact private car usage; our most optimistic scenario (*AV Advanced Technology*) results in $0.72/mile for labor costs alone and a total cost of $1.15/mile.

In addition to supporting conclusions about the economic competitiveness of robotaxis, the granularity in robotaxi labor roles revealed in our analysis extends our knowledge in two important ways. First, greater granularity allows researchers and practitioners to better understand the bounds for reducing labor costs based on critical technological and operational considerations. There are practical limits to how quickly a human can clean delicate sensors or how quickly a worker can travel to respond to an accident. For remote monitors, these limitations include challenges with maintaining situational awareness (Mutzenich et al., 2021). Service providers must consider labor ratios and labor costs not only to achieve target costs, but also to achieve target levels of quality and safety of their services. By cataloguing the many different labor roles involved in robotaxi services, this study enables researchers and practitioners to critically examine these operational considerations for different roles and how they might impact service quality and safety. Researchers may also use these additional considerations to refine future simulation studies of AV services.

Secondly, there is significant interest in how AV services will impact jobs, particularly regarding where job losses might occur, how many jobs may be affected, and the nature of new, emerging jobs (Leonard et al., 2020). The sensitivity of our model to utilization suggests that robotaxi services may remain limited to regions like dense urban areas that offer sufficiently high demand, potentially limiting where labor displacement for taxi and ride-hailing drivers might occur. We note that the populations of dense, urban regions are also predicted to have more positive perceptions of AVs and higher predicted AV adoption rates (Bansal et al., 2016; Krueger et al., 2016).

While we do not attempt to offer economy-level predictions about the numbers of jobs lost or gained due to vehicle automation[12], we do provide an early estimate for how robotaxis might impact labor forces on a more localized, sector-based scale based on the labor ratios and utilization rates for which robotaxi firms may strive. We find that these impacts could range from a potential 57 to 76% reduction in the number of frontline workers. However, the distribution of wages in jobs supporting robotaxi services is shifted up significantly higher than that of jobs supporting traditional taxi services. We emphasize that automation often reshapes labor in unexpected ways (NASEM, 2017) and that other jobs may also emerge to support robotaxi services in the future.

### 3.6 Limitations

We acknowledge a number of limitations in this study. As with prior studies, we base many of our assumptions on data for existing taxi services due to the limited scale of existing robotaxi deployments. Vehicle automation could impact operational costs in unexpected ways not captured by our scenarios. Moreover, we do not yet know how public preferences for autonomous services might unfold and impact demand (see Gkartzonikas and Gkritza (2019) for a review of stated preference and choice studies on this topic) and whether robotaxi firms could realistically achieve the capacity utilization rates and mileage values assumed in the *AV Baseline* scenario.

[12] See Beede et al., (2017), Groshen et al. (2018), and Chamber of Progress (2024) for U.S. estimates or Alonso Raposo et al. (2019) for European Union estimates.

In this study, we are focused on a U.S. context in which labor costs are relatively high. Becker et al. (2020) find that the cost-saving effects of automation are stronger in higher-income locations than in lower-income locations where labor costs may not be reduced as significantly by automation. Thus, the results of this study regarding robotaxi competitiveness, job losses, and wage changes would generalize to other higher-income contexts, but may not hold for lower-income locations.

We consider a specific set of labor roles that does not capture additional jobs that may be involved in the technology training, development, production, and distribution of AVs. Altering the system boundary of analysis could change the results in terms of the number of jobs required to support robotaxi services, their associated wages, and potentially the geographic location of those jobs (as occurred with prior forms of automation and offshoring of labor (Goos et al., 2014)). Additional roles such as an in-vehicle attendant may also be critical for early adoption of robotaxi services and for providing critical in-person support to specific rider populations for whom the service would otherwise be inaccessible (Kaplan & Helveston, 2023b; Kyriakidis et al., 2020).

A feature that could not only offer greater profitability for robotaxi firms but also promote more sustainable transportation systems is shared rides. Though not explicitly included in our model, shared rides would allow for higher per-trip fares without raising the trip price for individual riders and could increase capacity utilization for individual vehicles. As with existing taxi-type services, however, interest in shared rides is limited, with most riders preferring not to share rides (Kang et al., 2021; Kaplan & Helveston, 2023b; Krueger et al., 2016). Powertrain type could also impact the sustainability of AV services. We base our model on hybrid vehicles since they are used in the majority of current commercial operations, but we acknowledge the value of a combined electric and automated future. Switching to fully-electric fleets could reduce some operational costs (i.e., lower fuel cost) but at the expense of higher up-front prices, which would increase the vehicle financing costs (Fulton et al., 2017). Furthermore, AV computational requirements have been shown to reduce electric ranges by 10-15% (Mohan et al., 2020), which could limit their feasibility to achieve higher utilization rates and / or annual mileage.

There may be other costs that we have omitted; Litman (2023), for example, notes that vehicle automation would not only increase capital expenditures, but also add additional annual software, mapping, and subscription costs. We do not explicitly model costs these as we consider them part of the AV technology costs. Finally, this study assumes labor ratios based on current practice for robotaxi services that still operate in limited operational design domains. Further research within the domain of human factors engineering could provide better estimates for AV service labor ratios that are safe and economically efficient.

### 3.7 Conclusion

As robotaxis expand to an increasing number of cities, transportation planners and researchers need to consider the full operating costs of AV services and how they might realistically substitute or complement existing services. This competition will not only determine how AVs might impact the safety, environmental sustainability, and accessibility of transportation systems but also how AVs might impact the jobs of current transportation workers. This study refines prior AV cost models by detailing frontline labor roles involved in existing robotaxi services and incorporating technology estimates more reflective of current prices. We find that—after accounting for additional labor roles involved in current robotaxi services—labor costs for robotaxis are far higher than previously estimated. Nonetheless, despite these costs robotaxis can still out-compete traditional taxis on price, and utilization rates and annual mileage will ultimately serve as the limiting factors for robotaxi competitiveness. If jobs shift from traditional taxi to robotaxi services, the number of jobs could decrease by between 57 to 76%, though the distribution of wages would shift higher. Significant uncertainty remains regarding how robotaxi services will impact our transportation networks and the labor systems that support them. We hope that these results can help to inform dialogue between planners, policymakers, workers, and members of the public about how emerging technologies not only could—but should—interact with our transportation systems.

## Chapter 4: Public Preferences for AV versus Non-AV Modes

The objective of this study is to investigate public preferences for different autonomous (ride-hailing, shared ride-hailing, bus) and non-autonomous (ride-hailing, shared ride-hailing, bus, rail) modes. This chapter is based on Kaplan and Helveston (2023b), published in *Transportation Research Record*. In this chapter, we use the term automated to refer to highly automated (autonomous) vehicles in which the automated driving system performs the entire driving task.

### 4.1 Introduction

Autonomous vehicles (AVs) have the potential to dramatically disrupt current transportation patterns and practices, and how they will interact with or displace current transportation modes remains uncertain. Over the past decade, ride-hailing companies like Uber and Lyft have raised billions of dollars by promoting the promise of a future of driverless taxi fleets that could potentially replace car ownership entirely (Korosec, 2022; Shetty, 2020; Somerville, 2019). At the same time, transportation planners are grappling with how AVs might shape future transportation systems, especially public transportation systems.

Transit systems have already had to reckon with competition from ride-hailing services that offer greater flexibility and convenience than many transit options (Cats et al., 2022). If vehicle automation enables significant price decreases and increased availability for ride-hailing services, some fear that it could undercut public transit, which could have important implications for the environment and transportation equity (Creger et al., 2019; Williams et al., 2020b). Public transit plays a critical role in reducing emissions from transportation (L. Bailey et al., 2008), mitigating road congestion, and providing basic mobility for individuals with limited to no other transportation options. As one U.S. Federal Highway Administration report highlights, over 90% of public assistance recipients lack access to a vehicle and rely on public transit (FHWA, 2002).

Ultimately, the extent to which individuals adopt automated transportation modes will drive many system-level outcomes. Research on preferences for AVs is both immature and inconclusive, especially with regard to competition with transit. Some studies have found that individuals prefer automated modes over public transit (Krueger et al., 2016; Steck et al., 2018), while others find that current transit users lack significant interest in automated modes (Kim et al., 2019; Winter et al., 2020). Furthermore, public attitudes towards and preferences for public transit are often context dependent. Despite the AV testing and pilots occurring in multiple cities across the United States, limited research exists regarding the potential impacts of automation on the billions of annual public transportation trips taken in the U.S. each year (9.9 billion in 2019) (APTA, 2022). Prior U.S.-based studies have either focused on one mode or omitted transit, limiting the ability to compare preferences between different automated modes (Daziano et al., 2017; Haboucha et al., 2017; Kassens-Noor et al., 2020; Kim et al., 2019; Lavieri & Bhat, 2019; Nair & Bhat, 2021; Saeed et al., 2020; Zhong et al., 2020). This study aims to fill this gap by investigating the public preferences for transit and ride-hailing modes with and without automation. We center our analyses on the following two research questions:

1. What are individuals' preferences for automated modes (ride-hailing, shared ride-hailing, bus) and non-automated modes (ride-hailing, shared ride-hailing, bus, rail)?

2. Under what conditions might automated ride-hailing services be competitive with public transit modes?

We address these questions using data from an online choice-based conjoint survey fielded in the Washington, D.C. Metropolitan Region (N = 1,694) in October 2021. We estimate discrete choice models of public preferences for different automated and non-automated transportation modes, and then we use the estimated models to simulate future marketplace competition across a range of trip scenarios.

## 4.2 Literature on AV Preferences

Many studies on preferences for AVs have focused on factors associated with private AV ownership, such as consumers' perceived comfort with riding in an AV and their willingness to pay for features associated with different levels of automation (Daziano et al., 2017; Moody et al., 2020; Nair & Bhat, 2021; Shin et al., 2015). These studies often employ Likert scales (typically ranging from 1 to 5) or other similar rating systems to assess attitudes towards different automated modes. While these studies provide insights into general consumer perceptions of AVs, they lack the ability to gauge potential substitution patterns between automated and non-automated transportation modes.

To address this, some researchers have used choice-based conjoint (CBC) surveys. In CBC surveys, respondents choose from a set of options with varying attributes, and researchers estimate discrete choice models to infer the relative importance of each attribute and the relative desirability of each option. Conjoint surveys offer unique advantages, including the ability to explore hypothetical products, present multiple choice sets to the same respondent, fix all attributes of a given option, and avoid multicollinearities (Louviere et al., 2000). Rather than gauge preferences for different modes in isolation, conjoint surveys allow researchers to simulate the menu of transportation options available to an individual, typified by the experience of looking up directions via GoogleMaps or via a transportation planning app. Table 4-1 presents a selection of recent CBC studies investigating public preferences for different automated and non-automated transportation modes. The majority of these prior studies compare automated modes to conventional, non-automated private cars.

**Table 4-1:** Summary of modes investigated in prior AV conjoint studies.

| | | Non-Automated | | | | | Automated | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Study** | **Location** | **Private Car** | **Ride-hailing** | **Shared Ride-hailing** | **Transit** | **Other (walking, biking)** | **Private Car** | **Ride-hailing** | **Shared Ride-hailing** | **Transit** |
| Krueger et al. 2016* | Australia | X | X | X | X | X | | X | X | |
| Yap et al. 2016 | Netherlands | X | | | X | X | | X | X | |
| Steck et al. 2018 | Germany | | | | X | X | X | X | X | |
| Ashkrof et al. 2019 | Netherlands | X | | | X | | | X | | |
| Winter et al. 2020 | Netherlands | X | X | | X | | | X | | |
| Etzioni et al. 2020 | Cyprus, UK, Slovenia, Montenegro, Hungary, Iceland | X | | | | | X | X | X | |
| Daziano et al. 2017 | U.S. | X | | | | | X | | | |
| Haboucha et al. 2017 | U.S., Canada & Israel | X | | | | | X | X | | |
| Lavieri & Bhat 2019 | U.S. | | | | | | | X | X | |
| Gurumurthy & Kockelman 2020 | U.S. | | | | | | X | X | | |
| Zhong et al. 2020 | U.S. | X | | | | | X | X | X | |
| This study | Washington, D.C. | | X | X | X | | | X | X | X |

*Non-automated modes were collected as a self-reported reference trip

The general consensus across most of these studies is that conventional, non-automated vehicles continue to dominate preferences. For example, in Krueger et al.'s (2016) conjoint study of 435 residents of major metropolitan areas in Australia, respondents chose an automated mode in only 28% of the choice situations. Haboucha et al. (2017) surveyed 721 commuters in Israel, the United States, and Canada and found that 44% of respondents preferred conventional vehicles over private or shared AVs. This preference was even more pronounced among the North American respondents, with 54% preferring conventional vehicles. Yap et al. (2016) asked Dutch travelers about their interest in AVs as a transportation option for filling the last mile trip between a train station and a traveler's final destination, and even in this limited context respondents mostly selected the individual vehicle alternative over all other transportation options. Etzioni et al. (2020) surveyed 1,669 individuals across six EU countries and similarly found strong preferences for conventional vehicles, with respondents selecting conventional vehicles in 70% of the choices. Respondents in Zhong et al.'s (2020) survey of U.S. residents in small and medium metropolitan areas in the U.S. preferred their current private vehicles over private AVs and AV ride-hailing options. These studies signal that individuals are not likely to relinquish their personal vehicles in favor of AVs in the near future.

The strong preferences for conventional vehicles, however, may mask other potential substitution effects that could occur with the introduction of AVs. Many of the aforementioned studies restricted their survey sample to individuals who have a driver's license, with some also requiring that respondents drive a personal vehicle frequently (Ashkrof et al., 2019; Haboucha et al., 2017; Zhong et al., 2020). In doing so, these studies fail to capture the preferences of individuals who do not currently rely on personal vehicles as their primary mode of transportation, including individuals with disabilities or those who do not own a car. Such individuals are typically the primary users of public transit. Moreover, even individuals who typically use their private vehicles might use transit for specific types of trips (e.g., traveling within the city after commuting from the suburbs, trips where parking is expected to be difficult, etc.). Substitutions of these trips with AVs, in conjunction with changing transportation patterns for frequent transit users, would likely have a greater impact on transit ridership.

The existing literature on AV substitution with transit is limited and inconclusive. Some studies find a preference for AVs over transit modes, such as in Steck et al.'s (2018) survey of 173 Germans. In the study, respondents could select from among privately owned AVs, automated ride-hailing (both shared and non-shared), walking, biking, and public transit. Overall, respondents found the private AV option most attractive, followed by AV ride-hailing, and finally transit. Ashkrof et al. (2019) explored preferences for conventional cars, AV ride-hailing, and transit among a sample of 663 Dutch respondents. Individuals similarly preferred AVs over transit, especially when the choice question was framed in terms of a long-distance trip. Yet other studies suggest more limited competition of AVs with transit. In Yap et al.'s (2016) study of AVs as a potential egress mode for train trips, first-class train passengers valued AVs more than transit modes, but second-class train passengers actually preferred transit over AVs. Winter et al. (2020) identified different classes of users amongst a sample of 796 Dutch survey respondents and found that respondents who currently commute by public transport actually show the lowest preference for automated modes, affirming Krueger et al. (2016)'s finding that current transit users were not more likely to switch to an automated mode.

There are some mode features that are particularly relevant when considering an AV future. Ride-sharing (i.e., riding with a stranger who is traveling in a similar direction) is already available in some cities via services like UberPool and Lyft Shared (Lyft, 2022b; Uber, 2022b). Though ride-hailing companies canceled these services during the COVID-19 pandemic, some are now starting to reintroduce them. Sharing rides decreases the cost for both riders, and these cost savings could become even more substantial if the services are automated. Further, sustainability advocates emphasize that fleets of shared AVs are critical for ensuring a sustainable AV future (Creger et al., 2019). Despite enthusiasm from environmental advocates, the public seems less interested in a future of shared rides. As of 2017, pooled rides comprised just 20% of all Uber rides and 40% of all Lyft rides (Shaheen & Cohen, 2019), and current literature suggests that these preferences may persist in an AV future. In Lavieri and Bhat's (2019) conjoint study on automated ride-hailing with sharing and non-sharing options, respondents chose to ride alone in 48.3% of choice occasions with work trips and 54% of choice occasions for leisure trips. Over the past few years, greater exposure to ride-sharing services as well as the COVID-19 pandemic may have altered individuals' attitudes towards sharing. Thus, sharing as a feature of automated ride-hailing services warrants further investigation.

A second mode feature—the presence of an AV attendant—is associated with additional services that a driver might fulfill beyond operating the vehicle. Though AVs would be operated by computer systems, an attendant could help individuals enter and exit the vehicle—a potential barrier to AV use for elderly individuals and individuals with disabilities—and provide a social monitoring function. This monitoring function might affect who feels comfortable using shared AV services.

The consensus from many stated preference surveys and choice studies on AVs is that women appear less likely to use AVs than men (F. Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019), and some hypothesize that this hesitation towards AVs may stem in part from personal security concerns (Khoeini, 2021; Nair & Bhat, 2021; Polydoropoulou et al., 2021). Dong et al. (2019)'s survey of University of Pennsylvania employees found that only 13% of respondents would agree to ride an automated bus without an employee onboard. Similarly, in their multi-country survey on potential AV use, Kyriakidis et al. (2020) asked respondents about their willingness to use an AV when a human operator was and was not onboard. The study found that people were more willing to travel in an AV and to allow their children to travel in an AV with an operator present. These findings suggest that operator presence might be an important feature that might impact whether individuals would prefer AVs over traditional modes. While some AV companies are already operating their vehicles with attendants onboard in small pilots (Fort Worth Business Press, 2021), companies will eventually need to decide whether the attendant feature is worth the additional operating cost in large-scale deployments.

Conjoint studies have enabled an avenue of research to explore potential substitution patterns between various transportation modes in an AV future. This area of research, however, is still quite immature, with many studies conducted only within the past six years. Few studies have considered the impacts of AVs on current transit use, and no conjoint studies have examined impacts of AVs on transit in a U.S. context. Furthermore, there is a lack of understanding about key features associated with AV use, such as ride-sharing and the presence of an AV attendant. We address these gaps by fielding a U.S.-based conjoint study on preferences for automated (ride-hailing, shared ride-hailing, bus) and non-automated (ride-hailing, shared ride-hailing, bus, rail) modes.

### 4.3 Methods

AV services are primarily in the pilot and development phases, limiting the availability of revealed-preference data. In this study, we use a stated-preference conjoint approach to measure public preferences for various automated modes. Choice-based conjoint (CBC) analysis has a history of use in the automotive industry for evaluating preferences for both traditional vehicles and new vehicle technologies such as electric vehicles (Helveston et al., 2015). It has also been used in a number of recent studies on automated driving (Correia et al., 2019; Daziano et al., 2017; Haboucha et al., 2017; Krueger et al., 2016; Yap et al., 2016; Zhong et al., 2020). In CBC surveys, individuals evaluate a series of randomized alternatives and choose which option they prefer. From these selections, we can estimate discrete choice models to quantify the relative importance of each attribute and to simulate market competition between hypothetical choice sets. An advantage of CBC surveys is that one can create hypothetical choices in order to tease out preferences for different attributes that might otherwise be highly correlated in the marketplace (e.g., determining the importance of price versus travel time which are often directly correlated).

Ideally, we would calibrate the estimated models using real market data or combined revealed-preference (RP) and stated-preference (SP) data since real-world behavior may deviate from reported behavior on a survey for reasons such as social signaling and social adoption (Cherchi, 2017; Jensen et al., 2017). Unfortunately, RP and market data for the various types of automated modes explored in this study are not currently available. The inability to effectively calibrate model results remains a limitation of studies on automated vehicles, though we attempted to minimize this limitation by briefing respondents on the features of potential automated modes, further discussed below. The following sections describe the design of this study's CBC survey and subsequent modeling approach. Survey design and data analysis were conducted in R using the *cbcTools* package (Helveston, 2022), and the full survey, data, and code used is available at: https://github.com/lkaplan25/AV_conjoint_survey_2022

### 4.3.1 Survey design and target sample

The survey was created and administered using formr.org—a customizable, R-based survey platform (Arslan et al., 2020). The survey was fielded within the Washington, DC Metropolitan Region to situate decision tradeoffs within a local context. The survey included three main parts: 1) background information and current transportation routines, 2) choice-based conjoint questions, and 3) demographic questions. The background information section included a video clip describing the six levels of automation as defined by the Society of Automotive Engineers (Pennsylvania Department of Transportation, 2017; SAE, 2021). We defined automated modes as level 5 vehicles with the following description: "Vehicles that are automated would be operated by computer systems with no assistance from a human driver. No option to take control of the vehicle would be available." We also provided pictures and brief descriptions for how an automated bus, ride-hailing service, and shared ride-hailing service are expected to function.

In part two, we asked respondents eight choice-based conjoint questions. For each question, we asked respondents to imagine they were going out for an evening leisure activity and to choose between four modes (bus, rail, ride-hailing, and shared ride-hailing) with randomized attribute values. Figure 4-1 shows an example choice question. We selected this framing to provide new insights into AV preferences for non-commuting trips. The majority of prior AV preference studies have focused on commuting journeys, yet non-commuting trips account for approximately 78% of trips within the Washington, DC Metropolitan Region (Joh, 2020; Thomopoulos et al., 2021). Additionally, we hypothesized that focusing on evening trips would increase any potential value of having an attendant on board, per the aforementioned discussion regarding personal security. Future studies might investigate the extent to which time-of-day framing impacts individuals' responses.

The five attributes investigated in this study were mode, automation (yes/no), attendant (yes/no), total trip time, and price. While other attributes, such as wait time, have been found to impact individuals' mode choices (Krueger et al., 2016; Yap et al., 2016), respondents on initial pilot surveys reported feeling overwhelmed by the complexity of the choice questions that included more attributes, including wait time. Balancing design complexity with showing realistic choices remains a challenge with the CBC method, and as Cherchi and Hensher (2015) note, the acceptable level of design complexity can vary amongst contexts, with some researchers recommending inclusion of no more than six different attributes. During the first pilot test of our survey, respondents reported feeling overwhelmed by the complexity of the choice questions, which included wait time as an additional attribute. We subsequently chose to decrease the number of attributes to focus on identifying potential impacts of attendant presence for automated modes, which has received less attention in the literature, and we acknowledge this narrower focus as a limitation of our study.

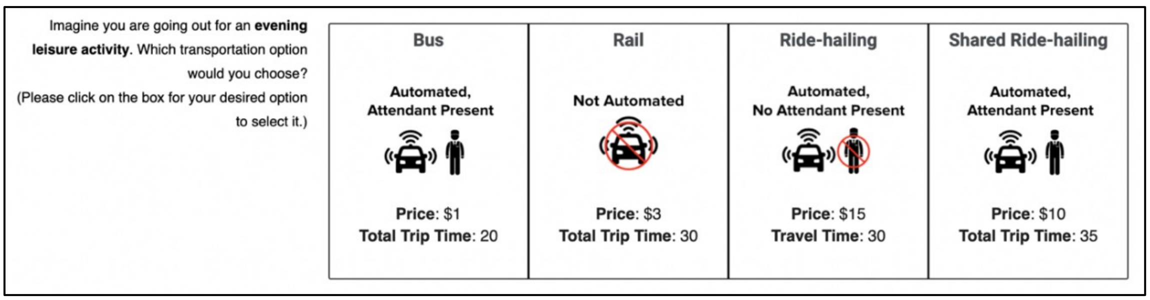



**Figure 4-1:** Sample choice-based conjoint question.

To ensure that the price and time levels shown were calibrated to local market conditions in the Washington, DC Metropolitan Region, we determined ranges for the attribute values for each mode based on current travel times and prices as determined by GoogleMaps, the CityMapper transportation planning app, and ride-hailing price calculators (see Table 4-2) (Cherchi & Hensher, 2015; Citymapper, 2022; Lyft, 2022a; Uber, 2022a). The times and prices were mode-specific (i.e., a bus trip could cost $1, $2, $3, $4, or $5 whereas a ride-hailing trip could cost $5, $7, $10, $12, or $15). We applied discounts of between 20-50% of the regular ride-hailing price to generate prices for the shared ride-hailing mode to simulate cost-savings from shared rides. Shared ride-hailing travel times were also set between 80-120% of the ride-hailing times. While shared rides often have longer trip times, shorter times can occur if an available shared vehicle is already closer to the rider than a solo vehicle. In addition to capturing status quo prices and travel times, we also included a limited number of more extreme values to reflect uncertainty about how automation might affect prices and travel times in the future. Only the bus, ride-hailing, and shared ride-hailing modes could be automated, and only automated modes could include an attendant. The survey explained the attendant feature as follows: "Vehicles with an attendant would have a company official on board to help passengers. This attendant would not be responsible for operating the vehicle."

To design our choice experiment, we started by creating a full factorial design of experiment (DOE) matrix using all of the combinations of attributes for each individual mode but with the restrictions previously described (e.g. only automated modes could have an attendant), resulting in a total of 40,000 possible choice questions. The choice questions were then arranged such that each respondent answered eight choice questions randomly drawn from this DOE, with checks added to ensure that no one respondent saw a repeated choice question and that each choice question showed each of the four available modes. The use of random choice set assignment over other design strategies (such as D-optimal designs) was chosen as a trade-off in parameter precision and the ability to observe potential interaction effects; a randomized design avoids confounding interaction and main effects at the expense of statistical precision (Louviere et al., 2000).

Rather than generate a single fractional factorial design, each respondent was shown a randomly generated set of choice sets drawn from the full set of possible combinations. This approach ensured sufficient variation across all combinations of attributes so as to be able to identify possible interaction effects. The primary disadvantage of this approach is that the resulting estimated standard errors may be larger than they otherwise could have been had we used a more efficient design. The researchers also checked to ensure that each respondent saw a variety of attribute levels and that no attribute level appeared to dominate. The final section of the survey collected demographic information including age, gender, race, education level, and household income. The survey also captured information that could help identify individuals who may face transportation barriers. These questions included whether the respondent has any type of disability, has a smartphone, and has access to a bank account (full survey available in Appendix C.1).

Prior to a full launch of the survey, we conducted two pilot surveys using Amazon Mechanical Turk (N = 287) to test for areas of confusion, potential dominant alternatives, and potential survey fatigue. As mentioned above, we adjusted the survey design following the initial pilot test and then performed a second pilot test to check the revised survey design. After pilot testing, we partnered with Dynata, a market research firm, to recruit the full survey sample. Dynata recruits survey respondents using multiple types of incentives including cash and donations to charity. We limited the survey sample to adults (individuals over 18) who live within the Washington, DC Metropolitan Region (screened for using zip codes).

**Table 4-2:** Full range of survey attributes and levels. Travel time and price are mode-specific.

| Attribute | Levels |
|---|---|
| **Mode** | Ride-hailing, Shared ride-hailing, Bus, Rail |
| **Automated** | Yes/No |
| **Attendant Present** | Yes/No |
| **Travel time (minutes)** | |
| Ride-hailing (Shared ride-hailing travel time set at between 80-120% of ride-hailing time) | 15, 20, 25, 30, 35 |
| Bus | 20, 25, 30, 35, 40 |
| Rail | 15, 20, 25, 30, 35 |
| **Price ($)** | |
| Ride-hailing (Shared ride-hailing set at 50-80% of the associated ride-hailing price) | 5, 7, 10, 12, 15 |
| Bus | 1, 2, 3, 4, 5 |
| Rail | 2, 3, 4, 5, 6 |

### 4.3.2 Model specification

We model choice using a random utility framework, which assumes that individuals will select the alternative that maximizes an underlying random utility model. The utility model is comprised of the observable attributes, $\boldsymbol{u_{ij}} = \boldsymbol{f_i}(\boldsymbol{x_j})$, as well as an error term, $\boldsymbol{\varepsilon_{ij}}$, that captures unobservable attributes. Using this model, we can calculate the probability, $\boldsymbol{P_{ij}}$, of an individual choosing a given alternative as the probability that the utility of one alternative $j$ is greater than the utilities of the other alternatives. We assume that the error term follows a Gumbel extreme value distribution, yielding equation 4.1, a convenient closed-form expression that an individual will choose option $j$ from the choice set $J_C$,, cf. Train (K. E. Train, 2009):

$$\boldsymbol{P_{ij}} = \frac{e^{v_j}}{\sum_{k \in J_c} e^{v_k}} \quad \forall\, \boldsymbol{c} \in \{\mathbf{1}, \mathbf{2}, \mathbf{3}, \ldots \boldsymbol{C}\},\ \boldsymbol{j} \in \boldsymbol{J_C} \tag{4.1}$$

In equation 4.1, $c$ indexes a set of $C$ choice sets, with $J_C$ representing the $c^{\text{th}}$ choice set and $\boldsymbol{v_j}$ capturing the observed portion of the utility model. The standard multinomial logit model (MNL) assumes that the error term is independently and identically distributed. Given that the survey collected several consecutive observations per respondent (often referred to as having a "pseudo-panel" structure), it violates this assumption of independence. To account for this pseudo-panel effect, we instead estimate mixed logit (MXL) models, a widely-used extension of the MNL model (Zhong et al., 2020). The MXL model allows for flexible substitution patterns and relaxes the assumption of independence of the error term (McFadden & Train, 2000). For this study, we assumed that the mode parameters are drawn from independent normal distributions across the respondent population. We also estimate separate travel time coefficients for each mode to capture how individuals may value their time differently when using different modes.

The general utility model yields coefficient estimates in the "preference space" in which coefficients represent the respondent utility for marginal changes in attribute values. We instead specify a "willingness-to-pay" (WTP) space utility model in which coefficient estimates have units of dollars and represent the valuation for marginal changes in attribute values. This has several advantages, in particular the ability the directly interpret the coefficients independent of one another and across different models; in contrast, utility coefficients must be interpreted relative to one another within each model as each model could have a different error scaling (Helveston et al., 2018; K. Train & Weeks, 2005). The general WTP space utility model is shown in equation 4.2:

$$\boldsymbol{u_j} = \boldsymbol{\lambda}(\boldsymbol{\omega}'\boldsymbol{x_j} - \boldsymbol{p_j}) + \boldsymbol{\varepsilon_j}\,, \tag{4.2}$$

where $\boldsymbol{p_j}$ is price, $\boldsymbol{\lambda}$ is a scale parameter, $\boldsymbol{x_j}$ is all non-price attributes, and $\boldsymbol{\omega}$ is a vector of WTP coefficients for non-price attributes. For mixed logit models, directly estimating

WTP provides greater control over how WTP is assumed to be distributed across the population and has been found to yield more reasonable distributions of WTP compared to WTP computed from preference space model coefficients (Helveston et al., 2018; Sonnier et al., 2007; K. Train & Weeks, 2005). Equation 4.3 shows the full model used in the study, with explanations of the variable names in Table 4-3:

**WTP model for Mode, Automated Mode, and Automated Mode + Attendant**
**(Relative to non-automated rail)**

$$\boldsymbol{u_j} = \boldsymbol{\lambda}\begin{pmatrix} \boldsymbol{\beta_1 x_j^{time} + \beta_2 x_j^{time}\delta^{bus} + \beta_3 x_j^{time}\delta^{RH} + \beta_4 x_j^{time}\delta^{sharedRH}} \\ \boldsymbol{+\beta_5\delta^{bus} + \beta_6\gamma\delta^{bus} + \beta_7\tau\gamma\delta^{bus}} \\ \boldsymbol{+\beta_8\delta^{RH} + \beta_9\gamma\delta^{RH} + \beta_{10}\tau\gamma\delta^{RH}} \\ \boldsymbol{+\beta_{11}\delta^{sharedRH} + \beta_{12}\gamma\delta^{sharedRH} + \beta_{13}\tau\gamma\delta^{sharedRH}} \\ \boldsymbol{-p_j} \end{pmatrix} + \boldsymbol{\varepsilon_j} \tag{4.3}$$

All models were estimated using the *logitr* R package which uses maximum simulated likelihood estimation to estimate mixed logit models (Helveston, 2021). The package includes the ability to appropriately account for data with a pseudo-panel structure by computing the probability that a respondent will make a sequence of choices when calculating the log-likelihood using the equation below (2009), where $\boldsymbol{P_{nj}}$ is defined by equation 4.4:

$$\boldsymbol{L = \sum_n^N \sum_j^J y_{nj} \ln P_{nj}}, \tag{4.4}$$

Given the non-convex nature of WTP space log-likelihood functions, we use a randomized multi-start search to identify multiple local minima in a search for a global solution.

**Table 4-3:** Description of conjoint model variables.

| Variable | Description |
|---|---|
| $p_j$ | Price in US dollars |
| $x_j^{travelTime}$ | Total trip travel time in minutes |
| $\delta^{bus}$ | Dummy coefficient for bus mode type {1: yes, 0: no} (base level is rail) |
| $\delta^{RH}$ | Dummy coefficient for ride-hailing mode type |
| $\delta^{sharedRH}$ | Dummy coefficient for shared ride-hailing mode type |
| $\gamma$ | Dummy coefficient for whether the mode is automated {1: yes, 0: no} |
| $\tau$ | Dummy coefficient for whether there is an attendant present {1: yes, 0: no} |

## 4.4 Results

### 4.4.1 Sample description

The final sample consisted of 2,023 respondents who completed the survey between October 4 and October 17, 2021. Respondents who answered all choice questions the same, whose total survey response times or conjoint question response times were too short, who incorrectly answered a simple attention check question, or who were missing demographic information necessary for the primary model and subgroup analyses were removed. After filtering the data based on these criteria, the final sample size was 1,694 respondents for a total of 13,712 choice-based conjoint responses. The final sample closely matched the demographics of the Washington, DC Metropolitan Region, as reported by the National Capital Region (NCR) Transportation Planning Board's 2017/2018 Regional Travel Survey, a once-in-a-decade survey that collected detailed demographic and travel behavior information from approximately 16,000 randomly selected area households within the Washington, DC Metropolitan Region (NCR TPB, 2021). The most significant difference between our sample and the reference sample was the over-representation of individuals who self-identified as male. Our results are robust with and without weights to account for this gender imbalance (weighted model results are available in Appendix C.2). Table 4-4 presents descriptive statistics of the final survey sample.

**Table 4-4:** Summary statistics of survey sample.

| Characteristic | N = 1,694[1] | Reference Sample (Regional Travel Survey) |
|---|---|---|
| **Gender** | | |
| Female | 668 (39%) | 52.3% |
| Male | 989 (58%) | 47.7% |
| Transgender/Gender Non-conforming | 37 (2.2%) | - |
| **Age** | | |
| 18-24 | 120 (7.1%) | 7.8% |
| 25-34 | 367 (22%) | 17.8% |
| 35-44 | 577 (34%) | 20.1% |
| 45-54 | 253 (15%) | 17.3% |
| 55-64 | 133 (7.9%) | 17.7% |
| 65-74 | 181 (11%) | 13.4% |
| 75-84 | 51 (3.0%) | 4.7% |
| 85+ | 4 (0.2%) | 1.3% |
| Unknown | 8 | - |
| **Annual Household Income** | | |
| Less than $15,000 | 66 (3.9%) | 3.0% |
| $15,000 - $24,999 | 42 (2.5%) | 2.7% |
| $25,000 - $34,999 | 73 (4.3%) | 3.2% |
| $35,000 - $49,999 | 126 (7.4%) | 6.4% |
| $50,000 - $74,999 | 202 (12%) | 12.9% |
| $75,000 - $99,999 | 189 (11%) | 15% |
| $100,000 - $149,999 | 260 (15%) | 24.8% |
| $150,000 or more | 736 (43%) | 31.9% |
| **Education** | | - |
| No High school or High School | 142 (8.4%) | |
| Some College/Associate's | 342 (20%) | - |
| Bachelor's degree | 564 (33%) | - |
| Graduate or Professional Degree | 639 (38%) | - |
| Unknown | 7 | - |
| **Bank Account Access** | | - |
| No | 28 (1.7%) | - |
| Yes | 1,537 (91%) | - |
| Doesn't use regularly | 129 (7.6%) | - |
| **Phone Access** | | |
| No cellphone | 28 (1.7%) | - |
| No smartphone | 290 (17%) | - |
| Has smartphone | 1,376 (81%) | - |
| **Disability** | | |
| None | 993 (59%) | - |
| Intellectual | 61 (3.6%) | - |
| Physical | 537 (32%) | - |
| Visual | 99 (5.8%) | - |
| Physical and Visual | 4 (0.2%) | - |

[1]n (%)

### 4.4.2 Effects of adding automation and an attendant

Table 4-5 presents the estimated coefficients from the multiple models we estimated. Standard errors are clustered at the individual level to account for the pseudo-panel data structure. Using the coefficients from the mixed logit model, we compute the willingness to pay (WTP) for automating modes and adding a vehicle attendant for the bus, ride-hailing, and shared ride-hailing modes. Using non-automated rail as the baseline, Figure 4-2 displays individuals' WTP for the three other modes, *all else equal* (e.g., same travel time). A negative WTP can be interpreted as requiring a discount relative to a rail trip for an individual to be ambivalent between choosing a specific mode over rail. Since it does not make sense to consider a zero minute trip, we plot mode preferences for a short trip and a long trip. The longer trip length does slightly increase the WTP values for the bus, ride-hailing, and shared ride-hailing modes, but it does not change the overall trends in how automation and the presence of an attendant impact mode preferences.

In the status quo (not automated) cases, individuals have negative WTPs for the bus, ride-hailing, and shared ride-hailing modes, with the exception of a slightly positive WTP for the ride-hailing mode for a long trip. Adding automation does not significantly change WTP for the three modes for either trip length. The addition of an attendant to the automated modes, however, does result in a significant shift to positive WTPs for automated buses, automated ride-hailing services, and automated shared ride-hailing services. In the discussion section, we hypothesize about the interpretation of this result.

### 4.4.3 Subgroup Analyses

We perform subgroup analyses to investigate potential preference differences based on income, race, and gender. The survey sample included 33 individuals who self-identified their gender identity as transgender male, transgender female, gender queer, or gender non-conforming. We grouped all of these individuals with respondents who identified as female, given the higher rates of violence and discrimination that transgender and gender non-conforming individuals face (Grant et al., 2011). We hypothesized that such experiences might affect their attitudes towards safety, especially in terms of sharing rides. Alternative groupings did not change the reported results in aggregate.

To perform the subgroup analyses, we directly estimated mixed logit WTP models for different subgroups. Since WTP-space estimation is independent of scale, we can directly compare the results from models for different groups, as opposed to estimating a single model with dummy parameter interactions. Prior studies have demonstrated that income, race, and gender impact attitudes towards conventional transportation modes and AVs (Gkartzonikas & Gkritza, 2019; Moody et al., 2020; Nair & Bhat, 2021). No consistent differences emerged in our results regarding racial differences, though we are limited by our sample which was mostly white. Higher income individuals expressed a higher WTP for automation and an attendant, perhaps due to their overall lower price sensitivity. A gender-based subgroup analysis revealed that although women and men shared similar baseline preferences for non-automated modes, men expressed significantly higher WTPs for automated modes and automated modes that also include an attendant for a long trip (Figure 4-3). For a short trip, gender differences only emerged when the automated modes also included an attendant.

Even with the addition of the attendant to the automated modes, women only demonstrated a positive WTP for the automated ride-hailing mode for a long trip. The gender subgroup analysis revealed that the positive WTPs from the whole-group analysis stemmed primarily from the men in our sample.

**Table 4-5:** Discrete choice model coefficients in WTP space.

| Attribute | Coef. | | MXL | Male | Female | Mid/High Income | Low Income |
|---|---|---|---|---|---|---|---|
| Lambda | | | 0.094 (0.006) *** | 0.074 (0.008) *** | 0.130 (0.011) *** | 0.083 (0.007) *** | 0.152 (0.018) *** |
| Travel time | $\boldsymbol{\beta_1}$ | | -0.573 (0.049) *** | -0.684 (0.086) *** | -0.460 (0.053) *** | -0.647 (0.065) *** | -0.353 (0.060) *** |
| Bus travel time | $\boldsymbol{\beta_2}$ | | 0.062 (0.049) | 0.133 (0.083) | -0.007 (0.056) | 0.086 (0.063) | 0.002 (0.067) |
| RH travel time | $\boldsymbol{\beta_3}$ | | 0.232 (0.053) *** | 0.366 (0.090) *** | 0.095 (0.061) | 0.267 (0.067) *** | 0.096 (0.082) |
| Shared RH travel time | $\boldsymbol{\beta_4}$ | | 0.203 (0.050) *** | 0.426 (0.087) *** | -0.014 (0.057) | 0.289 (0.064) *** | -0.055 (0.069) |
| Bus | $\boldsymbol{\beta_5}$ | $\boldsymbol{\mu}$ | -6.665 (1.454) *** | -9.267 (2.463) *** | -3.870 (1.605) * | -8.845 (1.898) *** | -1.526 (1.905) |
| *(base = Rail)* | | $\boldsymbol{\sigma}$ | -10.632 (0.835) *** | -13.032 (1.521)*** | -8.094 (0.858) *** | -12.299 (1.155) *** | -6.213 (0.926) *** |
| Bus - Automated | $\boldsymbol{\beta_6}$ | | 1.220 (0.725) | 5.489 (1.257) *** | -2.628 (0.907) ** | 2.739 (0.930) ** | -2.118 (1.042) * |
| Bus – Attendant present | $\boldsymbol{\beta_7}$ | | 9.822 (1.078) *** | 14.478 (2.067) *** | 5.072 (1.035) *** | 11.615 (1.453) *** | 4.595 (1.176) *** |
| Ride-hailing (RH) | $\boldsymbol{\beta_8}$ | $\boldsymbol{\mu}$ | -7.193 (1.573) *** | -11.883 (2.762)*** | -2.504 (1.716) | -8.106 (1.972) *** | -4.082 (2.406) |
| *(base = Rail)* | | $\boldsymbol{\sigma}$ | 13.168 (0.886) *** | -14.424 (1.554)*** | 11.830 (0.972) *** | -14.042 (1.158) *** | 10.506 (1.180) *** |
| RH - Automated | $\boldsymbol{\beta_9}$ | | 0.731 (0.802) | 4.772 (1.360) *** | -2.855 (0.992) ** | 1.573 (0.992) | -1.775 (1.267) |
| RH - Attendant present | $\beta_{10}$ | | 10.931 (1.106) *** | 16.180 (2.150) *** | 5.412 (1.064) *** | 12.456 (1.449) *** | 6.590 (1.474) *** |

Standard errors of estimates are presented in parentheses. Coefficient units are in USD $. * ≤0.05. ** ≤0.01. *** ≤0.0001.

*Table 4-6 (cont.): Discrete choice model coefficients in WTP space.*

| Attribute | Coef. | | MXL | Male | Female | Mid/High Income | Low Income |
|---|---|---|---|---|---|---|---|
| Shared RH | $\beta_{11}$ | $\mu$ | -11.535 (1.584) *** | -18.273 (2.957) *** | -4.819 (1.624) ** | -14.461 (2.102) *** | -2.732 (1.981) |
| *(base = Rail)* | | $\sigma$ | -12.503 (0.913) *** | 13.472 (1.513) *** | -11.212 (1.036) *** | 13.479 (1.179) *** | -9.824 (1.258) *** |
| Shared RH - Automated | $\beta_{12}$ | | 2.903 (0.815) *** | 8.047 (1.539) *** | -1.748 (0.974) | 4.338 (1.034) *** | -1.113 (1.305) |
| Shared RH, Attendant present | $\beta_{13}$ | | 8.560 (1.011) *** | 10.902 (1.720) *** | 6.195 (1.162) *** | 9.385 (1.276) *** | 6.253 (1.533) *** |
| Log-Likelihood: | | | -16,798.2 | -9,742.6 | -6,780.3 | -13,781.7 | -2,942.9 |
| Null Log-Likelihood: | | | -18,787.1 | -10,968.4 | -7,818.7 | -15,382.3 | -3,404.7 |
| AIC: | | | 33,630.3 | 19,519.3 | 13,594.6 | 27,597.4 | 5,919.9 |
| BIC: | | | 33,758.1 | 19,637.9 | 13,707.4 | 27,721.7 | 6,018.6 |
| McFadden R2: | | | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Adj McFadden R2: | | | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Number of Observations: | | | 13,552.0 | 7,912.0 | 5,640.0 | 11,096.0 | 2,456.0 |
| Number of Respondents: | | | 1,694.0 | 989.0 | 705.0 | 1,387.0 | 307.0 |

Standard errors of estimates are presented in parentheses. Coefficient units are in USD $. * ≤0.05. ** ≤0.01. *** ≤0.0001.

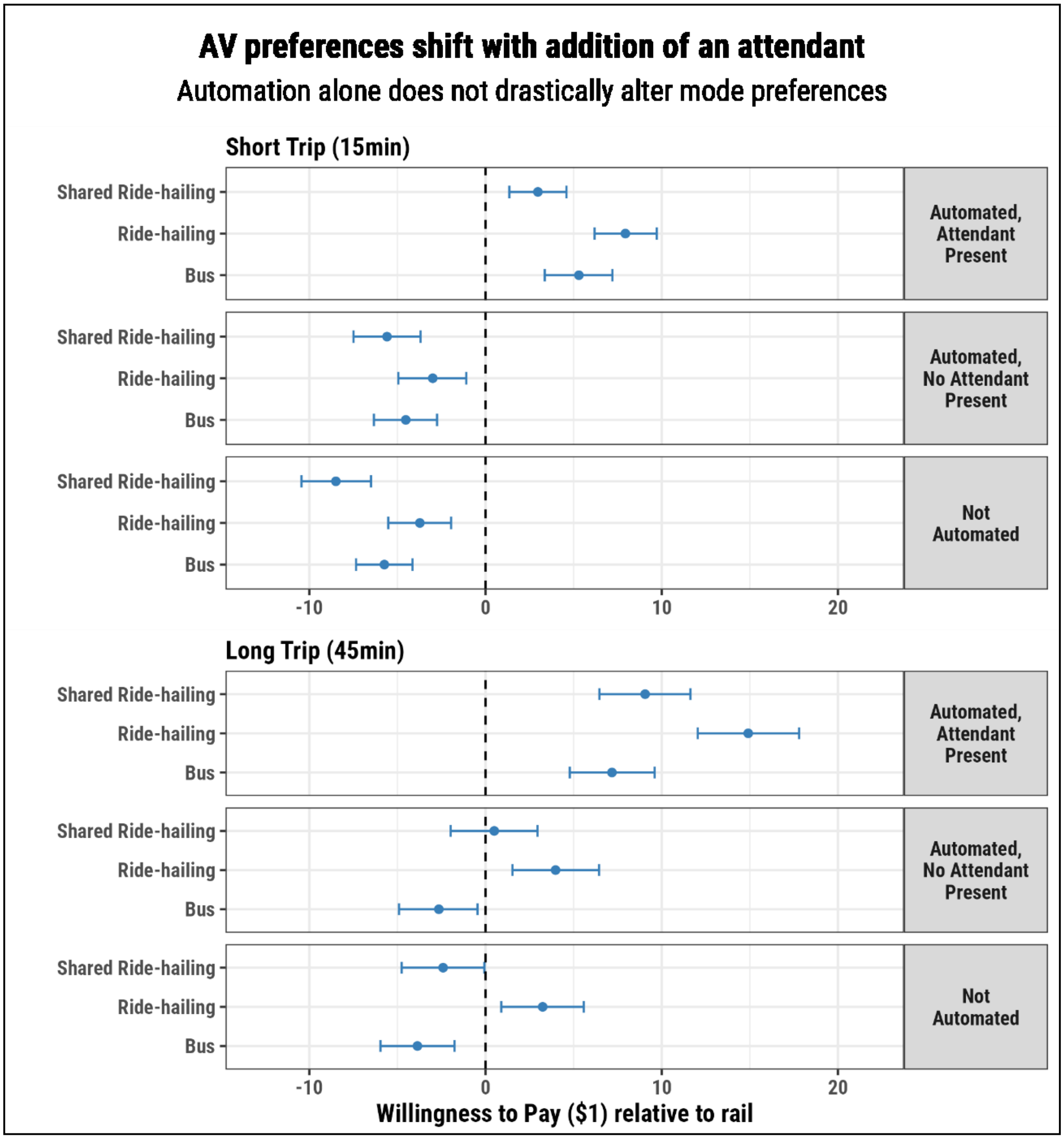



**Figure 4-2:** Average willingness-to-pay (WTP) values with 95% confidence interval bounds for the bus, ride-hailing, and shared ride-hailing modes relative to non-automated rail. Results shown for a short trip and a long trip.

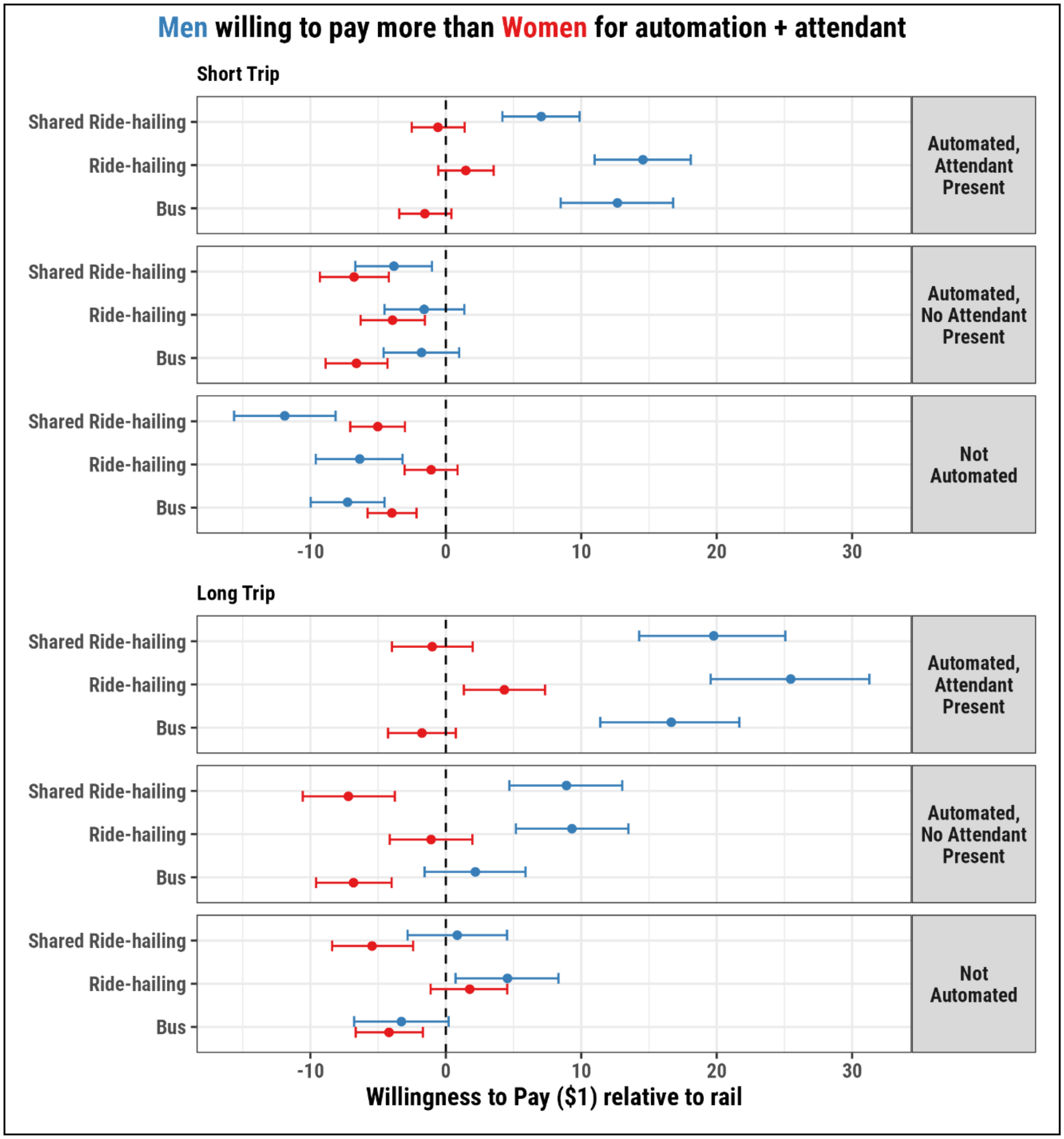



**Figure 4-3:** Gender differences in average willingness-to-pay (WTP) values
Shown with 95% confidence interval bounds for a short trip and a long trip.

### 4.4.4 Scenario analyses

The WTP estimates provide insights into preferences for the different modes, *all else equal*. In reality, any one trip is a combination of mode, price, and travel time. To understand respondent preferences for the joint combination of these attributes, we used the estimated mixed logit choice model to simulate how AVs might compete with transit. We explored six scenarios of characteristic trips across Washington, DC (Table 4-6). We used our “Low-Income Model” to conduct the scenario analysis for Scenario 5 (Trip from lower income area), recognizing that individuals making those types of trips may be members of lower-earning households. Considering the status quo times and prices as the baseline, we modeled how demand for each mode (evaluated in terms of predicted market share) might change in response to automating ride-hailing and shared ride-hailing services. Given that automation is expected to decrease prices, we also added in a 30% price decrease for the automated ride-hailing and shared-ride hailing modes.

We limited the price decrease to 30% based on the current operating budgets for Uber and Lyft, which dedicate only 20% of their annual operating expenses to paying for drivers (Lyft, 2020; Uber, 2020). These scenario analyses should not be interpreted as forecasts but rather as illustrative examples of the substitution patterns that our estimated choice model predicts for the limited respondent pool from our survey. The exercise reflects respondent preferences for the joint set of attributes associated with real trips individuals might take, as opposed to the *all else equal* context of WTP coefficients (Haboucha et al., 2017; Helveston et al., 2015). Real-world forecasts would need to consider preferences of a much broader population and (ideally) include revealed preference data when they become available.

**Table 4-7:** List of scenarios used in scenario analysis and associated attribute values.

| | | | Bus | | Rail | | Ride-hailing | | Shared Ride-hailing | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Scenario** | **Trip Type** | **Distance (mi)** | **Price** | **Time (min)** | **Price** | **Time (min)** | **Price** | **Time (min)** | **Price** | **Time (min)** |
| 1 | Long trip | 10.8 | $2.00 | 80 | $4.15 | 31 | $35 | 25 | $28 | 30 |
| 2 | Pro-rail | 3.8 | $2.00 | 27 | $2.00 | 15 | $13 | 15 | $10 | 20 |
| 3 | Rail with transfer | 3.8 | $2.00 | 40 | $2.25 | 28 | $15 | 25 | $12 | 30 |
| 4 | Pro-bus | 1.3 | $2.00 | 17 | $3.00 | 45 (bus to rail transfer) | $13 | 15 | $10 | 20 |
| 5 | Trip from lower income area | 4 | $2.00 | 40 | $2.29 | 18 | $11 | 10 | $9 | 15 |
| 6 | Bad transit options | 5 | $2.00 | 44 | $3.00 | 46 (bus to rail transfer) | $17 | 15 | $14 | 20 |

The six scenarios we developed capture various trips individuals might take, including those who might travel to the city from the outer-lying regions via one mode (e.g., personal vehicle or train) and then travel within the city using additional modes. We based the travel times and prices for the scenarios on estimated values from Google Maps, Lyft's and Uber's price estimators, the CityMapper travel planning app, and the Washington Metropolitan Area Transit Authority (WMATA) online price estimator (Citymapper, 2022; GoogleMaps, 2022; Lyft, 2022a; Uber, 2022a; WMATA, 2022). We selected scenarios that matched the median trip length (distance) for non-commute trips within the Washington, DC Metropolitan Region (Joh, 2020), as well as edge case scenarios in which we expected certain modes to be considered generally preferable. The scenario names indicate their archetypal trip type. For example, "Pro-Metro" indicates a trip in which the rail system has a direct route between the trip start and end points. Figure 4-4 illustrates the results of the scenario analyses. Status quo indicates current travel times and prices. Moving across the x-axis, we introduce automation, a discount, and having an attendant present for the ride-hailing and shared ride-hailing modes.

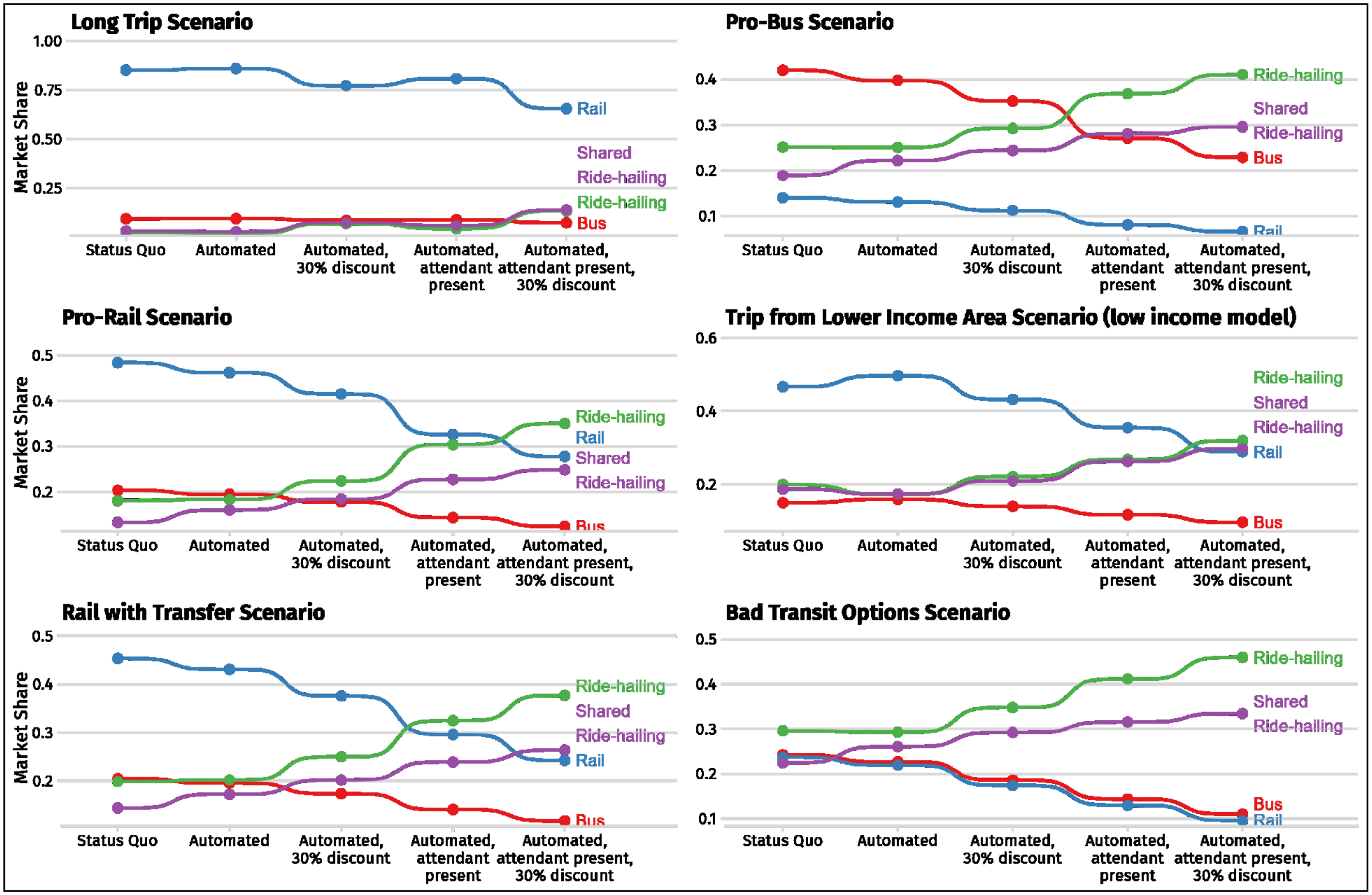



**Figure 4-4:** Mean estimated values for predicted market share based on introducing automation, an attendant, and price discounts for six trip scenarios.

As one moves left to right across the x-axis, additional features are added to the ride-hailing and shared ride-hailing modes. “Status Quo” indicates that none of the modes are automated or have an attendant, and that the modes’ prices reflect current prices. A version with 95% confidence interval error bars is available in Appendix C.3.

The following observations emerge from the scenario analyses:

1. Competition between transit modes and automated ride-hailing services (shared or not) stems more from price discounts than an inherent interest in automation.
2. For trips where rail dominates preferences in the status quo, it remains competitive even against discounted ride-hailing services that are automated, though is less competitive once an attendant is added to the automated modes.
3. Shared ride-hailing services, though less popular in the status quo, become more attractive with additional features and discounts.
4. For trips where people were already likely to use ride-hailing services, that likelihood increases with the addition of automation, an attendant, and a price discount. This supports the idea that automated ride-hailing could help to fill existing transportation gaps.

We are not able to directly compare the status quo results of the scenario analyses with actual market shares since we do not have data on real market shares for these specific types of trips. We are, however, able to compare the status quo results to data on aggregate usage of these different mode types using data from the NCR Regional Travel Survey (also used as our reference demographic sample), which collected information regarding mode usage for trips within the entire region and within areas that are categorized as Equity Emphasis Areas (Appendix C.4). Equity Emphasis Areas are defined as having higher concentrations of low-income individuals and/or traditionally disadvantaged racial and ethnic population groups. The “Trip from Lower Income Area” falls into one of these Equity Emphasis Areas. We find that the ordering of preferences in the status quo results of our scenarios generally matches that of mode use for non-commute trips in the region, with rail as typically most preferable. Bus and rail have more similar mode use within the EEAs in the region than our "Trip from Lower Income Area" scenario estimates. This difference could result from the specific trip that we selected for that scenario which, based on the trip characteristics, favors rail. While we acknowledge these differences, we emphasize that the focus of our study was on trying to understand the potential impact of automation on overall public transit use and feel that these minor differences do not detract from our overall study findings.

## 4.5 Discussion

The results of the study indicate that fears of a mass transition away from transit to AVs may be limited by people's willingness to use AVs, at least in the short term. Respondents to our survey on average were only willing to pay a premium for automated modes when a vehicle attendant was also present, limiting the potential cost savings that AV operators might achieve by removing the driver. Nonetheless, attendant presence may be a critical feature for early AV adoption. Even without a discount, respondents demonstrated a positive willingness-to-pay for automated modes with an attendant onboard.

In many respects, an AV with an attendant onboard is fairly equivalent to current non-automated ride-hailing modes with a human driver. It is then perhaps counterintuitive that individuals would pay more for this feature. One potential explanation is that respondents may perceive computer-driven vehicles as safer or more reliable than those operated by human drivers. Indeed, some prior public engagement research has found evidence of this type of reasoning. Stopher et al. (2021) conducted focus groups with participants of a recent AV pilot program between the AV ride-hailing company Waymo and the Valley Metro Regional Public Transportation Authority in Phoenix, AZ. Some focus group discussants expressed that they felt more comfortable with a computer driver than a traditional ride-hailing driver. Indeed, Waymo appears to be leveraging this perceived benefit with promotional advertisements asserting that, "You want a Driver you can trust" (Waymo, 2022). Yet people may not be fully comfortable ceding total control to automated systems, hence the desire for an attendant. Though our survey specified that the attendant's role was not to operate the vehicle, survey respondents may still have considered the attendant as a safety backup in case of emergency. Future qualitative studies could further explore perceptions of AV attendants and the multiple roles they might be expected to fill. Some studies have already started to explore public attitudes towards different types of attendants, finding preferences for onboard attendants versus remote monitoring (Abe et al., 2020). In the meantime, some AV companies are already choosing—or may be required by state regulations—to launch their services with a safety driver onboard (Schrock, 2021).

The presence of an AV attendant appears especially critical for women. Women only became ambivalent towards automated buses and automated shared ride-hailing services when the modes included an AV attendant. These results perhaps indicate that the presence of an attendant is an essential feature for women to consider using either of these modes, even at costs equivalent to rail.

Overall, competition with public transportation may remain limited by the types of individuals who currently express the greatest willingness-to-pay for AVs: men and higher income individuals. These two groups make up a smaller share of current public transportation users in the United States (Clark et al., 2017), thus ridership losses among those two demographic groups would yield smaller impacts on overall ridership numbers. Nevertheless, the authors recognize that siphoning even small portions of riders away from public transportation modes could still negatively impact the system.

Although the Washington, DC Metropolitan Region has featured some AV pilots and testing (Argo AI, 2021; Kurzius, 2016), we expect that the majority of survey respondents had minimal (if any) experience with an automated vehicle. Approximately 62% of our sample reported having prior experience with ride-hailing services. Individuals' attitudes towards AVs might change as automated transportation modes become more widespread and they gain either exposure to or experience with using automated modes, as has been found with other emerging transportation technologies. For instance, riding in an electric vehicle (EV) for just three to five minutes was found to significantly improve individuals' attitudes towards plug-in EVs (Roberson & Helveston, 2020). This study provides a valuable data point of preferences as they currently stand—a snapshot of the market that both AV developers and transportation planners must face as they plan for an automated future.

In the six aforementioned simulation scenarios, this study focused primarily on competition of automated ride-hailing services with transit. These scenarios did not, however, consider the potential benefits from automating buses. Given that buses are already typically the least expensive transportation option (at least in terms of user costs), automating buses is not expected to further decrease costs to consumers. Instead, proposed benefits include decreasing operating costs which could allow for increased service frequency and geographic coverage, or smaller AV shuttles could help fill gaps in the existing system (Cohn et al., 2019; Whitmore et al., 2022). To avoid excessive cognitive burden of the choice-based conjoint questions, our survey design did not include frequency, wait time, or reliability as choice attributes. Thus, the final model did not include sufficient information to explore scenarios in which buses benefit from automation. Future studies could further explore public interest in potential enhancement of public transportation with automated modes, in addition to competition.

Finally, it is important to recognize some of the limitations of our findings. First, we framed our experiment around taking an evening leisure trip since non-commuting trips account for the majority of trips in the DC area. Results may differ for AV commuting scenarios, though we cannot conclude whether WTPs would be higher or lower for commute trips since the relative value of each trip attribute may differ in these scenarios. We also selected a particular set of attributes which allowed us to focus on the potential impacts of automation and an attendant, but neglected other trip attributes such as wait time which may influence individuals' choice preferences. Our sample included a large portion of higher-income and well-educated individuals who may not be as representative of general public transit users. Nonetheless, the sample was fairly representative of the study region, where costs of living are also higher than many other U.S. cities. While residents in the study region may have higher incomes, it does not necessarily mean that they are any more or less price sensitive to travel costs than in other locations. Thus, while the study results may not generalize to all cities, they may reflect preferences in other large cities that have similarly high costs of living, higher-earning households (on average), and multiple transit modes including buses and rail systems. Moreover, we attempted to highlight preferences of lower-income individuals by specifically using our low income model as part of our scenario analysis. Finally, the emergent nature of AVs means that we are unable to compare our results to actual market data, though "status quo" outputs of our scenario analyses generally reflect the relative usage of current rail, bus, and ride-hailing services.

## 4.6 Conclusions

With the continued development and gradual deployment of automated vehicles, AV companies, mobility providers, and transportation planners will all need to understand how quickly and willing the public is to adopt AVs. In particular, potential competition between AVs and public transit systems could further detract from transit usage, yielding negative environmental and equity impacts. System-level impacts will largely depend upon public uptake of automated transportation modes.

In this study, we investigated the previously unexplored question of the extent to which automated ride-hailing services might compete with public transit modes in the United States. Using data from an online choice-based conjoint survey fielded in the Washington, DC Metropolitan Region, we estimated discrete choice models and used them to simulate choice probabilities for a variety of trips. We find that public interest in automated ride-hailing services stems primarily from the potential to achieve lower prices rather than an inherent interest in automation. Given the current business models for ride-hailing companies, potential competition of automated ride-hailing and shared ride-hailing services with transit modes will likely be limited, since driver costs only account for approximately 20% of ride-hailing companies' current operating budgets (Lyft, 2020; Uber, 2020). Furthermore, for trips where desirable transit modes are available (i.e., low cost and relatively low travel time), transit modes remain competitive even against discounted and automated ride-hailing modes. Thus, investment in improving transit options could also stem future competition with AVs.

Our results also suggest that a vehicle attendant is critically important for increasing AV use. Individuals primarily expressed a positive willingness-to-pay for automated modes only when an attendant was also present. Gender differences also play a role, with men expressing a greater average WTP for automated modes than women. On average, women only expressed a positive WTP for automated ride-hailing services when an attendant was also onboard.

Gaining a greater understanding of public preferences for automated and non-automated modes enables transportation planners to begin designing future transportation systems that account for shifting preferences while still providing critical public transit services. Automated mobility providers can also use this information when making important design and service decisions, such as whether to include an onboard attendant and setting prices. At present, keeping attendants onboard appears critical for both men and women, though these preferences could change as AV deployment expands and users gain more experience with these systems.

# Chapter 5: Policy Implications and Recommendations

This chapter examines the policy implications of the presented research, contributing to ongoing conversations about AI and the Future of Work and the deployment of autonomous vehicle services. This chapter also discusses the potential impacts of robotaxis on Transportation Network Companies.

## 5.1 AI and the Future of Work

Though excitement abounds for emerging AI technologies and their allegedly unlimited potential, these technologies will not be suitable for every use case nor every work system. Even though AI-enabled technologies can now perform a wider range of tasks than prior forms of automation[13], Study 1 demonstrated that *tasks* are not the same as *jobs*, especially when evaluated as part of a full work system (e.g., a driver does more than drive). An AI technology capable of performing a task within a controlled environment may not be suitable for completion of that same task within an actual work system or may necessitate expansions of, or changes to, the work system. Firms should carefully assess whether implementation of an AI technology is suitable for their work system, and proactively consider what larger work-system changes they may need to implement as a result of AI introduction.

[13] While not examined in this dissertation, *how* AI technologies are able to perform these more complex tasks (i.e., their development processes) also raises important questions regarding the legal rights to the training data AI firms use, the treatment of workers involved in AI training and retraining processes, and the environmental impacts of AI technologies' resource use. See Crawford and Joler's (2018) artwork "Anatomy of an AI System: The Amazon Echo As An Anatomical Map of Human Labor, Data and Planetary Resources" for a powerful visual depiction of some of these additional factors.

A limiting factor for AI's expansion into different work systems will be the cost of labor to perform the remaining tasks that the AI technology cannot complete, as well as the costs of newly-introduced work tasks that may emerge. These costs are often underestimated and will influence where AI technologies make sense to implement. This dissertation research revealed that driverless robotaxi services still require human labor for multiple roles (Study 1) and that these roles add non-negligible costs (Study 2). Though higher than prior estimates, these labor costs are not currently precluding robotaxi deployment. Contrastingly, Amazon recently shifted away from its cashier-less grocery stores equipped with "Just Walk Out" technologies due to the high cost of validating customers' purchases using offshored labor in India (Maruf, 2024).

Another force counteracting a jobless future is that AI, like past technological revolutions, will create new jobs, some of which domain-specific decision-makers could predict using the patterns discussed in Study 1, and others which will be difficult to foresee. The quality of these jobs depends on intentional planning decisions. Positive worker and AI technology performance outcomes need not be viewed as goals in tension with one another; rather, workers and intentionally-designed work systems can and should play an essential role in supporting the trustworthy AI systems we all desire. Emerging frontline robotaxi roles, for instance, are critical for supporting the safe deployment of robotaxi services on public roads and are currently being designed in a way that promotes worker agency (further discussed below). Human labor will remain a critical element of designing, verifying, and validating that AI technologies are part of trustworthy systems (i.e., are valid, reliable, safe, fair, bias is managed, secure, resilient, accountable, transparent, explainable, interpretable, and privacy-enhanced (NIST, 2023)).

## 5.2 Impacts of Robotaxis on TNCs

This dissertation primarily drew on taxi services as a point of comparison for emerging robotaxi services since the structure of current robotaxi firms more closely resembles that of a centralized taxi firm than a decentralized (with regard to frontline workers) Transportation Network Company (TNC, e.g., Uber). Nevertheless, the expansion of robotaxi services will likely impact TNCs and the gig workers that engage on their platforms, as they offer comparable services.

If robotaxi firms become direct competitors with TNCs, TNCs may have to lower their fares in order to compete, though doing so could threaten the economic viability of TNCs that are still struggling to achieve consistent profitability (Saul, 2024). To offset lower fares, TNCs could increase fees on drivers—decreasing drivers' net pay—potentially reintroducing challenges with attracting and maintaining drivers on their platforms (Gregg, 2024) and exacerbating ongoing legal battles with localities over platform driver minimum wages (Rothenberg, 2024). As companies with a global presence, TNCs could also focus their operations on areas in which robotaxi deployment is less likely to occur (i.e., areas with lower utilization, per Study 2's findings), as well as their other types of service offerings (e.g., e-scooters, e-bikes, rental cars).

Alternatively, TNCs could incorporate robotaxi vehicles onto their platforms, an approach Uber is pursuing via its partnerships with Waymo and other AV technology developers (Uber, 2024). Such partnerships could impact the cost structures and business models for both AV firms and TNCs. Negro et al. (2021) note that TNCs annually spend millions of dollars on driver incentives and referrals. This spending could shift towards incentivizing AV firms to post their vehicles onto the TNCs' platforms to meet rider demand. Study 2 found that robotaxi operating costs are lower than those of taxi services. Assuming human TNC drivers' internalized costs are more similar to taxis than robotaxis, human drivers would need higher incentives to drive to offset their higher operating costs. By switching from incentives for human drivers to incentives for AV firms, TNCs could decrease their overall spending on incentives. Yet the opposite may also be possible. Robotaxi firms may require higher incentives to ensure their profitability or may demand contracts that guarantee a certain level of utilization of their vehicles.

The aforementioned contract structures assume that AV firms would continue filling both the technology developer and fleet operator roles, yet the long-term business models for these firms remains undetermined. In a 2022 SEC filing, the AV trucking company Aurora explicitly stated that the company ultimately plans to transition to a supplier of AV technology, not an owner or operator of large vehicle fleets (Aurora Innovation, Inc., 2023). If AV firms transition away from serving as fleet operators, TNCs or different entities would need to fill that function. One interviewed AV Operations Expert described how traditional vehicle fleet operators could fill this role:

> Who could serve as [the] fleet operator? Well, there's a lot of companies. I mean, there are companies that already serve as fleet operators, right? You've got trucking companies out there, is one obvious example, they serve as fleet operators, in many cases. Rental car companies serve as fleet operators, they rent cars out. Could they conceivably do [it]? Maybe, I'm not sure. But there are sort of other models, there are other companies out there who are not in the AV space who may actually longer-term be interested in being fleet operators for a fleet of autonomous vehicles because they can take advantage of sort of efficiencies they have in their business already to handle something that looks like it, whether it's renting cars to humans, or driving trucks or operating shuttles or what have you in terms of the fleet operator ecosystem (Interview with AV Operations Expert, February 24, 2023).

Study 1 revealed that the introduction of AVs introduces additional tasks and roles that support both the vehicles and the passengers. Whatever firm ultimately takes on the fleet operator role—if not performed by the AV developer—would need to reorient its work system to accommodate these new tasks and roles. This transition would require careful planning, as separating the technology developers from the operational workforce could compromise how well certain roles able to manage incidents that occur with the vehicles, for either remote or direct forms of support. One interviewed Frontline Worker acknowledged the potential for such a transition, but highlighted some of the drawbacks with disaggregating company roles:

> For my own personal opinion, I think that it's doable. I think heavily skilled training is really involved in it as well…really having like, for lack of a better term, like your ducks in a row when you're training these new companies to take over the technology. I personally think it works a lot better when you're all together...But it's also definitely doable if you package it all together and, you know, describe to them what kind of roles and positions you would need…I think [AV company] has done such a good job of defining all of that, that it's hard for me to see it all separated (Interview with Frontline Worker, August 9, 2023).

Traditional fleet operators looking to transition to management of AV fleets should not undervalue the organizational learnings robotaxi firms have accrued and the embedded knowledge of their workforces. Transitioning to an AV fleet will require not only investment in the new technologies, but also investment in upskilling and retraining their workforce.

How might these evolving business models impact current TNC drivers? Uber's webpage on autonomous futures asserts that they "…imagine a future where autonomous vehicles and human drivers seamlessly work together to make transportation more reliable, affordable, sustainable, and safer. Our vision is one of a shared, electric, and multimodal future, with AVs operating alongside drivers and couriers, each bringing their unique capabilities to the table" (Uber, 2024). Though robotaxi vehicles might not completely displace human drivers on TNC platforms, their availability as an alternative mode choice could cut into the number of trips available for human drivers. This increased competition for rides could put downward pressure on earning for human drivers.

Remaining trips available for human drivers could include those perceived as less desirable or those that require more in-person support. Robotaxi firms may not send their vehicles into areas that are geographically difficult to navigate or those in which they fear damage to their vehicles[14]. Human drivers undoubtedly have their own personal safety concerns—and biases—that influence what trips they accept, but may be more flexible in terms of the geographic regions in which they operate.

Available trips could also include those that require more in-person support. TNC drivers could compete with taxi services to offer specialized types of transportation services like non-emergency medical transport (e.g., Uber Health or Lyft Healthcare). Gig workers could also focus on food and goods delivery services. Some AV firms like Nuro are working on purpose-built goods delivery vehicles and are partnering with large companies like Walmart and FedEx to perform goods delivery (Nuro, 2024). Nonetheless, AV services may be less suitable for engaging with different types of goods providers. Consider, for instance, the diverse types of storefronts and restaurant operations that a typical UberEats driver may navigate on any given day. Developing technologies to accommodate every environment and situation may be more costly than continuing to fill these trips with human drivers. As Study 1 noted, the non-automatable tasks and hidden subtasks that these drivers are performing will influence whether or not

[14] In some regions, robotaxi firms have faced problems with vandalism to their vehicles, including vehicles that have had their windows smashed and been set on fire (Davis, 2024).

their role can be eliminated within a given work system.

Visions of a shared future in which human drivers and AVs can collaborate to meet demand for passenger and goods delivery services are indeed ideal. Achieving such futures will require proactively engaging with TNC drivers to make sure their voices receive equal weight as AV developers when designing that future.

### 5.3 Recommendations for an AV Future

The following recommendations are based on both the research findings presented in this dissertation, as well as the author's broader engagement with the autonomous vehicle research and policy communities.

1. **Invest in and improve transit services, and foster rich transportation ecosystems.**

During this period of still-limited AV deployment and uncertainty regarding the future of the AV industry, transportation planners should continue pursuing other approaches for solving current transportation problems. Study 3 finds that based on current public preferences, AV ride-hailing services may only compete with trips for which poor transit options exist. Continuing to invest in and improve transit services may stave off future competition from AVs or, viewed more optimistically, direct AV services to fill in transit service gaps and improve overall transportation access.

Cities should also continue exploring other forms of transportation services that might reduce dependency on individually-owned vehicles, including micromobility programs (e.g., bikeshare, e-scooters) and microtransit services. The results from Study 2's *AV Advanced Technology* scenario suggest that even with cost-reducing technology advancements, robotaxi services are unlikely to achieve lower costs than personal vehicle ownership. Nonetheless, fostering a rich transportation ecosystem could help address issues of environmental sustainability and traffic congestion in the short-term and could lay the groundwork for allowing shared AV services to integrate into, and further enhance, rich transportation ecosystems. Arlington, Texas, already uses an on-demand rideshare service as its primary public transportation offering and has been integrating AVs into this service for the past few years (Khan et al., 2022). Their approach could be used as a model for phased introduction of AVs, especially for cities that similarly lack traditional transit services.

2. **Identify where AV deployment and job losses are (and are not) likely to occur.**

Autonomous vehicles are unlikely to replace all driver jobs in the near or long term. In the short term, AV firms will likely continue to deploy their services in locations that offer simpler operating conditions and will continue to scale on a city-by-city or even a route-by-route basis, limiting AVs' impact on the transportation workforce. As one interviewed AV Regulation Expert described:

> I just see this as a very multistage deployment. Thereby the impacts are going to be multistage. And even if it was all to happen right now, I still think the economics would not justify broad-scale…coast-to-coast deployment, at least in the short term (Interview with AV Regulation Expert, November 08, 2022).

As noted by the interviewee and highlighted in Study 2's findings, the competitiveness of certain AV services like robotaxis is highly sensitive to utilization. AV firms will likely limit their services to domains in which they can achieve sufficient utilization to offset their higher technology costs.

Moreover, AVs may never be suitable for all types of transportation services. In certain trucking sectors, firms may want (or be required) to keep drivers onboard to help prevent freight theft or to handle regulated materials (Gittleman & Monaco, 2020). Study 3's findings also suggest that some passenger transportation riders may still require, or at least prefer, in-person support. On average, individuals were only willing to pay a premium for autonomous modes that had an attendant present.

Though robotaxi firms have, as Study 1 reveals, redistributed many of the taxi driver's tasks to remote roles, this redistribution may not be sufficient for all situations. As another interviewed AV/Taxi Regulation Expert explained:

> …there's a certain element of customer service that has evolved. And I think there may be some people who always, even in [highly] automated vehicles, keep someone in the vehicle…[For] non-emergency medical transport, I think drivers or assistants will have their jobs reclassified and there will be people that ride along, get paid by insurance, [help] people get to and from dialysis. In the limousine industry, there's no way that there's going to be no driver that's going to meet somebody in luggage if they're an entertainer. Even if it's an automated limo, there's still going to be a chauffeur who's going to serve as a concierge (Interview with AV/Taxi Regulation Expert, February 15, 2023).

Though robotaxi firms are using a combination of technology and human labor to provide many forms of passenger support, in-vehicle support may always be necessary for certain types of transportation services. These situations still call for either human-driven services or, as the interviewee suggested, AV services with an onboard attendant.

AV firms could partner with human-driven services to handle such situations. These partnerships could be part of a "three-tier" transportation ecosystem in which AV technology suppliers, Transportation Network Companies (e.g., Uber, Lyft), and human independent contractor drivers all coexist in the marketplace (Freund et al., 2022). As Uber policy lead Miriam Chaum once described, AVs could be introduced to fill trips "where and when [they're] best suited" (Chaum, 2023). Ideally, this "three-tier" model would support the richening of the transportation ecosystem, but regulators may need to play a role in ensuring that the different competing services do not spur a race to the bottom that harms both human workers and riders[15]. Ultimately, restricted AV operational domains and demand for forms of in-person support will limit AV job displacement.

3. **Investigate the root causes of existing transportation labor shortages and lack of workforce diversity, and implement strategies to address them.**

Given that driving jobs will likely persist in both the short and long term, transportation companies, government agencies, and researchers should continue to investigate the root causes of existing labor shortages and lack of diversity in the transportation workforce, and implement identified strategies to address them (see Agrawal et al. (2024) and APTA (2023) for proposed strategies focused on the public transit domain).

AV firms may be able to leverage perception of their companies as exciting AI technology developers to attract workers and may face fewer shortages as a result. One interviewed Senior Manager at a robotaxi firm attributed the relative ease with which he could recruit workers to this novelty factor: "I think part of the reason is the job, like straight up, the job is so cool that people are like, 'Man, this is awesome. I want to be a part of this'" (Interview with Senior Manager, August 10, 2023). This novelty factor may help attract workers to the AV industry, but absent competitive wages and benefits, AV firms may face similar issues with worker retention and labor shortages as are present in other transportation sectors.

[15] The International Association of Transportation Regulators' "Best Practices, Guiding Principles and Model Regulations for 'Robotaxis'" offers some guidance for how regulators might best implement AV regulation in the passenger transportation sectors (IATR, 2022).

Decision-makers should engage directly with workers and should be open to alternative perspectives on what constitutes a "good job," and how that definition might differ by amongst various populations. One interviewed Operator believed working for a robotaxi firm was better than driving for a TNC. As the worker explained:

> I would say, without a doubt, it's better to work at [Robotaxi Firm]. Because as [an] Uber driver, you're essentially taking on all the risks…you're an independent contractor. At [Robotaxi Firm], you're already a good driver. So you enjoy driving, I would assume, if you're doing it. You're doing essentially the same thing but you're learning a new technology. [You] have the chance to grow within a company, hopefully. And you get great benefits (Interview with Operator, September 30, 2022).

Though this worker appeared to value the stability and benefits of full-time employment with a robotaxi firm, not all workers may share the same perspective. As Matthew Daus, former Commissioner/Chair/CEO of the New York City Taxi and Limousine, explained:

> …drivers don't want to work as employees. A lot, most of them do not, in my experience. They don't want to be told what time to go to work. They don't want to wear a uniform, but they want benefits that employees get (Personal Correspondence, 2024).

Though perhaps offering better stability and benefits, full-time robotaxi firm roles may not offer the flexibility and independence that current taxi and TNC drivers desire. Taxi and TNC workers that either cannot or lack the desire to pivot into AV industry roles will require alternative career paths.

4. **Proactively identify alternative career paths for displaced workers and bolster the quality of jobs that remain.**

Study 2's results suggest that if jobs shift from traditional taxi to robotaxi services, the total number of frontline jobs could decrease by between 57% to 76%. Researchers should proactively investigate alternative career paths for displaced workers within the taxi industry and other potentially-affected sectors. Some workers could transition into the robotaxi industry since many of the frontline roles do not require advanced degrees and involve many of the same tasks and skills as current frontline taxi roles (Study 1). Beyond within-taxi or even within-transportation transitions, Wang et al. (2023) identified a number of potential job alternatives for truck drivers based on the knowledge, skills, interests, and values of current trucking jobs. Future research should identify transition occupations for taxi workers and engage with those workers to evaluate the desirability of alternative occupations. Taxi driver roles are often filled by immigrants and racial minorities for whom full-time wage work is unavailable (Dubal, 2017), raising questions regarding whether those individuals could realistically pivot into other full-time roles.

Decision-makers must also work to ensure that remaining driving jobs in an AV future do not diminish in quality and are not entirely displaced by more precarious work arrangements (i.e., performed by gig workers on a part-time rather than full-time employment basis and lacking in labor protections). Thus far, many of these frontline labor roles resemble mid-skill, mid-wage positions but are often contractor positions (Study 1). As the industry matures and stabilizes and roles become more defined, firms should shift these roles to full employees to ensure workers receive benefits and labor protections.

Another approach to bolster quality jobs could be through licensing or certification requirements, particularly when such requirements could also improve service quality. Taxi drivers, for instance, have become more involved in non-emergency medical transport services. These services sometimes require certifications to engage with healthcare insurance providers and local transportation programs (Cluett, 2024; DFHV, 2019). Such certifications could ensure that passengers receive the support they require and that the workers providing that support get meaningful compensation and labor protections.

Navigating the labor transition from traditional to autonomous modes of transportation will require significant coordination between AV firms, workers and worker-advocates, and policymakers. While undoubtedly challenging, the criticality of this issue cannot be understated. As one interviewed AV Regulatory Expert asserted, “Labor is the single most important issue that can make or break this movement completely, or push it back significantly… it will make or break it more than any other issue that's out there, even more than safety” (Interview with AV Regulatory Expert, February 15, 2023).

5. **Develop tools and training programs that support quality jobs.**

AV technologies are already creating, and will continue to create, new jobs. These jobs include not only roboticists and engineers involved in technology development, but also frontline roles that support AV services. As identified in Study 1, some of these roles are created from redistributed tasks and others emerge to support specialized functions or emergent information processing needs. Decision-makers should work to shape emerging roles into high quality jobs.

One element of that shaping process is the design of tools with which workers interface with the technologies. AV firms have designed tooling that allows for less-technical individuals to engage with the vehicles and fill frontline labor roles. As one

Frontline Worker with multiple years of experience in the AV industry explained:

> Very early day autonomy you had to have a lot of computer skill[s] and a lot of computer knowledge to understand how to work and how to do these [frontline] positions…it's been really cool to see the way that things have been shaped into making these roles very accessible for everybody. Even, you know, you may not be a computer whiz, but you can definitely work in [remote monitoring] now, where I don't think maybe 5-10 years ago, you would have been able to do that. It would've been very engineering focused (Interview with Frontline Worker, August 9, 2023).

Though simplified tooling can create more accessible job opportunities, overly-simplified tooling could lead to negative worker outcomes. As Cesafsky et al. (2019) describe, if firms limit remote monitors' situational awareness too much, they could turn the remote monitor role into a rote (likely low-paying) microwork job akin to repetitive assembly-line work.

At current robotaxi firms, intentional tooling design and worker training still allow the frontline workers to exact a sense of agency and draw on critical thinking skills. One interviewed Mid-Level Manager at a robotaxi firm described the firm's training process as follows:

> I always equate it to tools, like in a shed…I'm not going to be able to tell you if you're building a house, you nail it this way, if you're building a bucket, you hammer it this way. I'm just going to teach you this is the hammer and you swing it to hit a nail. And that's kind of how our training is. We teach you how our tools are used so that when you're in a situation, you know, "Ah, this one requires the screwdriver, I need to pull that out. Oh, wait, no, this one requires the saw, I need to pull that one out." So we're going to teach you what the tools are so you know which tool to use. And from there, you have to manipulate it to where it will provide the path of success for the vehicle to get out of the situation. So that is where the critical thinking comes in (Interview with Mid-Level Manager, September 26, 2023).

AV firms should continue designing tooling and training programs that balance technical complexity with worker empowerment and agency.

Moving forward, public-private partnerships could play a role in shaping AV jobs into mid-skill professions and supporting workforce development programs to fill these roles. As one example, the Contra Costa Transportation Authority's GoMentum Station is leveraging public-private partnerships to promote not only AV technology development, but also AV workforce development and training (CCTA, 2024). At the federal level, the U.S. Department of Energy recently established an Office of Energy Jobs to ensure that job creation, job quality, and equitable access to jobs are taken into consideration in DOE funding, initiatives, and priorities. Some of this Office's programs support jobs focused on electric vehicles and electric vehicle infrastructure. These programs could translate to the AV realm, as some AV firms are developing vehicles that are both autonomous and electric. Alternatively, the Department of Transportation (DOT) could establish a similar office focused on vehicle automation jobs, or could expand the National Highway Traffic Administration Office of Automation's purview to track AV worker outcomes.

AV firms have already begun partnering with community colleges to meet their emerging workforce needs, and even offer paid opportunities for students as part of these programs (Interview with AV Operations Expert, October 22, 2022). Firms might also consider establishing Registered Apprenticeship programs that similarly combine paid work experience with industry-specific instruction. The U.S. DOT has already issued guidance for state transportation agencies on developing Registered Apprenticeship programs for the EV workforce, which could potentially be adapted into similar AV-focused programs (USDOT, 2024). One factor that may limit the development of AV apprenticeship programs is variation in AV firms' technical approaches. AV firms may need to collaboratively develop best practices for required skills and training requirements for emerging AV workforce roles to ensure that an apprenticeship program would be broadly applicable.

6. **Incorporate workforce considerations into safety cases and safety management systems.**

Researchers, regulators, and AV firms are working to determine how best to evaluate the safety of AV systems. These efforts have brought about standards for AV safety cases (Underwriters Laboratories, 2022) and safety case roadmaps (Wagner & Carlan, 2024). Often, the boundary of analysis for the “AV system” is the vehicle system. Study 1 reveals, however, that workers also play critical roles in ensuring the safety of AV systems and highlights the need to consider work systems as part of safe AV system design. AV firms should establish strong safety cultures and draw on best practices from related domains like the airline industry to incorporate workforce training into their safety management systems. Indeed, as Study 1 discusses, AV firms are already recruiting workers from the airline industry.

Though Study 2 finds that robotaxi firms will require fewer frontline workers to support their fleets, AV firms should also weigh the potential cost savings from labor reductions against potential negative service performance and quality impacts. As the study notes, striving for the lowest possible number of workers may offer minimal additional cost savings but could negatively affect worker performance outcomes. Human-computer interaction research should investigate worker performance impacts at varying labor ratios to inform optimal work system design. When (or if) the AV industry becomes sufficiently mature and standardized, these work system designs could become codified in regulation in a similar manner as the aviation industry. As one interviewed

Senior Manager with aviation experience described:

> …you literally get a book [from the Federal Aviation Administration] of what you can and can't do, and that includes people that have to be in certain roles. But that is from a hundred years of law and aviation safety and a long history that has got us to that point. And all that is very nascent in the self-driving space where we're still trying to figure out what business models work, what is the best kind of operational design domain, what is the most commercially viable [model]. Much less, you know, not even to consider the different types of technology that are used. All that is being developed. But I see it eventually getting [to] a similar structure...[There] needs to be kind of a system of accountability and some normal things to expect from these different companies (Interview with Senior Manager, September 5, 2023).

Much of the discussion about AV safety regulation thus far has been focused on the design of the vehicle, with calls for the National Highway Traffic Safety Administration (NHTSA) to develop standards for AVs (Markey et al., 2024). Evaluations of AV safety must consider the broader work systems that monitor and support the AV services and their users.

The author would like to acknowledge the many dedicated individuals already working on these issues and hopes that the research and policy recommendations in this dissertation can further ongoing discourse and efforts in these critical domains.

# Chapter 6: Conclusion

## Summary of research contributions and proposed future research

We live in a time of both optimism and trepidation regarding new artificial intelligence (AI) technologies that are entering the public sphere and becoming increasingly intertwined in our lives. This dissertation explored autonomous vehicles (AVs) as a case study of the potential effects of AI-enabled automation in the physical world, in particular examining AVs' impacts to labor and transportation systems via competition with other modes. AVs hold promise of helping to address many of the persistent problems that plague our transportation systems—issues related to environmental sustainability, accessibility, equity, and labor shortages. Yet there is also potential for AVs and other AI-enabled automation technologies to cause harm, or at least promote an inequitable distribution of benefits. The research presented in this dissertation aims to not only inform dialogue regarding potential AI and AV impacts, but also to empower technologists, decision-makers, and all of us who have a stake in an AI future to engage with and shape that future.

### 6.2 Summary of Contributions and Proposed Future Research

Study 1 investigated how the introduction of AVs to a taxi work system reshaped tasks and labor roles and provided the first detailed description of frontline labor roles in emerging robotaxi services. It is the first study to empirically demonstrate that the introduction of AI-enabled automation technology to a work system centered on a non-routine manual task spurs a rebundling of tasks and labor roles, and the study's granular analysis revealed that this rebundling occurs via three archetypal patterns: *distributing*, *consolidating*, and *scaffolding.* These patterns of role change can be used to refine labor outcome analyses and predict labor impacts at the task, role, and sector or economy levels.

The study's findings suggest that prior analyses may have miscounted the number of the number of affected occupations—undercounting impacts in some respects and over-counting impacts in others. By taking a work-systems approach, Study 1 demonstrated that AI introduction can affect multiple roles, not just the primary role associated with an automatable task, signaling that prior labor analyses may have underestimated AI impacts. Yet it also highlighted that evaluating a role solely through the lens of an automatable task can lead to over-counting of the number of impacted jobs; the remaining tasks *not* performed by AI technologies could limit or preclude use of AI in certain sectors and curb job displacement. Consideration of connected roles and of the technology deployment context could improve the accuracy of AI impact analyses.

Though integration of AI technologies in the physical world will always involve a level of uncertainty, the patterns identified in Study 1 increase the predictability of changes that might occur. By evaluating changes in terms of *distributing* and *consolidating* roles, firms can better plans for the types roles they might require, and whether they might need *scaffolding* roles as part of a transition state. The identified patterns also allow researchers to refine their categorization of AI impacts to focus less on end-states and more on the processes by which changes are occurring, opening up opportunities to design roles in ways the support positive worker outcomes. The identified patterns may generalize to other work systems in which non-routine manual tasks are central to the work performed. Future research should test the generalizability of the patterns to work systems that primarily rely on other types of tasks.

Study 1 also offered preliminary insights regarding sociodemographic information and current training requirements for the emergent robotaxi workforce which could inform the design of workforce development programs for robotaxi services. Similar labor roles and labor requirements may be required for autonomous public transit services. Future research should perform a more extensive survey of the AV frontline labor force to collect more information on the sociodemographics of the frontline workers and should examine how these labor roles and their quality might change as the AV industry matures.

Study 2 leveraged the findings from the first study to develop a more refined ground-up cost model for a robotaxi service, improving model precision regarding the cost of AV technologies and the labor costs needed to operate a robotaxi service. The model revealed that labor remains a significant cost for robotaxi services but that robotaxi operating costs are still lower than those of taxi services. Fare per mile values were highly sensitive to low worker to vehicle ratios (i.e., workers can manage fewer vehicles), but firms could reach economies of scale relatively quickly. Regulation that limits how many vehicles each robotaxi worker can monitor could result in higher costs for robotaxi firms and limit their competitiveness against existing services. Striving for the lowest possible number of workers, however, may not be necessary either. After an initial steep decline, fare per mile values are relatively similar for labor ratios of 1:15 (worker to vehicle) or higher. AV firms will have to weigh marginal labor cost reductions against impacts to service quality for their passengers and performance consequences for their employees (e.g., mental workload, situational awareness).

Though labor remains an important consideration, utilization rates and annual mileage will ultimately determine the competitiveness of robotaxi services. The results from Study 2 suggest that if jobs shift from taxi to robotaxi services, the total number of frontline jobs could decrease by between 57% to 76%, but the distribution of worker wages would shift higher. This estimate is based on the specific frontline roles included in the study and does not capture additional jobs that may be involved in the technology training, development, production, and distribution of AVs, which could change the results in terms of the number of jobs required to support robotaxi services and their associated wages. Nevertheless, it offers a preliminary estimate for labor impacts to taxi services.

Study 2's *AV Advanced Technology* scenario captured a future in which technology costs decline significantly. Future work should track the rate at which costs actually decline, and whether additional technology costs are later introduced. Overall, Study 2's findings highlight the need to continue accounting for labor costs in an AI future. Purported cost savings of AVs, as well as other capital-intensive AI technologies, should be considered in light of remaining labor costs, and economic viability may depend on the technology's intended operational context.

Finally, Study 3 investigated potential mode competition between AVs and transit based on public preferences for autonomous and non-autonomous transportation modes. The choice-based conjoint experiment revealed that competition between autonomous ride-hailing services and transit may remain limited based on individuals' current preferences. On average, individuals were only willing to pay a premium for autonomous modes that had an attendant present, limiting discounts that ride-hailing firms could provide. The scenario analyses in the study also revealed that transit remained competitive with autonomous ride-hailing modes for trips where good transit options were available.

Study 3 also identified the presence of an in-vehicle attendant as a potentially critical feature for early AV adoption, especially for women. On average, women only expressed a positive willingness-to-pay for AV ride-hailing services when an attendant was also onboard. Future research should examine the underlying reasons behind the stated interest in the attendant feature—are members of the public wary of the technology or do individuals truly value the presence of a human worker? As members of the public gain more exposure to and experience with AV services, their preferences may shift and the attendant feature may decrease in importance. Study 3's choice experiment could be fielded again to evaluate preference changes over time. Ultimately, developers of AVs and other AI technologies should carefully consider multiple design factors that might influence public adoption of emerging AI technologies.

## 6.2 Navigating the Future of AI-Enabled Technologies

Autonomous vehicles are one of a number of emergent AI-enabled technologies that promise to revolutionize our current systems. This dissertation filled three gaps in the existing literature about AV impacts and drew out lessons applicable to other AI-enabled automation technologies that can perform non-routine manual tasks. AI technologies are powerful tools that can perform more complex tasks than prior forms of automation. Nonetheless, they may not suitable for use in all contexts, and their integration into complex systems requires thoughtful planning.

AI-enabled automation technologies deployed in the physical world will not eliminate the need for human labor but will reshape the work systems in which they are introduced. Whether firms choose to eliminate labor roles following AI-introduction and how they choose to redistribute tasks amongst new and existing roles are important decisions that will shape work system design. Transition states may also occur as AI-technologies improve over time, impacting tasks and roles. When researchers focus on the end-states of roles, they miss many of these important decision points.

AI technology implementation will also be sensitive to deployment context. The remaining tasks not performed by AI technologies—potentially influenced by regulatory constraints or public preferences—may determine whether the technologies are introduced within a specific sector at all. Labor ratios will impact the relative cost-competitiveness of AI solutions, especially for high-cost AI technologies that may need labor cost savings to offset higher capital costs. Utilization will also drive relative competitiveness; firms will likely deploy AI technologies in contexts that ensure high utilization to maximize revenue generation. Cost is not, however, the only consideration for AI technology adoption. Firms looking to integrate AI technologies to perform non-routine manual tasks need to weigh potential cost reductions against impacts to workers and to service quality and accessibility. Moreover, users may still want or need the involvement of human workers in order to use the system.

Autonomous vehicle deployment is unfolding amidst a broader movement toward widespread implementation of AI technologies in nearly every aspect of our daily lives. As we gain these early insights into the impacts of AVs and other AI-enabled automation technologies, we create the opportunity to proactively shape societal outcomes toward desirable futures.

## References


AAA. (2023, October 3). *National Average Gas Prices*. AAA. https://gasprices.aaa.com/

Abe, R., Kita, Y., & Fukuda, D. (2020). An Experimental Approach to Understanding the Impacts of Monitoring Methods on Use Intentions for Autonomous Vehicle Services: Survey Evidence from Japan. *Sustainability*, *12*(6), Article 6. https://doi.org/10.3390/su12062157

Acemoglu, D., & Autor, D. (2011). Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics* (Vol. 4, pp. 1043–1171). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, *108*(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, *33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Adecco. (2023). *Adecco @ Cruise: Driverless Support Specialist*.

Agrawal, A., Blumenberg, E., Loukaitou-Sideris, A., & Lu, B. (2024). Understanding Workforce Diversity in the Transit Industry: Establishing a Baseline of Diversity Demographics. *Mineta Transportation Institute*. https://doi.org/10.31979/mti.2024.2213

Alonso Raposo, M., Ciuffo, B., Ardente, F., Alves, D., Aurambout, J. P., Baldini, G., Baranzelli, C., Braun, R., Christidis, P., Christodoulou, A., Duboz, A., Felici, S., Bobba, S., & Cassio, L. (2019). *The Future of Road Transport—Implications of Automated, Connected, Low-Carbon and Shared Mobility* (EUR 29748; pp. 78–84). Publications Office of the European Union.

Ammann, D. (2020, January 21). *The Cruise Origin will help deliver a better future | Cruise*. The Cruise Origin Story. https://getcruise.com/news/blog/2020/the-cruise-origin-story/

Appleyard, B., & Riggs, W. (2017). *Measuring and Doing the Right Things: A Livability, Sustainability and Equity Framework for Autonomous Vehicles* (SSRN Scholarly Paper ID 3040783). Social Science Research Network. https://doi.org/10.2139/ssrn.3040783

APTA. (2022, March 10). Public Transportation Facts. *American Public Transportation Association*. http://www.apta.com/news-publications/public-transportation-facts/

APTA. (2023). *Transit Workforce Shortage Synthesis Report*. American Public Transportation Association. https://www.apta.com/wp-content/uploads/APTA-Workforce-Shortage-Synthesis-Report-03.2023.pdf

Arbib, J., & Seba, T. (2017). *Rethinking Transportation 2020-2030* (p. 144). RethinkX. https://static1.squarespace.com/static/585c3439be65942f022bbf9b/t/591a2e4be6f2e1c13df930c5/1494888038959/RethinkX+Report_051517.pdf

Argo AI. (2021, December 20). *Argo AI Conforms to Autonomous Vehicle Testing Standards According to Leading Independent Auditor*. Argo AI. https://www.argo.ai/company-news/argo-ai-conforms-to-autonomous-vehicle-testing-standards-according-to-leading-independent-auditor/

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis*. OECD. https://doi.org/10.1787/5jlz9h56dvq7-en

Arslan, R. C., Walther, M. P., & Tata, C. S. (2020). formr: A study framework allowing for automated feedback generation and complex longitudinal experience-sampling studies using R. *Behavior Research Methods*, *52*(1), 376–387. https://doi.org/10.3758/s13428-019-01236-y

Ashkrof, P., Correia, G. H. de A., Cats, O., & van Arem, B. (2019). Impact of Automated Vehicles on Travel Mode Preference for Different Trip Purposes and Distances. *Transportation Research Record*, *2673*(5), 607–616. https://doi.org/10.1177/0361198119841032

Aurora Innovation, Inc. (2023). *Form 10-K*. https://ir.aurora.tech/sec-filings/all-sec-filings/content/0001828108-23-000069/0001828108-23-000069.pdf

Autor, D. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, *29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D. (2022). *The Labor Market Impacts of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty* (Working Paper 30074). National Bureau of Economic Research. https://doi.org/10.3386/w30074

Autor, D., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration*. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

BACP. (2020). *Chicago's Guide to Licensing Public Passenger Vehicles*. Business Affairs and Consumer Protection. https://www.chicago.gov/content/dam/city/depts/bacp/publicvehicleinfo/medallionowners/publicvehiclelicensingguide20200127.pdf.

Bailey, D. E. (2022). Emerging Technologies at Work: Policy Ideas to Address Negative Consequences for Work, Workers, and Society. *ILR Review*, *75*(3), 527–551. https://doi.org/10.1177/00197939221076747

Bailey, L., Mokhtarian, P. L., & Little, A. (2008). *The broader connection between public transportation, energy conservation and greenhouse gas reduction* (No. TCRP Project J-11/Task 3). ICF International Fairfax, VA.

Baldwin, C. Y., & Clark, K. B. (2000). *Design rules: The power of modularity* (Vol. 1). MIT press.

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, *67*, 1–14. https://doi.org/10.1016/j.trc.2016.01.019

Bauchwitz, B., & Cummings, M. (2022). Effects of Individual Vehicle Differences on Advanced Driver-Assist System Takeover Alert Behavior. *Transportation Research Record*, *2676*(5), 489–499. https://doi.org/10.1177/03611981211068362

Bauer, G. S., Greenblatt, J. B., & Gerke, B. F. (2018). Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. *Environmental Science & Technology*, *52*(8), 4920–4928. https://doi.org/10.1021/acs.est.7b04732

BCG. (2015, August 21). *Revolution in the Driver's Seat: The Road to Autonomous Vehicles*. BCG Global. https://www.bcg.com/publications/2015/automotive-consumer-insight-revolution-drivers-seat-road-autonomous-vehicles

Becker, F., & Axhausen, K. W. (2017). Literature review on surveys investigating the acceptance of automated vehicles. *Transportation*, *44*(6), 1293–1306. https://doi.org/10.1007/s11116-017-9808-9

Becker, H., Becker, F., Abe, R., Bekhor, S., Belgiawan, P. F., Compostella, J., Frazzoli, E., Fulton, L. M., Guggisberg Bicudo, D., Murthy Gurumurthy, K., Hensher, D. A., Joubert, J. W., Kockelman, K. M., Kröger, L., Le Vine, S., Malik, J., Marczuk, K., Ashari Nasution, R., Rich, J., … Axhausen, K. W. (2020). Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide. *Transportation Research Part A: Policy and Practice*, *138*, 105–126. https://doi.org/10.1016/j.tra.2020.04.021

Beede, D., Powers, R., & Ingram, C. (2017). *The Employment Impact of Autonomous Vehicles* (ESA Issue Brief 05–17; p. 33). Office of the Chief Economist, U.S. Department of Commerce. https://www.commerce.gov/sites/default/files/migrated/reports/Employment%20Impact%20Autonomous%20Vehicles_0.pdf

Bessen, J. E. (2016). *How Computer Automation Affects Occupations: Technology, Jobs, and Skills* (SSRN Scholarly Paper 2690435). https://doi.org/10.2139/ssrn.2690435

Bessen, J. E., Goos, M., Salomons, A., & Van den Berge, W. (2019). *Automatic Reaction—What Happens to Workers at Firms that Automate?* (SSRN Scholarly Paper 3328877). https://doi.org/10.2139/ssrn.3328877

Blumenthal, M. S., Fraade-Blanar, L., Best, R., & Irwin, J. L. (2020). *Safe Enough: Approaches to Assessing Acceptable Safety for Automated Vehicles*. RAND Corporation. https://doi.org/10.7249/RRA569-1

Bodine, R., & Walker, D. (2023, June 21). *Auto Insurance for Taxi Cabs (2023)*. AutoInsurance.Org. https://www.autoinsurance.org/auto-insurance-for-taxi-cabs/

Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2018). Cost-based analysis of autonomous mobility services. *Transport Policy*, *64*, 76–91. https://doi.org/10.1016/j.tranpol.2017.09.005

Bresnahan, T. (2021). Artificial Intelligence Technologies and Aggregate Growth Prospects. In J. W. Diamond & G. R. Zodrow (Eds.), *Prospects for Economic Growth in the United States*. Cambridge University Press. https://books.google.com/books?id=4chCEAAAQBAJ

Breuer, H., Du, J., & Rakha, H. A. (2020). Ride-hailing Impacts on Transit Ridership: Chicago Case Study. *arXiv:2011.11130 [Physics]*. http://arxiv.org/abs/2011.11130

Bridges, R. (2018). *Our Driverless Future: Heaven Or Hell?* Understanding Disruption, Incorporated.

Brownell, C., & Kornhauser, A. (2014). A Driverless Alternative: Fleet Size and Cost Requirements for a Statewide Autonomous Taxi Network in New Jersey. *Transportation Research Record*, *2416*(1), 73–81. https://doi.org/10.3141/2416-09

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, *358*(6370), 1530–1534. https://doi.org/10.1126/science.aap8062

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What Can Machines Learn, and What Does It Mean for Occupations and the Economy? *AEA Papers and Proceedings*, *108*, 43–47. https://doi.org/10.1257/pandp.20181019

Bureau of Labor Statistics. (2023a, May). *Dispatchers, Except Police, Fire, and Ambulance*. https://www.bls.gov/oes/current/oes435032.htm

Bureau of Labor Statistics. (2023b, May). *Taxi Drivers*. https://www.bls.gov/oes/current/oes533054.htm#st

Bureau of Labor Statistics, U. S. D. of L. (2023c, November 28). *Taxi Drivers, Shuttle Drivers, and Chauffeurs: Occupational Outlook Handbook: : U.S. Bureau of Labor Statistics*. Occupational Outlook Handbook. https://www.bls.gov/ooh/transportation-and-material-moving/taxi-drivers-and-chauffeurs.htm

Burns, L. D., Jordan, W. C., & Scarborough, B. A. (2012). *Transforming Personal Mobility, Technical Report* (p. 42). Columbia University. http://wordpress.ei.columbia.edu/mobility/files/2012/12/Transforming-Personal-Mobility-Aug-10-2012.pdf

Cameron, L. (2020). *The rise of algorithmic work: Implications for managerial control and career pathways*. University of Michigan.

Cameron, L. D. (2022). “Making Out” While Driving: Relational and Efficiency Games in the Gig Economy. *Organization Science*, *33*(1), 231–252. https://doi.org/10.1287/orsc.2021.1547

Cats, O., Kucharski, R., Danda, S. R., & Yap, M. (2022). Beyond the dichotomy: How ride-hailing competes with and complements public transport. *PLOS ONE*, *17*(1), e0262496. https://doi.org/10.1371/journal.pone.0262496

CCTA. (2024). *GoMentum Station*. GoMentum Station. https://gomentumstation.net/

Cesafsky, L., Stayton, E., & Cefkin, M. (2019). Calibrating Agency: Human-Autonomy Teaming and the Future of Work amid Highly Automated Systems. *Ethnographic Praxis in Industry Conference Proceedings*, *2019*(1), 65–82. https://doi.org/10.1111/1559-8918.2019.01265

Chamber of Progress. (2024). *Opportunity AV: How Many and What Types of Jobs Will Be Created by Autonomous Vehicles?* https://progresschamber.org/wp-content/uploads/2024/03/Opportunity-AV-How-Many-and-What-Type-of-Jobs-Will-Be-Created-by-Autonomous-Vehicles.pdf

Chaum, M. (2023, July 11). *Power of the Platform: Uber’s Vision for a Safe, Efficient, and Delightful Hybrid Network*. TRB Automated Road Transportation Symposium 2023, San Francisco, CA. https://trb.secure-platform.com/a/solicitations/109/sessiongallery/schedule/items/1825/application/11298

Cherchi, E. (2017). A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles. *Transportation Research Part A: Policy and Practice*, *100*, 88–104. https://doi.org/10.1016/j.tra.2017.04.009

Cherchi, E., & Hensher, D. A. (2015). Workshop Synthesis: Stated Preference Surveys and Experimental Design, an Audit of the Journey so far and Future Research Perspectives. *Transportation Research Procedia*, *11*, 154–164. https://doi.org/10.1016/j.trpro.2015.12.013

City of Chicago. (2023, November 8). *Taxi Trips | City of Chicago | Data Portal*. https://data.cityofchicago.org/Transportation/Taxi-Trips/wrvz-psew

Citymapper. (2022, February 14). *Citymapper—The Ultimate Transport App*. Citymapper. https://citymapper.com/dc?lang=en

Clark, H. M., Basinger, K., Maloney, K., & Whiteman, C. (2017). *Who Rides Public Transportation* (p. 86). American Public Transportation Association. https://www.apta.com/research-technical-resources/research-reports/who-rides-public-transportation/

Cluett. (2024). *Non-Emergency Medical Transportation (NEMT) Driver Training Guide*. Cluett Commercial Insurance Agency, Inc. https://www.cluettinsurance.com/nemt-driver-training-certification.html

Cohen, T., Stilgoe, J., & Cavoli, C. (2018). Reframing the governance of automotive automation: Insights from UK stakeholder workshops. *Journal of Responsible Innovation*, *5*(3), 257–279. https://doi.org/10.1080/23299460.2018.1495030

Cohen, T., Stilgoe, J., Stares, S., Akyelken, N., Cavoli, C., Day, J., Dickinson, J., Fors, V., Hopkins, D., Lyons, G., Marres, N., Newman, J., Reardon, L., Sipe, N., Tennant, C., Wadud, Z., & Wigley, E. (2020). A constructive role for social science in the development of automated vehicles. *Transportation Research Interdisciplinary Perspectives*, *6*, 100133. https://doi.org/10.1016/j.trip.2020.100133

Cohn, J., Ezike, R., Martin, J., Donkor, K., Ridgway, M., & Balding, M. (2019). Examining the Equity Impacts of Autonomous Vehicles: A Travel Demand Model Approach. *Transportation Research Record*, *2673*(5), 23–35. https://doi.org/10.1177/0361198119836971

Combemale, C., Whitefoot, K. S., Ales, L., & Fuchs, E. R. H. (2021). Not all technological change is equal: How the separability of tasks mediates the effect of technology change on skill demand. *Industrial and Corporate Change*, *30*(6), 1361–1387. https://doi.org/10.1093/icc/dtab026

Compostella, J., Fulton, L. M., De Kleine, R., Kim, H. C., & Wallington, T. J. (2020). Near- (2020) and long-term (2030–2035) costs of automated, electrified, and shared mobility in the United States. *Transport Policy*, *85*, 54–66. https://doi.org/10.1016/j.tranpol.2019.10.001

Cooper, J., Mundy, R., & Nelson, J. (2016). *Taxi! Urban economies and the social and transport impacts of the taxicab*. Routledge.

Correia, G. H. de A., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. *Transportation Research Part A: Policy and Practice*, *119*, 359–382. https://doi.org/10.1016/j.tra.2018.11.016

Cramer, J., & Krueger, A. B. (2016). Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review*, *106*(5), 177–182. https://doi.org/10.1257/aer.p20161002

Crawford, K., & Joler, V. (2018). *Anatomy of an AI System: The Amazon Echo As An Anatomical Map of Human Labor, Data and Planetary Resources* [Graphic]. https://anatomyof.ai/

Creger, H., Espino, J., & Sanchez, A. S. (2019). *Autonomous Vehicle Heaven or Hell? Creating a Transportation Revolution that Benefits All*. http://greenlining.org/wp-content/uploads/2019/01/R4_AutonomousVehiclesReportSingle_2019_2.pdf

Cruise. (2023a). *Contract Opportunities at Cruise*. https://getcruise.com/contingent-worker-roles/

Cruise. (2023b). *Driverless Delivery*. https://getcruise.com/delivery/

Cruise. (2023c). *How we're wired*. Cruise. https://getcruise.com/technology/

Data USA. (2021). *Automotive service technicians & mechanics | Data USA*. Automotive Service Technicians & Mechanics. https://datausa.io/profile/soc/automotive-service-technicians-mechanics#gender-and-age

Daus, M. W. (2023, September 28). *"Robotaxis": Guiding Principles for Equitable AV Implementation*. International Association of Transportation Regulators Annual Conference, Scottsdale, AZ.

Davidson, P., & Spinoulas, A. (2015). Autonomous vehicles: What could this mean for the future of transport. *Australian Institute of Traffic Planning and Management (AITPM) National Conference, Brisbane, Queensland*.

Davis, W. (2024, February 11). *A crowd destroyed a driverless Waymo car in San Francisco*. The Verge. https://www.theverge.com/2024/2/11/24069251/waymo-driverless-taxi-fire-vandalized-video-san-francisco-china-town

Daziano, R. A., Sarrias, M., & Leard, B. (2017). Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 150–164. https://doi.org/10.1016/j.trc.2017.03.003

De Anza College. (2024). *Autonomous and Electric Vehicle Technician Pathway*. Autonomous and Electric Vehicle Technician Pathway. https://www.deanza.edu/autotech/av.html

DFHV. (2019, September 6). *Request for Applications (RFA): FY 2020 Non-Emergency Medical Transportation (NEMT) "Right Care, Right Now" Nurse Triage Line, Taxicab Transit Initiative*. DC Department of For-Hire Vehicles. https://dfhv.dc.gov/sites/default/files/dc/sites/dc%20taxi/page_content/attachments/FY%202020%20NEMT%20GRANT%20PROGRAM%20RFA%20.pdf

Doellgast, V., & Wagner, I. (2022). Collective regulation and the future of work in the digital economy: Insights from comparative employment relations. *Journal of Industrial Relations*, *64*(3), 438–460. https://doi.org/10.1177/00221856221101165

Dong, X. (2020). Trade Uber for the Bus? *Journal of the American Planning Association*, *86*(2), 222–235. https://doi.org/10.1080/01944363.2019.1687318

Dong, X., DiScenna, M., & Guerra, E. (2019). Transit user perceptions of driverless buses. *Transportation*, *46*(1), 35–50. https://doi.org/10.1007/s11116-017-9786-y

Dubal, V. B. (2017). The drive to precarity: A political history of work, regulation, & labor advocacy in San Francisco's taxi & Uber economies. *Berkeley Journal of Employment and Labor Law*, 73–135.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*(4), 532–550.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory Building from Cases: Opportunities and Challenges. *The Academy of Management Journal*, *50*(1), 25–32.

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). *GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models* (arXiv:2303.10130). arXiv. http://arxiv.org/abs/2303.10130

EPA. (2021). *The 2020 EPA Automotive Trends Report* (EPA-420-R-21-003; p. 50). U.S. Environmental Protection Agency. https://www.epa.gov/sites/default/files/2021-01/documents/420r21003.pdf

Etzioni, S., Hamadneh, J., Elvarsson, A. B., Esztergár-Kiss, D., Djukanovic, M., Neophytou, S. N., Sodnik, J., Polydoropoulou, A., Tsouros, I., Pronello, C., Thomopoulos, N., & Shiftan, Y. (2020). Modeling Cross-National Differences in Automated Vehicle Acceptance. *Sustainability*, *12*(22), Article 22. https://doi.org/10.3390/su12229765

Fagnant, D. J., & Kockelman, K. M. (2016). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation*, *45*(1), 143–158. https://doi.org/10.1007/s11116-016-9729-z

Farooque, M., Lloyd, J., Tomblin, D., & Quach, K. (2021, July 15). *Driverless Cars and the Public: Right Answers or Wrong Questions?* Automated Road Transportation Symposium.

Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, *42*(12), 2195–2217. https://doi.org/10.1002/smj.3286

Felten, E. W., Raj, M., & Seamans, R. (2023). *Occupational Heterogeneity in Exposure to Generative AI* (SSRN Scholarly Paper 4414065). https://doi.org/10.2139/ssrn.4414065

Fernández-Macías, E., & Bisello, M. (2020). *A Taxonomy of Tasks for Assessing the Impact of New Technologies on Work* (JRC120618). European Commission. https://publications.jrc.ec.europa.eu/repository/handle/JRC120618

FHWA. (2002). *Status of the nation's highways, bridges, and transit: 2002 conditions and performance report*. Federal Highway Administration.

Fitts, P. M. (Ed.). (1951). *Human engineering for an effective air-navigation and traffic-control system* (pp. xxii, 84). National Research Council, Div. of.

Fort Worth Business Press, F. (2021, March 23). Arlington partnering with Via, May Mobility on self-driving vehicle program for downtown, UTA. *Fort Worth Business Press*. https://fortworthbusiness.com/business/arlington-is-expanding-its-self-driving-vehicle-program__trashed/

Freund, D., Lobel, I., & Zhao, J. (2022). *On the Supply of Autonomous Vehicles in Open Platforms* (SSRN Scholarly Paper 4178508). https://doi.org/10.2139/ssrn.4178508

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Fulton, L., Mason, J., & Meroux, D. (2017). *Three Revolutions in Urban Transportation: How To Achieve the Full Potential of Vehicle Electrification, Automation, and*

*Shared Mobility in Urban Transportation Systems Around the World by 2050* (STEPS-2050). Article STEPS-2050. https://trid.trb.org/view/1466512

Gehrke, S. R., Felix, A., & Reardon, T. G. (2019). Substitution of Ride-Hailing Services for More Sustainable Travel Options in the Greater Boston Region. *Transportation Research Record*, *2673*(1), 438–446. https://doi.org/10.1177/0361198118821903

Gittleman, M., & Monaco, K. (2020). Truck-Driving Jobs: Are They Headed for Rapid Elimination? *ILR Review*, *73*(1), 3–24. https://doi.org/10.1177/0019793919858079

Gkartzonikas, C., & Gkritza, K. (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 323–337. https://doi.org/10.1016/j.trc.2018.12.003

Gonzalez, C. M. (2021, October 14). *Infotainment Options for Self-Driving Vehicles—ASME*. The American Society of Mechanical Engineers. https://www.asme.org/topics-resources/content/infographic-future-infotainment-features-for-self-driving-cars

GoogleMaps. (2022, February 16). *Google Maps*. Google Maps. https://www.google.com/maps

Goos, M., Manning, A., & Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, *104*(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Grant, J. M., Motter, L. A., & Tanis, J. (2011). *Injustice at every turn: A report of the national transgender discrimination survey*. National Center for Transgender Equality. https://d1wqtxts1xzle7.cloudfront.net/31122982/NTDS_Report-with-cover-page-v2.pdf?Expires=1646237922&Signature=MLR5jfgl7G0LL8E2suyKk2WI~qr~LxR5Xhw2yTYOk36Q~dqxA3S6~ITvEaXJ-JTUfVC9Dl3ECKqROIvlkouHMmqgfVKuxJAeKFPuxpiB~84bj~n-LTH2MWKU-d2SrQ1EAGi~4YgydxOAU63EsIifuU9C8FPPnLuR7poTbDByYMgz-nLjfot0UyofxdUPcxKE335j0T46gZIJzpCrTX75~Ym7eCd1CGK8buFB8ysDhaeOXrRTX-2WcYprvvjXp2krpI3zF9vLyyfT03LG9p-zNlvXPnuzYMMw~KvS4Iq7612farS6Gh-I-EUvYCIWm1r9~DLsryX4QLlh75RmFQFoxw__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA

Greenblatt, J. B., & Saxena, S. (2015). Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nature Climate Change*, *5*(9), Article 9. https://doi.org/10.1038/nclimate2685

Gregg, A. (2024, February 14). *Uber, Lyft shares soar as riders return in record numbers—The Washington Post*. https://www.washingtonpost.com/business/2024/02/14/uber-lyft-profits/

Groshen, E. L., Helper, S., MacDuffie, J. P., & Carson, C. (2018). *Preparing U.S. Workers and Employers for an Autonomous Vehicle Future*. W.E. Upjohn Institute. https://doi.org/10.17848/tr19-036

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 37–49. https://doi.org/10.1016/j.trc.2017.01.010

Hancock, P. A., Kajaks, T., Caird, J. K., Chignell, M. H., Mizobuchi, S., Burns, P. C., Feng, J., Fernie, G. R., Lavallière, M., Noy, I. Y., Redelmeier, D. A., & Vrkljan, B. H. (2020). Challenges to Human Drivers in Increasingly Automated Vehicles. *Human Factors*, *62*(2), 310–328. https://doi.org/10.1177/0018720819900402

Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation Research Part C: Emerging Technologies*, *72*, 1–9. https://doi.org/10.1016/j.trc.2016.09.003

Hawkins, A. J. (2018, August 21). *A day in the life of a Waymo self-driving taxi*. The Verge. https://www.theverge.com/2018/8/21/17762326/waymo-self-driving-ride-hail-fleet-management

Hazan, J., Lang, N., Ulrich, P., Chua, J., Doubara, X., & Steffens, T. (2016). *Will autonomous vehicles derail trains?* Boston Consulting Group. https://www.bcg.com/publications/2016/transportation-travel-tourism-automotive-will-autonomous-vehicles-derail-trains

Heineke, K., Heuss, R., Kampshoff, P., Kelkar, A., & Kellner, M. (2022). *The road to affordable autonomous mobility*. McKinsey & Company. https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-road-to-affordable-autonomous-mobility#/

Helveston, J. P. (2021). *Logitr: Fast Estimation of Multinomial and Mixed Logit Models with Preference Space and Willingness to Pay Space Utility Parameterizations. R package version 0.5.0* [Computer software]. https://jhelvy.github.io/logitr/

Helveston, J. P. (2022). *cbcTools: Tools For Designing Conjoint Survey Experiments* (Version R package version 0.0.2) [Computer software]. https://jhelvy.github.io/cbcTools/

Helveston, J. P., Feit, E. M., & Michalek, J. J. (2018). Pooling stated and revealed preference data in the presence of RP endogeneity. *Transportation Research Part B: Methodological*, *109*, 70–89. https://doi.org/10.1016/j.trb.2018.01.010

Helveston, J. P., Liu, Y., Feit, E. M., Fuchs, E., Klampfl, E., & Michalek, J. J. (2015). Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. *Transportation Research Part A: Policy and Practice*, *73*, 96–112. https://doi.org/10.1016/j.tra.2015.01.002

Hilgarter, K., & Granig, P. (2020). Public perception of autonomous vehicles: A qualitative study based on interviews after riding an autonomous shuttle. *Transportation Research Part F: Traffic Psychology and Behaviour*, *72*, 226–243. https://doi.org/10.1016/j.trf.2020.05.012

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

IATR. (2022). *IATR's Best Practices, Guiding Principles & Model Regulations for "Robotaxis": Testing & Implementation of Shared-Connected-Automated-Electric For-Hire Vehicles (S-CAEVs)*. International Association of Transportation Regulators.

https://www.dropbox.com/s/f7dttn93enbn27w/Notice%20of%20Hearing%20and%20Opportunity%20to%20Comment%20on%20IATR%23s%20Best%20Practices,%20Guiding%20Principles%20%20%20Model%20Regulations%20for%20%23Robotaxis%23.%20(11988651).pdf?dl=0

ICONMA. (2023). *ICONMA @ Cruise: Assistance Advisor*. https://www2.jobdiva.com/portal/?a=9bjdnw2mlhip8doaz2t0q9w4wphk960418ms6mtfp5oxvgnr76bfafpnr8c62y27&compid=0#/jobs/18844530

Indeed. (2023). *Beep Inc Jobs and Careers*. indeed.com.

Ivanov, S. H., Webster, C., & Berezina, K. (2017). *Adoption of Robots and Service Automation by Tourism and Hospitality Companies* (SSRN Scholarly Paper 2964308). https://papers.ssrn.com/abstract=2964308

Jensen, A. F., Cherchi, E., Mabit, S. L., & Ortúzar, J. de D. (2017). Predicting the Potential Market for Electric Vehicles. *Transportation Science*, *51*(2), 427–440. https://doi.org/10.1287/trsc.2015.0659

Joh, K. (2020). *2017-2018 REGIONAL TRAVEL SURVEY BRIEFING: INITIAL FINDINGS OF OBSERVED DAILY TRIPS*. 40.

Johnson, B. (2015). *Disruptive mobility*. Research Report, Barclays. https://www.cib.barclays/content/dam/barclaysmicrosites/ibpublic/documents/investment-bank/global-insights/barclays-disruptive-mobility-pdf-120115-459kb.pdf

Johnson, C., & Walker, J. (2016). *Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services*. Rocky Mountain Institute. https://rmi.org/insight/peak-car-ownership-report/

Kang, S., Mondal, A., Bhat, A. C., & Bhat, C. R. (2021). Pooled versus private ride-hailing: A joint revealed and stated preference analysis recognizing psycho-social factors. *Transportation Research Part C: Emerging Technologies*, *124*, 102906. https://doi.org/10.1016/j.trc.2020.102906

Kaplan, L., & Helveston, J. P. (2023a). Undercutting Transit? Exploring Potential Competition Between Automated Vehicles and Public Transportation in the United States. *Transportation Research Record*. https://doi.org/10.1177/03611981231208976

Kaplan, L., & Helveston, J. P. (2023b). Undercutting transit? Exploring potential competition between automated vehicles and public transportation in the U.S. *Transportation Research Record: Journal of the Transportation Research Board*. https://doi.org/10.1177/03611981231208976

Kaplan, L., Nurullaeva, L., & Helveston, J. P. (2024). *Modeling the Operational and Labor Costs of Autonomous Robotaxi Services*.

Kaplan, L., Szajnfarber, Z., & Helveston, J. P. (2024). *Mapping the AI-Enabled Transformation of Labor in Taxi Services by Autonomous Vehicles*.

Kassens-Noor, E., Kotval-Karamchandani, Z., & Cai, M. (2020). Willingness to ride and perceptions of autonomous public transit. *Transportation Research Part A: Policy and Practice*, *138*, 92–104. https://doi.org/10.1016/j.tra.2020.05.010

Khan, M. A., Etminani-Ghasrodashti, R., Shahmoradi, A., Kermanshachi, S., Rosenberger, J. M., & Foss, A. (2022). Integrating Shared Autonomous Vehicles into Existing Transportation Services: Evidence from a Paratransit Service in Arlington, Texas. *International Journal of Civil Engineering*. https://doi.org/10.1007/s40999-021-00698-6

Khoeini, S. (2021, July 15). *Autonomous Vehicles: Familiarity, Awareness, and Perceptions.* Automated Road Transportation Symposium 2021, Virtual. https://tomnet-utc.engineering.asu.edu/wp-content/uploads/sites/5/2020/07/abcsfuturemobility8_avfamiliarity_khoeini.pdf

Kim, S. H., Circella, G., & Mokhtarian, P. L. (2019). Identifying latent mode-use propensity segments in an all-AV era. *Transportation Research Part A: Policy and Practice*, *130*, 192–207. https://doi.org/10.1016/j.tra.2019.09.015

Kolodny, L. (2023, March 22). *Cruise robotaxis blocked a road in San Francisco after a storm downed trees and wires*. CNBC. https://www.cnbc.com/2023/03/22/cruise-robotaxis-blocked-a-road-in-san-francisco-after-storm.html

Korosec, K. (2019, March 6). Waymo to start selling standalone LiDAR sensors. *TechCrunch*. https://techcrunch.com/2019/03/06/waymo-to-start-selling-standalone-lidar-sensors/

Korosec, K. (2022, February 1). Cruise, loaded with another $1.35B from SoftBank, opens up driverless ride-hailing to the public. *TechCrunch*. https://social.techcrunch.com/2022/02/01/cruise-loaded-with-another-1-35b-from-softbank-opens-up-driverless-ride-hailing-to-the-public/

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *69*, 343–355. https://doi.org/10.1016/j.trc.2016.06.015

Kuhnimhof, T., & Eisenmann, C. (2023). Mobility-on-demand pricing versus private vehicle TCO: How cost structures hinder the dethroning of the car. *Transportation*, *50*(2), 707–731. https://doi.org/10.1007/s11116-021-10258-5

Kurzius, R. (2016, June 16). *Meet Olli, The Driverless Vehicle Cruising Around National Harbor*. DCist. https://dcist.com/story/16/06/16/meet-your-new-robot-overlord/

Kyriakidis, M., Sodnik, J., Stojmenova, K., Elvarsson, A. B., Pronello, C., & Thomopoulos, N. (2020). The Role of Human Operators in Safety Perception of AV Deployment—Insights from a Large European Survey. *Sustainability*, *12*(21), Article 21. https://doi.org/10.3390/su12219166

Lappin, J. (2023, September 27). *AV Level Setting – "Where are we Now"?* International Association of Transportation Regulators 36th Annual Conference.

Lavieri, P. S., & Bhat, C. R. (2019). Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. *Transportation Research Part A: Policy and Practice*, *124*, 242–261. https://doi.org/10.1016/j.tra.2019.03.009

Leonard, J. J., Mindell, D. A., & Stayton, E. L. (2020). *Autonomous Vehicles, Mobility, and Employment Policy: The Roads Ahead*. https://workofthefuture.mit.edu/wp-content/uploads/2020/08/WotF-2020-Research-Brief-Leonard-Mindell-Stayton.pdf

Levy, K. (2022). *Data driven: Truckers, technology, and the new workplace surveillance*.

Litman, T. (2023). *Autonomous Vehicle Implementation Predictions* (p. 48). Victoria Transport Policy Institute. https://www.vtpi.org/avip.pdf

Litwin, A. S., Hammerling, J. H., Carré, F., Tilly, C., Benner, C., Mason, S., Viscelli, S., Gutelius, B., & Theodore, N. (2022). A Forum on Emerging Technologies. *ILR Review*, *75*(4), 807–856. https://doi.org/10.1177/00197939221095527

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated Choice Methods: Analysis and Applications*. Cambridge University Press.

Lyft. (2020, December 31). *SEC Filing (Form 10-K)*. Lyft, Inc.
Lyft. (2022a, February 14). *Get Fare Estimates for Your City—Lyft Price Estimate | Lyft*. https://lyft.com/rider/fare-estimate
Lyft. (2022b, February 14). *Lyft Shared rides for riders—Lyft Help*. https://help.lyft.com/hc/e/articles/115013078848-Lyft-Shared-rides-for-riders
Machek, E., Burkman, E., Crayton, T., Cregger, J., Diggs, D., Fischer, S., Mortensen, S., Peirce, S., Richardson, H., Thomas, A., Torng, G.-W., Valdes, V., & John A. Volpe National Transportation Systems Center (U.S.). (2018). *Strategic Transit Automation Research Plan* (FTA Report No. 0116). https://doi.org/10.21949/1503427
Markey, E. J., Blumenthal, R., Welch, P., Warren, E., Ray Lujan, B., & Sanders, B. (2024, April 18). *Letter from U.S. Senators to Deputy NHTSA Administrator Sophie Shulman*. https://www.markey.senate.gov/imo/media/doc/av_nhtsa_letter_41824.pdf
Maruf, R. (2024, April 3). *Amazon's cashier-less technology was supposed to revolutionize grocery shopping. It's been a flop | CNN Business*. CNN. https://www.cnn.com/2024/04/03/business/amazons-self-checkout-technology-grocery-flop/index.html
McAslan, D., Najar Arevalo, F., King, D. A., & Miller, T. R. (2021). Pilot project purgatory? Assessing automated vehicle pilot projects in U.S. cities. *Humanities and Social Sciences Communications*, *8*(1), Article 1. https://doi.org/10.1057/s41599-021-01006-2
McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447–470. https://doi.org/10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1
Mickle, T., Metz, C., & Lu, Y. (2023, November 3). G.M.'s Cruise Moved Fast in the Driverless Race. It Got Ugly. *The New York Times*. https://www.nytimes.com/2023/11/03/technology/cruise-general-motors-self-driving-cars.html
Milakis, D., Kroesen, M., & van Wee, B. (2018). Implications of automated vehicles for accessibility and location choices: Evidence from an expert-based experiment. *Journal of Transport Geography*, *68*, 142–148. https://doi.org/10.1016/j.jtrangeo.2018.03.010
Milakis, D., & van Wee, B. (2020). Chapter 4—Implications of vehicle automation for accessibility and social inclusion of people on low income, people with physical and sensory disabilities, and older people. In C. Antoniou, D. Efthymiou, & E. Chaniotakis (Eds.), *Demand for Emerging Transportation Systems* (pp. 61–73). Elsevier. https://doi.org/10.1016/B978-0-12-815018-4.00004-8
Mo, B., Cao, Z., Zhang, H., Shen, Y., & Zhao, J. (2021). Competition between shared autonomous vehicles and public transit: A case study in Singapore. *Transportation Research Part C: Emerging Technologies*, *127*, 103058. https://doi.org/10.1016/j.trc.2021.103058
Mohan, A., Sripad, S., Vaishnav, P., & Viswanathan, V. (2020). Trade-offs between automation and light vehicle electrification. *Nature Energy*, *5*(7), 543–549.

Moody, J., Bailey, N., & Zhao, J. (2020). Public perceptions of autonomous vehicle safety: An international comparison. *Safety Science*, *121*, 634–650. https://doi.org/10.1016/j.ssci.2019.07.022

Moradi, P., & Levy, K. (2020). *The Future of Work in the Age of AI: Displacement or Risk-Shifting?* (SSRN Scholarly Paper 3647367). Social Science Research Network. https://papers.ssrn.com/abstract=3647367

Moreno, J. (2021, January 25). *Elon Musk Responds To Waymo CEO: 'Tesla Has Better AI Hardware And Software Than Waymo.'* Forbes. https://www.forbes.com/sites/johanmoreno/2021/01/25/elon-musk-responds-to-waymo-ceo-tesla-has-better-ai-hardware--software-than-waymo/

Mundy, R. A. (2011). *Tennessee Transportation & Logistics Foundation*.

Mundy, R. A. (2022). Using History to Develop Future Regulation of TNCs and Autonomous Taxis. In S. Hakim, R. M. Clark, & E. A. Blackstone (Eds.), *Handbook on Public Private Partnerships in Transportation, Vol I: Airports, Water Ports, Rail, Buses, Taxis, and Finance* (pp. 285–303). Springer International Publishing. https://doi.org/10.1007/978-3-030-83484-5_15

Mutzenich, C., Durant, S., Helman, S., & Dalton, P. (2021). Updating our understanding of situation awareness in relation to remote operators of autonomous vehicles. *Cognitive Research: Principles and Implications*, *6*(1), 9. https://doi.org/10.1186/s41235-021-00271-8

Nair, G. S., & Bhat, C. R. (2021). Sharing the road with autonomous vehicles: Perceived safety and regulatory preferences. *Transportation Research Part C: Emerging Technologies*, *122*, 102885. https://doi.org/10.1016/j.trc.2020.102885

NASEM. (2017). *Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here?* The National Academies Press. https://doi.org/10.17226/24649.

NCR TPB. (2021, February 16). *Regional Transportation Data Clearinghouse (open data)*. National Capital Region Transportation Planning Board. https://rtdc-mwcog.opendata.arcgis.com/search?tags=rts

Negro, P., Ridderskamp, D., Paul, M., Fehn, F., Belzner, H., & Bogenberger, K. (2021). Cost Structures of Ride-Hailing Providers in the Context of Vehicle Electrification and Automation. *2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, 1–8. https://doi.org/10.1109/MT-ITS49943.2021.9529308

New York City Taxi & Limousine Commission. (2023a). *TLC Trip Record Data*. NYC Taxi & Limousine Commission. https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page

New York City Taxi & Limousine Commission. (2023b, September 20). *Medallion Transfers—TLC*. NYC Taxi & Limousine Commission. https://www.nyc.gov/site/tlc/businesses/medallion-transfers.page

NHTSA. (2024). *Automated Vehicles for Safety* [Text]. https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety

NIST. (2023). *AI Risk Management Framework: AI RMF (1.0)* (NIST AI 100-1). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.100-1

Norton, T. A., Ruhl, M., Armitage, T., Matthews, B., & Miles, J. (2021). Cross-National Focus Group Response to Autonomous Vehicles. *Transportation Research Record*, *2675*(6), 339–351. https://doi.org/10.1177/0361198121992363

Nunes, A., & Hernandez, K. D. (2020). Autonomous taxis & public health: High cost or high opportunity cost? *Transportation Research Part A: Policy and Practice*, *138*, 28–36. https://doi.org/10.1016/j.tra.2020.05.011

Nuro. (2024). *Nuro—On a mission to better everyday life through robotics.* Nuro. https://www.nuro.ai/

Ohnsman, A. (2019, December 16). *Amazon-Backed Aurora Readies An Air-Traffic Control System For Self-Driving Cars*. https://www.forbes.com/sites/alanohnsman/2019/12/16/amazon-backed-aurora-readies-air-traffic-control-system-for-self-driving-cars/?sh=26bfc421a161

Ohnsman, A. (2020, January 17). *Phantom Of The Operator: Self-Driving Tech's Slowing Timetable Creates Opening For This Monitoring And Guidance Startup*. Forbes. https://www.forbes.com/sites/alanohnsman/2020/01/17/phantom-of-the-operator-self-driving-techs-slowing-timetable-creates-opening-for-this-monitoring-and-guidance-startup/

O*NET. (2017, November 16). *About the Survey*. O*NET- Data Collection Program. https://onet.rti.org/survey.cfm

O*NET. (2024). *O*NET OnLine Help: Summary Report*. https://www.onetonline.org/help/online/summary

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *30*(3), 286–297. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans. https://doi.org/10.1109/3468.844354

Parrott, J. A., & Reich, M. (2018). *An Earnings Standard for New York City's App-Based Drivers* [Report for the New York City Taxi and Limousine Commission]. Center for New York City Affairs. https://static1.squarespace.com/static/53ee4f0be4b015b9c3690d84/t/5b3a3aaa0e2e72ca74079142/1530542764109/Parrott-Reich+NYC+App+Drivers+TLC+Jul+2018jul1.pdf

Pennsylvania Department of Transportation (Director). (2017, September 11). *What are automated vehicles?* [Video recording]. https://www.youtube.com/watch?v=1lUkyCYdAEY

Perez, S. (2018, July 25). Waymo partners with Walmart, Avis, AutoNation and others to expand access to self-driving cars. *TechCrunch*. https://techcrunch.com/2018/07/25/waymo-partners-with-walmart-avis-autonation-and-others-to-expand-access-to-self-driving-cars/

Polydoropoulou, A., Tsouros, I., Thomopoulos, N., Pronello, C., Elvarsson, A., Sigþórsson, H., Dadashzadeh, N., Stojmenova, K., Sodnik, J., Neophytou, S., Esztergár-Kiss, D., Hamadneh, J., Parkhurst, G., Etzioni, S., Shiftan, Y., & Di Ciommo, F. (2021). Who Is Willing to Share Their AV? Insights about Gender Differences among Seven Countries. *Sustainability*, *13*(9), Article 9. https://doi.org/10.3390/su13094769

R Core Team. (2024). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rainstorm Car Wash. (2023, December 29). How Much Does a Car Wash Really Cost? A Comprehensive Guide. *Rainstorm Car Wash*. https://rainstormcarwash.com/how-much-does-a-car-wash-really-cost-a-comprehensive-guide/

Reich, M., & Parrott, J. A. (2020). *A Minimum Compensation Standard for Seattle TNC Drivers*. Center for New York City Affairs. https://escholarship.org/uc/item/1fw4q65g

Roberson, L. A., & Helveston, J. P. (2020). Electric vehicle adoption: Can short experiences lead to big change? *Environmental Research Letters*, *15*(9), 0940c3. https://doi.org/10.1088/1748-9326/aba715

Rodnitzky, A. (2022, July 14). *Sensing Breakdown: Waymo Jaguar I-Pace RoboTaxi. LiDAR, radar, cameras, ultrasonic, oh my!* https://www.tangramvision.com/blog/sensing-breakdown-waymo-jaguar-i-pace-robotaxi

Rothenberg, E. (2024, May 19). *Minnesota lawmakers strike minimum pay deal for Uber, Lyft drivers | CNN Business*. CNN. https://www.cnn.com/2024/05/19/business/uber-lyft-drivers-pay-minnesota/index.html

SAE. (2021, April). *J3016: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*. https://www.sae.org/standards/content/j3016_201806/

Saeed, T. U., Burris, M. W., Labi, S., & Sinha, K. C. (2020). An empirical discourse on forecasting the use of autonomous vehicles using consumers' preferences. *Technological Forecasting & Social Change*, *158*(120130).

Saul, D. (2024, February 7). *Uber Sets Profit Record As Lyft And DoorDash Keep Losing Money*. Forbes. https://www.forbes.com/sites/dereksaul/2024/02/07/uber-sets-profit-record-as-lyft-and-doordash-keep-losing-money/

Schaller Consulting. (2006). *The New York City Taxicab Fact Book*. http://www.schallerconsult.com/taxi/taxifb.pdf

Schrock, S. (2021, March 23). *City of Arlington Launches First-of-its-Kind, On-Demand Self-Driving Shuttle Service with RAPID Program*. https://www.arlingtontx.gov/news/my_arlington_t_x/news_stories/arlington_rapid_launch

Sebastian, R., & Biagi, F. (2018). *The Routine Biased Technical Change hypothesis: A critical review*. European Commission.

Shaheen, S., & Cohen, A. (2019). Shared ride services in North America: Definitions, impacts, and the future of pooling. *Transport Reviews*, *39*(4), 427–442. https://doi.org/10.1080/01441647.2018.1497728

Sheehan, A., & Le Dantec, C. A. (2023). Making Meaning from the Digitalization of Blue-Collar Work. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW2), 345:1-345:21. https://doi.org/10.1145/3610194

Shetty, S. (2020, January 28). *Uber's self-driving cars are a key to its path to profitability*. CNBC. https://www.cnbc.com/2020/01/28/ubers-self-driving-cars-are-a-key-to-its-path-to-profitability.html

Shin, J., Bhat, C. R., You, D., Garikapati, V. M., & Pendyala, R. M. (2015). Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types. *Transportation Research Part C: Emerging Technologies*, *60*, 511–524. https://doi.org/10.1016/j.trc.2015.10.003

Shladover, S. E. (2018, May 14). *Practical Challenges to Deploying Highly Automated Vehicles*. Drive Sweden, Goteborg, Sweden. https://www.drivesweden.net/sites/default/files/content/bilder/practicalchallenges4drivesweden.pdf

Sjoberg, D. (2021). *Ggsankey* [R]. https://github.com/davidsjoberg/ggsankey?tab=readme-ov-file

Somerville, H. (2019, April 19). Uber's self-driving unit valued at $7.25 billion in new investment. *Reuters*. https://www.reuters.com/article/us-uber-softbank-group-selfdriving-idUSKCN1RV01P

Sonnier, G., Ainslie, A., & Otter, T. (2007). Heterogeneity distributions of willingness-to-pay in choice models. *Quantitative Marketing and Economics*, *5*(3), 313–331. https://doi.org/10.1007/s11129-007-9024-6

Sperling, D., Pike, S., & Chase, R. (2018). Will the Transportation Revolutions Improve Our Lives—Or Make Them Worse? In D. Sperling (Ed.), *Three Revolutions: Steering Automated, Shared, and Electric Vehicles to a Better Future* (pp. 1–20). Island Press/Center for Resource Economics. https://doi.org/10.5822/978-1-61091-906-7_1

Stayton, E., & Cefkin, M. (2018). Designed for care: Systems of care and accountability in the work of mobility. *Ethnographic Praxis in Industry Conference Proceedings*, *2018*(1), 334–350.

Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S., & Lenz, B. (2018). How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting. *Transportation Research Record*, *2672*(46), 11–20. https://doi.org/10.1177/0361198118757980

Steckler, B., Howell, A., Larco, N., & Kaplowitz, G. (2021, January). *A Framework for Shaping the Deployment of Autonomous Vehicles and Advancing Equity Outcomes—Urbanism Next*. Urbanism Next. https://www.urbanismnext.org/resources/a-framework-for-shaping-the-deployment-of-autonomous-vehicles-and-advancing-equity-outcomes

Stephens, T. S., Gonder, J., Chen, Y., Lin, Z., Liu, C., & Gohlke, D. (2016). *Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles* (NREL/TP--5400-67216, 1334242; p. NREL/TP--5400-67216, 1334242). https://doi.org/10.2172/1334242

Stilgoe, J. (2021). How can we know a self-driving car is safe? *Ethics and Information Technology*. https://doi.org/10.1007/s10676-021-09602-1

Stopher, P. R., Maggasy, T. B., Pendyala, R. M., McAslan, D., Arevalo, F. N., & Miller, T. (2021, August). *An Evaluation of the Valley Metro–Waymo Automated Vehicle RideChoice Mobility on Demand Demonstration (Report 0198) | FTA*. https://www.transit.dot.gov/research-innovation/evaluation-valley-metro-waymo-automated-vehicle-ridechoice-mobility-demand

Szajnfarber, Z., & Gralla, E. (2017). Qualitative methods for engineering systems: Why we need them and how to use them. *Systems Engineering*, *20*(6), 497–511. https://doi.org/10.1002/sys.21412

Thomopoulos, N., Cohen, S., Hopkins, D., Siegel, L., & Kimber, S. (2021). All work and no play? Autonomous vehicles and non-commuting journeys. *Transport Reviews*, *41*(4), 456–477. https://doi.org/10.1080/01441647.2020.1857460

Tolan, S., Pesole, A., Martínez-Plumed, F., Fernández-Macías, E., Hernández-Orallo, J., & Gómez, E. (2021). Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks. *Journal of Artificial Intelligence Research*, *71*, 191–236. https://doi.org/10.1613/jair.1.12647

Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press.

Train, K., & Weeks, M. (2005). Discrete Choice Models in Preference Space and Willingness-to-Pay Space. In R. Scarpa & A. Alberini (Eds.), *Applications of Simulation Methods in Environmental and Resource Economics* (pp. 1–16). Springer Netherlands. https://doi.org/10.1007/1-4020-3684-1_1

Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *Academy of Management. The Academy of Management Review (Pre-1986)*, *3*(000003), 613.

Uber. (2020, December 31). *SEC Filing (Form 10-K)*. Uber Technologies, Inc. https://www.sec.gov/Archives/edgar/data/1543151/000154315121000014/uber-20201231.htm

Uber. (2022a, February 14). *Uber Estimate—Get a Price Estimate in Your City*. Uber. https://www.uber.com/global/en/price-estimate/

Uber. (2022b, February 14). *UberX Share | Share your ride for a chance at savings*. Uber. https://www.uber.com/us/en/ride/uberx-share/

Uber. (2024). *Uber: Driving autonomous forward*. Uber. https://www.uber.com/us/en/autonomous/

UBS Global Research. (2017). *How disruptive will a mass adoption of robotaxis be?* (Q Series). https://neo.ubs.com/shared/d1gAiLhfW3FA/

UITP. (2020). *Global Taxi Benchmarking Study 2019*. International Association of Public Transport. https://cms.uitp.org/wp/wp-content/uploads/2020/11/Statistics-Brief-TAxi-Benchmarking_NOV2020-web.pdf

Underwriters Laboratories. (2022, March). *ANSI/UL 4600 Standard for Safety for the Evaluation of Autonomous Products*. https://users.ece.cmu.edu/~koopman/ul4600/index.html

US Census Bureau. (2020). *U.S. Census Bureau QuickFacts: Seattle city, Washington; Chicago city, Illinois; United States*. US Census Bureau. https://www.census.gov/quickfacts/fact/table/seattlecitywashington,chicagocityillinois,US/PST045222

USDOT. (2024). *Creating a Skilled and Diverse Workforce for Infrastructure Projects Through Registered Apprenticeships*. US Department of Transportation. https://www.transportation.gov/grants/dot-navigator/creating-skilled-and-diverse-workforce-infrastructure-projects-through

Viscelli, S. (2018). *Driverless? Autonomous Trucks and the Future of the American Trucker* (p. 73). UC Berkeley Center for Labor Research and Education and Working Partnerships. http://driverlessreport.org/files/driverless.pdf

Wadud, Z. (2017). Fully automated vehicles: A cost of ownership analysis to inform early adoption. *Transportation Research Part A: Policy and Practice*, *101*, 163–176. https://doi.org/10.1016/j.tra.2017.05.005

Wadud, Z., MacKenzie, D., & Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice*, *86*, 1–18. https://doi.org/10.1016/j.tra.2015.12.001

Wadud, Z., & Mattioli, G. (2021). Fully automated vehicles: A cost-based analysis of the share of ownership and mobility services, and its socio-economic determinants. *Transportation Research Part A: Policy and Practice*, *151*, 228–244. https://doi.org/10.1016/j.tra.2021.06.024

Wagner, M., & Carlan, C. (2024). *The Open Autonomy Safety Case Framework* (arXiv:2404.05444). arXiv. https://doi.org/10.48550/arXiv.2404.05444

Wang, S., Mack, E. A., Van Fossen, J. A., Medwid, L., Cotten, S. R., Chang, C.-H., Mann, J., Miller, S. R., Savolainen, P. T., & Baker, N. (2023). Assessing alternative occupations for truck drivers in an emerging era of autonomous vehicles. *Transportation Research Interdisciplinary Perspectives*, *19*, 100793.

Waymo. (2022, February 16). *Waymo*. Waymo. https://waymo.com/

Waymo. (2023). *Waymo Driver*. Waymo. https://waymo.com/waymo-driver/

Waymo. (2024, March 13). *Scaling Waymo One safely across four cities this year*. Waymo. https://waymo.com/blog/2024/03/scaling-waymo-one-safely-across-four-cities-this-year

Whitmore, A., Samaras, C., Hendrickson, C. T., Scott Matthews, H., & Wong-Parodi, G. (2022). Integrating public transportation and shared autonomous mobility for equitable transit coverage: A cost-efficiency analysis. *Transportation Research Interdisciplinary Perspectives*, *14*, 100571. https://doi.org/10.1016/j.trip.2022.100571

Wigand, K.-M., Brandt, T., & Neumann, D. (2020). *The Effect of Autonomous Vehicles on Consumer Welfare in Ride-Hailing Markets* (SSRN Scholarly Paper 3664415). https://doi.org/10.2139/ssrn.3664415

Williams, E., Das, V., & Fisher, A. (2020a). Assessing the Sustainability Implications of Autonomous Vehicles: Recommendations for Research Community Practice. *Sustainability*, *12*(5), Article 5. https://doi.org/10.3390/su12051902

Williams, E., Das, V., & Fisher, A. (2020b). Assessing the Sustainability Implications of Autonomous Vehicles: Recommendations for Research Community Practice. *Sustainability*, *12*(5), Article 5. https://doi.org/10.3390/su12051902

Winter, K., Cats, O., Martens, K., & van Arem, B. (2020). Identifying user classes for shared and automated mobility services. *European Transport Research Review*, *12*(1), 36. https://doi.org/10.1186/s12544-020-00420-y

WMATA. (2022, February 16). *Cost to Ride | WMATA*. https://www.wmata.com/fares/basic.cfm

Yap, M. D., Correia, G., & van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips.

*Transportation Research Part A: Policy and Practice*, *94*, 1–16. https://doi.org/10.1016/j.tra.2016.09.003

Yin, R. K. (2018). *Case study research and applications: Design and methods* (Sixth edition.). SAGE Publications, Inc.

ZF. (2023, January 4). *ZF announces partnership with mobility provider Beep to bring new-generation autonomous Level 4 shuttle to U.S. market*. https://press.zf.com/press/en/releases/release_49664.html

Zhong, H., Li, W., Burris, M. W., Talebpour, A., & Sinha, K. C. (2020). Will autonomous vehicles change auto commuters' value of travel time? *Transportation Research Part D: Transport and Environment*, *83*(102303). https://doi.org/10.1016/j.trd.2020.102303

Zhu, L., Zhao, Z., & Wu, G. (2021). Shared Automated Mobility with Demand-Side Cooperation: A Proof-of-Concept Microsimulation Study. *Sustainability*, *13*(5), Article 5. https://doi.org/10.3390/su13052483

# Appendix A: Supplemental information for Chapter 2

## A.1 Detailed summary of semi-structured interviews

| Num. | Category | Org. | Position | Number of Interviews | Total Length of Interviews (min) | Date | General Location | Recorded and Transcribed |
|---|---|---|---|---|---|---|---|---|
| 1 | Commercial Deployment | Firm A | Frontline Worker | 1 | 30 | 9-Aug-23 | Central Command Center | Yes |
| 2 | | Firm A | Frontline Worker | 1 | 30 | 9-Aug-23 | Central Command Center | Yes |
| 3 | | Firm A | Frontline Worker | 1 | 30* | 10-Aug-23 | Fleet Depot | Yes |
| 4 | | Firm B | Frontline Worker | 1 | 78 | 30-Sep-22 | Coffee Shop | Yes |
| 5 | | Firm C | Frontline Worker | 1 | 60 | 26-Oct-22 | Coffee Shop | No (Hand-written notes) |
| 6 | | Firm D | Frontline Worker | 1 | 52 | 8-Nov-22 | Zoom | Yes |
| 7 | | Firm A | Mid-Level Manager | 1 | *(same interview) | 10-Aug-23 | Fleet Depot | Yes |
| 8 | | Firm A | Mid-Level Manager | 1 | 52 | 26-Sep-23 | Central Command Center | Yes |
| 9 | | Firm A | Mid-Level Manager | 1 | 30 | 10-Aug-23 | Fleet Depot | Yes |
| 10 | | Firm A | Mid-Level Manager | 1 | 30 | 9-Aug-23 | Central Command Center | Yes |
| 11 | | Firm B | Mid-Level Manager | 1 | 54 | 3-Jan-23 | Zoom | Yes |
| 12 | | Firm A | Senior Manager | 1 | 30 | 10-Aug-23 | Fleet Depot | Yes |
| 13 | | Firm A | Senior Manager | 2 | 60 | 27-Dec-22, 9-Aug-2023 | Zoom, Central Command Center | Yes, No (Hand-written notes) |
| 14 | | Firm A | Senior Manager | 1 | 30 | 10-Aug-23 | Fleet Depot | Yes |
| 15 | | Firm C | Senior Manager | 1 | 34 | 5-Sep-23 | Zoom | Yes |
| 16 | | Firm E | Senior Manager | 1 | 55 | 30-Jun-23 | Zoom | Yes |

## Appendix A.1 (cont.)

| Num | Category | Org. | Position | # of Interviews | Total Length (min) | Date | Location | Recorded and Transcribed |
|---|---|---|---|---|---|---|---|---|
| 17 | Pilot Program or Government -Run Service | Gov. | Operations Management | 1 | 55 | 19-Oct-22 | Zoom | Yes |
| 18 | | Gov. | Operations Management | 1 | 63 | 18-Oct-22 | Zoom | Yes |
| 19 | | Gov. | Operations Management | 1 | 64** | 11-Oct-22 | Zoom | Yes |
| 20 | | Gov. | Policy/ Communication | 1 | **(same interview) | 11-Oct-22 | Zoom | Yes |
| 21 | | Nonprofit | Policy/ Communication | 1 | 32 | 27-Oct-22 | Zoom | Yes |
| 22 | External Perspective | Nonprofit | AV Operations Expert | 1 | 29 | 20-Oct-22 | Zoom | Yes |
| 23 | | Industry | AV Operations Expert | 1 | 60 | 24-Feb-23 | Zoom | Yes |
| 24 | | Consulting | AV Operations Expert | 1 | 42 | 7-Nov-22 | Zoom | Yes |
| 25 | | Consulting | AV Regulation Expert | 1 | 63 | 21-Feb-23 | Office Building | Yes |
| 26 | | Consulting | AV Regulation Expert | 1 | 68 | 15-Feb-23 | Zoom | Yes |
| 27 | | Industry | AV Regulation Expert | 1 | 53 | 8-Nov-22 | Coffee Shop | Yes |
| 28 | | Industry | Taxi Manager | 1 | 30 | 12-Mar-24 | Zoom | No (Hand-written notes) |

## Appendix A.2: Detailed summary of direct observations

| Num. | Category | Observation/Event description | Duration | Date(s) |
|---|---|---|---|---|
| 1 | Ride | Daytime ride in robotaxi vehicle, operator onboard. Had informal conversation with operator. | 31 min | 7-Jul-22 |
| 2 | | Evening ride in robotaxi vehicle, operator onboard. Had informal conversation with operator. | 32 min | 7-Jul-22 |
| 3 | | Daytime ride in robotaxi vehicle, operator onboard. No conversation with operator. | 16 min | 8-Jul-22 |
| 4 | | Daytime ride in robotaxi vehicle, operator onboard. Had informal conversation with operator. | 15 min | 8-Jul-22 |
| 5 | | Daytime ride in robotaxi vehicle, operator onboard. Had informal conversation with operator. | 14 min | 8-Jul-22 |
| 6 | | Daytime ride in robotaxi, no operator onboard. Included call with customer service agent. | 18 min | 9-Jul-22 |
| 7 | | Daytime ride in robotaxi, no operator onboard. Attempted call to customer service agent but received notice that there was trouble connecting. | 20 min | 9-Jul-22 |
| 8 | | Nighttime ride in robotaxi, no operator onboard. | 17 min | 9-Jul-22 |
| 9 | | Nighttime ride in robotaxi, no operator onboard. | 14 min | 10-Jul-22 |
| 10 | | Nighttime ride in robotaxi, no operator onboard. Included call with customer service agent. | 15 min | 10-Jul-22 |
| 11 | | Evening ride in robotaxi vehicle, no operator onboard. Included call with customer service agent. | 16 min | 11-Jul-22 |
| 12 | | Nighttime ride in robotaxi, no operator onboard. Included call with customer service agent. | 15 min | 10-Aug-23 |
| 13 | | Nighttime ride in robotaxi, no operator onboard. | 14 min | 10-Aug-23 |
| 14 | Non-participant observation | Non-participant observations of a robotaxi central command center. Engaged in informal conversations with remote monitors, customer service agents, information coordinators, and managers. | 6 hours | 9-Aug-23 |
| 15 | | Non-participant observations of a robotaxi fleet depot. | 2 hours | 10-Aug-23 |
| 16 | Conference | Automated Road Transportation Symposium in San Francisco, CA. Participation in Workforce Development for 21st Century Automated Mobility breakout session. | 5 days | 10-July-23 to 14-Jul-23 |
| 17 | | Texas Department of Transportation Virtual Connected and Autonomous Vehicles Peer Symposium | 3.5 hours | 7-Mar-23 |
| 18 | | International Association of Transportation Regulators Annual Conference in Scottsdale, AZ. Robotaxi vehicles from Cruise and Waymo present at the conference, along with operators from both firms who were available to answer general questions. Engaged in informal conversations with operators. | 4 days | 27-Sep-23 to 30-Sep-23 |
| 19 | | Transportation Research Board Conference sessions and committee meetings on AVs | 9 hours | 7-Jan-24 to 11-Jan-24 |

## Appendix A.3: Detailed summary of archival documents

| Num. | Category | Role(s) Discussed | Document Description | Year | # Pages |
|---|---|---|---|---|---|
| 1 | Academic article | App, Driver | PhD Dissertation by Lindsey Cameron on the work of ride-hailing drivers and the rise of algorithm management systems | 2020 | 205 |
| 2 | Academic article | Driver | Journal article by Veena Dubal on a history of work, regulation, and labor advocacy in San Francisco's Taxi & Uber Economies | 2017 | 65 |
| 3 | Government data | Dispatcher | O*NET data on "Dispatchers, Except Police, Fire, and Ambulance" | 2024 | 1 |
| 4 | Government data | Driver | O*NET data on tasks for "Taxi Drivers" | 2024 | 1 |
| 5 | Government data | Manager | Data from the U.S. Bureau of Labor Statistics on "Transportation, Storage, and Distribution Managers" | 2023 | 1 |
| 6 | Government data | Mechanic | Data from the U.S. Census Bureau ACM PUMS 5-Year Estimate on "Automotive Service Technicians and Mechanics" | 2021 | 1 |
| 7 | Government data | Mechanic | O*NET data on training requirements for "Automotive Service Technicians and Mechanics" | 2024 | 1 |
| 8 | Interview supplement | App, Customer Service, Information Coordinator, Operator, Remote Monitor, Vehicle | Written supplement from interviewee about roles at Firm F | 2024 | 2 |
| 9 | Interview supplement | App, Driver, Operator, Vehicle | Written supplement from AV Regulation Expert detailing operational differences between traditional taxis and robotaxis. Also includes information about current regulation for presence of an operator in different U.S. states. | 2023 | 11 |
| 10 | Interview supplement | App, Manager, Mechanic, Operator, Remote Monitor | Email response answering questions about labor roles for Firm G | 2023 | 1 |
| 11 | Interview supplement | Vehicle | Spreadsheet detailing the operating status and charging requirements for 1 month of service of an autonomous vehicle shuttle service | 2021 | 3 |
| 12 | Job posting | Customer Service | Job posting for Customer Service Representative by a transportation labor contractor | 2023 | 2 |
| 13 | Job posting | Customer Service | Job posting for Customer Service Shuttle Specialist in Port Saint Lucie, FL | 2023 | 2 |
| 14 | Job posting | Customer Service | Job posting for Customer Service Shuttle Specialist in Orlando, FL | 2023 | 2 |
| 15 | Job posting | Customer Service | Job posting for Customer Service Shuttle Specialist in Altamonte Springs, FL | 2023 | 2 |
| 16 | Job posting | Field Support | Job posting for Driverless Support Specialist in San Francisco, CA | 2023 | 2 |

## Appendix A.3 (cont.)

| Num. | Category | Role(s) Discussed | Document Description | Year | # Pages |
|---|---|---|---|---|---|
| 17 | Job posting | Field Support | Job posting for Driverless Support Specialist in Phoenix, AZ | 2023 | 2 |
| 18 | Job posting | Field Support, Remote Monitor, Operator | Webpage with starting wage information for frontline contingent worker positions | 2023 | 2 |
| 19 | Job posting | Incident Expert | Job posting for Incident Expert in Scottsdale, AZ | 2023 | 2 |
| 20 | Job posting | Information Coordinator | Job posting for information coordinator postition | 2022 | 2 |
| 21 | Job posting | Information Coordinator | Webpage with estimated salary information for Watch Officer position and position description | 2023 | 2 |
| 22 | Job posting | Manager | Job posting for Site Manager | 2023 | 2 |
| 23 | Job posting | Manager | Job posting for Team Lead, Rider Operation | 2023 | 2 |
| 24 | Job posting | Manager | Job posting for Rider-Only Manager | 2024 | 3 |
| 25 | Job posting | Manager | Job posting for night manager | 2024 | 4 |
| 26 | Job posting | Manager, Remote Monitor | Job posting for Associate Manager, Command Center Operations | 2023 | 2 |
| 27 | Job posting | Mechanic | Job posting for Site Autonomy Engineer | 2024 | 2 |
| 28 | Job posting | Operator | Job posting for Autonomous Vehicle Operator by a transportation labor contractor | 2023 | 2 |
| 29 | Job posting | Operator | Job posting for Autonomous Vehicle Operator in Grand Rapids, MN | 2023 | 2 |
| 30 | Job posting | Operator | Job posting for Autonomous Vehicle Operator in Arlington, TX | 2023 | 2 |
| 31 | Job posting | Operator | Job posting for Autonomous Vehicle Operations Specialist in Houston, TX | 2023 | 2 |
| 32 | Job posting | Operator | Job posting for Level 5 Vehicle Operator | 2023 | 2 |
| 33 | Job posting | Operator | Job posting for Autonomous Vehicle Safety Driver | 2023 | 2 |
| 34 | Job posting | Operator | Job posting for Autonomous Vehicle Driver by a transportation labor contractor | 2024 | 1 |
| 35 | Job posting | Remote Monitor | Job posting for Assistance Advisor in Scottsdale, AZ | 2023 | 2 |
| 36 | News article | App, Customer Service, Field Support, Mechanic, Operator, Remote Monitor | News article describing Waymo's depot where fleet management occurs | 2018 | 16 |
| 37 | News article | Frontline workers (unspecified) | News article about staff reductions by Cruise after the company's involvement in an accident in San Francisco | 2023 | 8 |
| 38 | News article | Other | News article about test tracks operated by Waymo | 2017 | 12 |
| 39 | News article | Remote Monitor | News article describing companies developing technology to support for Remote Monitors | 2019 | 5 |
| 40 | News article | Remote Monitor | News article about companies developing remote monitoring software platforms | 2020 | 6 |
| 41 | News article | Remote Monitor | News article describing role of remote monitors for May Mobility's service | 2023 | 9 |
| 42 | News article | Vehicle | News article about how Waymo is designing their vehicles to interact with pedestrians | 2023 | 8 |

## Appendix A.3 (cont.)

| Num. | Category | Role(s) Discussed | Document Description | Year | # Pages |
|---|---|---|---|---|---|
| 43 | Other | Mechanic | Course requirements for De Anza Community College Autonomous and Electric Vehicle Technician Pathway | 2024 | 2 |
| 44 | Presentation | Driver, Operator, Vehicle | Presentation on Guiding Principles for Equitable AV Implementation of Robotaxis by Matthew Daus | 2022 | 19 |
| 45 | Report | App, Customer Service, Field Support, Incident Expert, Remote Monitor, Vehicle | Cruise Passenger Safety Plan | 2021 | 35 |
| 46 | Report | App, Customer Service, Field Support, Incident Expert, Remote Monitor, Vehicle | Waymo Passenger Safety Plan | 2022 | 71 |
| 47 | Report | App, Driver, Operator, Vehicle | International Association of Transportation Regulators' Best Practices, Guiding Principles & Model Regulations for "Robotaxis" | 2023 | 4 |
| 48 | Report | App, Operator, Remote Monitor, Vehicle | Proposal for government-run deployment of a commercial rideshare service | 2021 | 16 |
| 49 | Report | Driver, Operator, Remote Monitor | Report on suggested policies, laws, and regulation for operation of autonomous vehicles across the New England region | 2022 | 214 |
| 50 | Report | Field Support | MIT report quoting a news article about Waymo 'chase vans' that include two Waymo representatives (p.14) | 2020 | 34 |
| 51 | Report | Operator | Cruise safety report appendix detailing operator training and evaluation | 2018 | 6 |
| 52 | Report | Operator, Vehicle | SAE J3016: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles | 2021 | 2 |
| 53 | Report | Vehicle | Nuro's petition for temporary exemption from various<br>requirements of vehicle safety standards for their all-electric AV | 2019 | 36 |
| 54 | Report | Vehicle | General Motors' petition for temporary exemption from various requirements of vehicle safety standards for their all-electric AV | 2022 | 40 |

## Appendix B: Supplemental information for Chapter 3

Equations used for cost estimation and their assumed distributions can be accessed via online appendices at: https://github.com/lkaplan25/av_labor_cost_2024

## Appendix C: Supplemental information for Chapter 4

### Appendix C.1 Full Survey

# Transportation Research Study

INTRODUCTION

You are invited to take part in a research study being conducted by John Helveston, Ph.D., Assistant Professor in Engineering Management and Systems Engineering at the George Washington University.

You are being asked if you want to take part in this study because you are a resident in the Washington D.C. metro area. Please read this form and ask us any questions that will help you decide if you want to be in the study. Taking part is completely voluntary and even if you decide you want to, you can quit at any time.

You must be at least 18 years old to take part in this study. You are 1 of up to 5,000 people taking part in this study at by GWU.

PROCEDURES

The total amount of time you will spend in this study is 10 minutes.

RISKS & CONFIDENTIALITY

The study has no anticipated risks.

You are free to skip any questions or stop taking the survey at any point. We are not collecting your name or other identifiable information about you, and all data will be encrypted. The records of this study will be kept private. In any published articles or presentations, we will not include any information that will make it possible to identify you as a subject. Your records for the study may be reviewed by departments of the University responsible for overseeing research safety and compliance. Once all data are collected, anonymized versions of the data will be made publicly available on a repository on GitHub.

You need not respond to the demographic questions at the end, including questions about age, gender identification, ethnicity, and formal education. We collect this information strictly for the purposes of performing demographic comparisons of the data with that of the general public. Survey responses without answers to demographic question may exclude your response from being included in some of these comparisons. Data without demographics may still be presented in some summary totals.

BENEFITS

Taking part in this research will not help you directly, however the benefit to society will be a better understanding peoples' preferences for different automated transportation modes in the United States.

COMPENSATION

This survey is made available to respondents via Dynata, which offers great diversity in incentives as some people are motivated by cash, points, or by being able to donate to charity. A cash reward is simply a monetary value in $USD. Points are values that can be traded in for different, non-monetary rewards on the research platform. Finally, donations to a charity of your choice can also be selected as a reward. Dynata aims to respond to all of these individual motivations in order to provide a sample which is diverse and as representative as possible of the target population. Dynata uses a reasonable level of reward based on the amount of effort required, the population, and appropriate regional customs. Regardless of the type of incentive, the value is the same for every respondent in a given study.

QUESTIONS

Talk to the research team if you have questions, concerns, complaints, or think you have been harmed. You can contact the Principal Investigator listed on the front of this form at 202-994-7173. For questions regarding your rights as a participant in human research call the GWU Office of Human Research at 202-994-2715 or by email at ohrirb@gwu.edu.

To ensure anonymity your signature is not required. Your willingness to participate in this research study is implied if you proceed.

THE GEORGE WASHINGTON UNIVERSITY

WASHINGTON, DC

[Next page]

Thank you for your interest in this survey.

To start, please enter your zip code: ______________

[Next page]

*If zip code is not within Washington metropolitan area:*

Sorry, we are only looking for individuals who live in the Washington metropolitan area to participate in this survey.

# What are automated vehicles?

This survey will ask about your preferences for different automated and non-automated transportation modes. To start, let's learn a little bit more about what automated vehicles are.

Automated vehicles or “driverless cars” are vehicles that are operated by computer systems instead of human drivers. Many cars today include automated features like automatic braking and lane-keeping assistance. In a fully automated vehicle, a computer system would perform all driving tasks with no assistance from a human driver.

The following short video will explain a little more about different levels of vehicle automation and how automated vehicles work.

Video: https://vimeo.com/578614475
Source: Pennsylvania Department of Transportation

This survey will ask you to compare nonautomated and automated transportation modes. When the survey describes a mode as automated, it is referring to a level 5 fully-automated vehicle, meaning that the vehicle would drive itself at all times and in all situations without any human assistance.

To start, we’d like to learn a little bit about your current transportation routine and your general thoughts about automated vehicles.

[Next page]

# Your current transportation routine

This section includes questions related to your transportation routines and attitudes towards automated vehicles. Given that your transportation routine may have changed due to the COVID-19 pandemic, please consider your transportation routine prior to the pandemic.

(1) Which of the following modes of transportation do you use regularly (at least 3-5 times per week)?
   a. Personal vehicle
   b. Bus
   c. Rail
   d. Ride-hailing service
   e. Shared ride-hailing service
   f. MetroAccess
   g. Other:

(2) Which of the following modes of transportation do you use occasionally (a few times per month)?
   a. Personal vehicle
   b. Bus
   c. Rail
   d. Ride-hailing service
   e. Shared ride-hailing service
   f. MetroAccess
   g. Other:

(3) Which of the following modes of transportation have you never used?
   a. Personal vehicle
   b. Bus
   c. Rail
   d. Ride-hailing service
   e. Shared ride-hailing service
   f. MetroAccess

[Next page]

(4) For each of the following transportation modes, please check how your use of the mode has changed due to the COVID-19 pandemic:

| | Use more than before | Use the same as before | Use less than before |
|---|---|---|---|
| Bus (e.g., Metrobus, ART, Ride On) | | | |
| Rail (Metrorail or DC Streetcar) | | | |
| Ride-hailing service (e.g., Lyft, Uber, Via) | | | |
| Shared ride-hailing service e.g., Lyft Shared or UberPool) | | | |

[Next page]

(5) To what degree do you agree with the following statements?

| | Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|---|
| I am familiar with the concept of automated vehicles. | | | | | |
| I would feel comfortable riding in a fully-automated vehicle. | | | | | |
| Automated vehicles will increase transportation costs. | | | | | |
| Automated vehicles will be safer than human-driven vehicles | | | | | |
| Automated vehicles will cause more problems than they will solve. | | | | | |
| Automated vehicles will improve the availability of transportation options. | | | | | |
| I am willing to share an automated vehicle with people I don't know. | | | | | |
| I have easy access to public transportation where I live. | | | | | |
| I have easy access to a personal vehicle | | | | | |

[Next page]

# Transportation Mode Options

Now that you've shared about your current transportation routine, we'd like you to consider a future in which you can choose from various automated and non-automated transportation options.

Let's learn about these potential transportation options.

# Transportation Mode Options

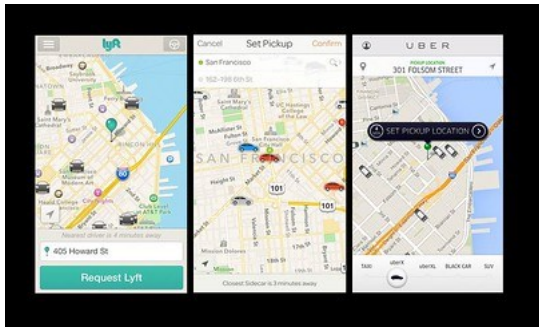
## Bus (e.g., Metrobus, ART, Ride On)


Please imagine that in the future, buses could be automated or non-automated.
Automated buses would follow the same pre-determined routes as non-automated buses but would not have a bus driver.

## Rail (Metrorail, DC Streetcar)

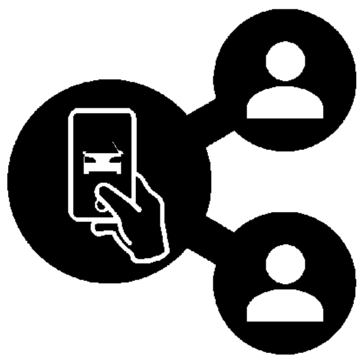
Please imagine that in the future, rail systems (Metrorail, DC Streetcar) would remain non-automated.
They would function the same as they do now and would follow the same routes.

## Ride-hailing Service (e.g., Lyft, Uber, Via)




Please imagine that in the future ride-hailing services could be automated or non-automated.
The ride-hailing service would be similar to Uber, Lyft or Via.
You would order a vehicle using a smartphone and could select both your pickup and drop-off locations.

## Shared Ride-hailing Service (e.g., Lyft Shared, UberPool)



Created by Advier Mobilisaert
from Noun Project

Please imagine that in the future shared ride-hailing services could be automated or non-automated.
The service would be similar to UberPool or Lyft Shared.
You would order a vehicle using a smartphone and could select both the pickup and drop-off locations. Rides would be shared with other passengers who are not a part of your group but are traveling along a similar route.

[Next page]

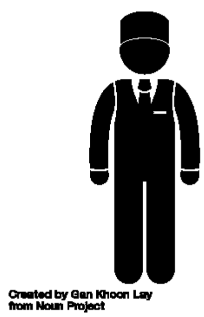
# Mode Features

Some of the transportation modes can have special features. These features include being automated or having an attendant on board.

## Automated

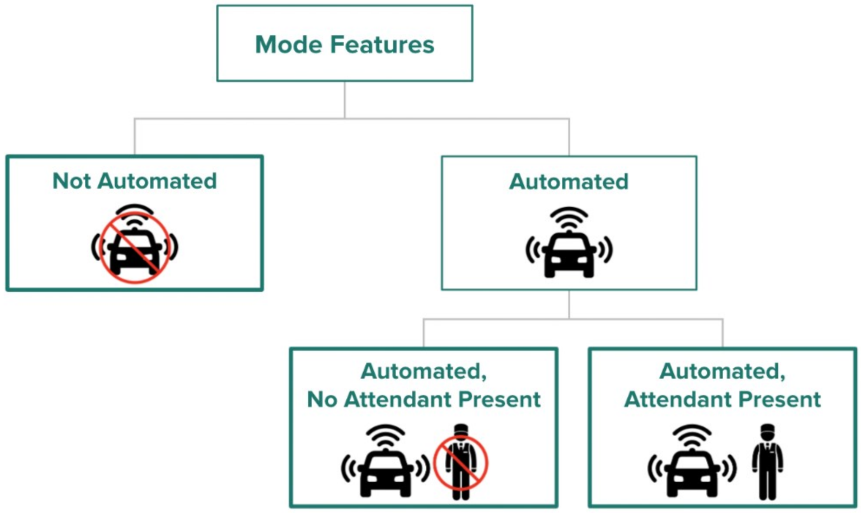

Vehicles that are automated would be operated by computer systems with no assistance from a human driver. No option to take control of the vehicle would be available.

## Attendant




Vehicles with an attendant would have a company official on board to help passengers. This attendant would not be responsible for operating the vehicle.

Only automated modes would have the potential to have an attendant on board, as shown in the diagram below.


Mode Features
Not Automated
Automated
Automated,
No Attendant Present
Automated,
Attendant Present

[Next page]

# Checking in

Which of the following options does the image above describe?

- Not automated
- Automated, No attendant present
- Automated, Attendant present

# Going out on a leisure trip

Now that you've learned about the different potential modes, we would like to learn about your preferences for those modes.

For this next section, imagine you are going out on an evening leisure trip and are deciding how to get there. You will be presented with four different options for transportation modes that you could take. Consider the four options and click on the box to select the option that you would choose.

Let's start with a practice question.

# Let's practice!

Imagine you are going out on an evening leisure activity. Which transportation option would you choose? (Please click on the box for your desired option to select it.)

| Bus | Rail | Ride-hailing | Shared Ride-hailing |
|---|---|---|---|
| Price: $1<br>Wait time: 5<br>Travel time: 20 | Price: $3<br>Wait time: 5<br>Travel time: 20 | Price: $15<br>Wait time: 5<br>Travel time: 30 | Price: $10<br>Wait time: 5<br>Travel time: 35 |
| **Automated, Attendant Present**<br> | **Not Automated**<br> | **Automated, No Attendant Present**<br> | **Not Automated**<br> |

[Next page]

Great work!

Now let's begin the choice tasks. You will be asked 8 questions in total. For each scenario, please imagine that you are going out on an evening leisure activity.

[Next page]

# Conjoint questions

*Subject answered 8 choice questions posed in the manner below. The modes remained fixed for the four options but the attributes (price, total trip time, automation, attendant) were randomized for each question and each participant based on the individual's respondent ID.*

(1 of 8) Imagine you are going out on a leisure activity. Which transportation option would you choose?

| Bus<br>Price: $2<br>Wait time: 5<br>Travel time: 25 | Rail<br>Price: $3.85<br>Wait time: 5<br>Travel time: 25 | Ride-hailing<br>Price: $10<br>Wait time: 5<br>Travel time: 15 | Shared Ride-hailing<br>Price: $7<br>Wait time: 5<br>Travel time: 26 |
|---|---|---|---|
|  |  |  |  |

[Next page]

## Nice job!

For the previous 8 choice questions, which best describes the type of evening leisure activity you were imagining?

- Personal business
- Drop off/pick up
- Shop/meal
- Social/recreation
- Other (please describe below)

If you selected “Other”, please describe what type of evening leisure activity you were imagining:

[Next page]

## Almost done!

We'd like to ask you just a few final demographic questions. We collect the following information to contribute to further data analysis.

1. In what year were you born? (select from drop-down)

2. What is your gender?
    a. Female
    b. Male
    c. Trans male/trans man
    d. Trans female/trans woman
    e. Genderqueer/gender non-conforming
    f. Prefer not to say
    g. Different identity (please state):

3. I identify my race as (select all that apply):
    a. Asian
    b. Black/African American
    c. White
    d. Hispanic/Latinx
    e. American Indian/Alaska Native
    f. Native Hawaiian/Pacific Islander
    g. Prefer not to say
    h. Different identity (please state):

4. What is the highest degree or level of school you have completed? If currently enrolled, please use the highest degree received.

a. Less than a high school diploma
b. High school degree or equivalent (e.g. GED)
c. Some college or university, no college degree
d. Trade/technical/vocational training, no degree awarded
e. Associate's degree (e.g., AA, AS)
f. Bachelor's degree (e.g. BA, BS)
g. Graduate or Professional degree (e.g. PhD, MD, JD, MS)
h. Prefer not to say

5. What is your annual household income (from all sources) before taxes and other deductions from pay?
    a. Less than $25,000
    b. $25,000 - $34,999
    c. $35,000 - $49,000
    d. $50,000 - $74,999
    e. $75,000 - $99,999
    f. $100,000 - $149,999
    g. $150,000 - $199,999
    h. $200,000 - $249,999
    i. $250,000 - $299,999
    j. $300,000 - $399,999
    k. Greater than $400,000
    l. Prefer not to say

6. Do any of the following descriptions apply to you that impact what transportation modes you use (select all that apply):
    a. I have a physical disability.
    b. I have a visual impairment.
    c. I have an intellectual disability.
    d. None of the above apply.
    e. Other (please explain):

7. If you have a cellphone, is it a smartphone?
    a. Don't have a cellphone
    b. Have a cellphone but not a smartphone
    c. Have a smartphone

8. Do you have access to a bank account that you use regularly?
    a. Yes
    b. No
    c. Have but don't use regularly

Please let us know if you have any other thoughts or feedback on this survey. Your feedback will help us make future improvements ☺

[Submit]

Thank you, your responses have been recorded. You can now close this window.

## Appendix C.2 Weighted Utility Model Results

**Table C.2**: Discrete choice model coefficients in WTP space

| Attribute | Coef | | MXL | MXL Weighted |
|---|---|---|---|---|
| Lambda | | | 0.094 (0.006) *** | 0.100 (0.007) *** |
| Travel time | $\beta_1$ | | -0.573 (0.049) *** | -0.547 (0.047) *** |
| Bus travel time | $\beta_2$ | | 0.062 (0.049) | 0.046 (0.047) |
| RH travel time | $\beta_3$ | | 0.232 (0.053) *** | 0.202 (0.051) *** |
| Shared RH travel time | $\beta_4$ | | 0.203 (0.050) *** | 0.155 (0.048) *** |
| Bus | $\beta_5$ | $\mu$ | -6.665 (1.454) *** | -6.063 (1.396) *** |
| *(base = Rail)* | | $\sigma$ | -10.632 (0.835) *** | -10.096 (0.788) *** |
| Bus - Automated | $\beta_6$ | $\mu$ | 1.220 (0.725) | 0.365 (0.706) |
| Bus – Attendant present | | $\sigma$ | 9.822 (1.078) *** | 8.812 (0.985) *** |
| Ride-hailing (RH) | $\beta_7$ | $\mu$ | -7.193 (1.573) *** | -6.162 (1.504) *** |
| *(base = Rail)* | | $\sigma$ | 13.168 (0.886) *** | 12.855 (0.841) *** |
| RH - Automated | $\beta_8$ | | 0.731 (0.802) | -0.070 (0.782) |
| RH - Attendant present | $\beta_9$ | | 10.931 (1.106) *** | 9.773 (1.006) *** |
| Shared RH | $\beta_{10}$ | | -11.535 (1.584) *** | -10.042 (1.489) *** |
| *(base = Rail)* | $\beta_{11}$ | | -12.503 (0.913) *** | -12.227 (0.879) *** |
| Shared RH - Automated | $\beta_{12}$ | | 2.903 (0.815) *** | 1.872 (0.773) * |
| Shared RH, Attendant present | $\beta_{13}$ | | 8.560 (1.011) *** | 8.040 (0.958) *** |
| | | Log-Likelihood: | -16,798.2 | -15,365.3 |
| | | Null Log-Likelihood: | -18,787.1 | -17,217.8 |
| | | AIC: | 33,630.3 | 30,764.5 |
| | | BIC: | 33,758.1 | 30,892.3 |
| | | McFadden R2: | 0.1 | 0.1 |
| | | Adj McFadden R2: | 0.1 | 0.1 |
| | | Number of Observations: | 13,552.0 | 13,552.0 |
| | | Number of Clusters | 1,694.0 | 1,694.0 |

Standard errors of estimates are presented in parentheses. Coefficient units are in USD $. * $\leq 0.05$. ** $\leq 0.01$. *** $\leq 0.0001$.

## Appendix C.3 Scenario Analyses Results

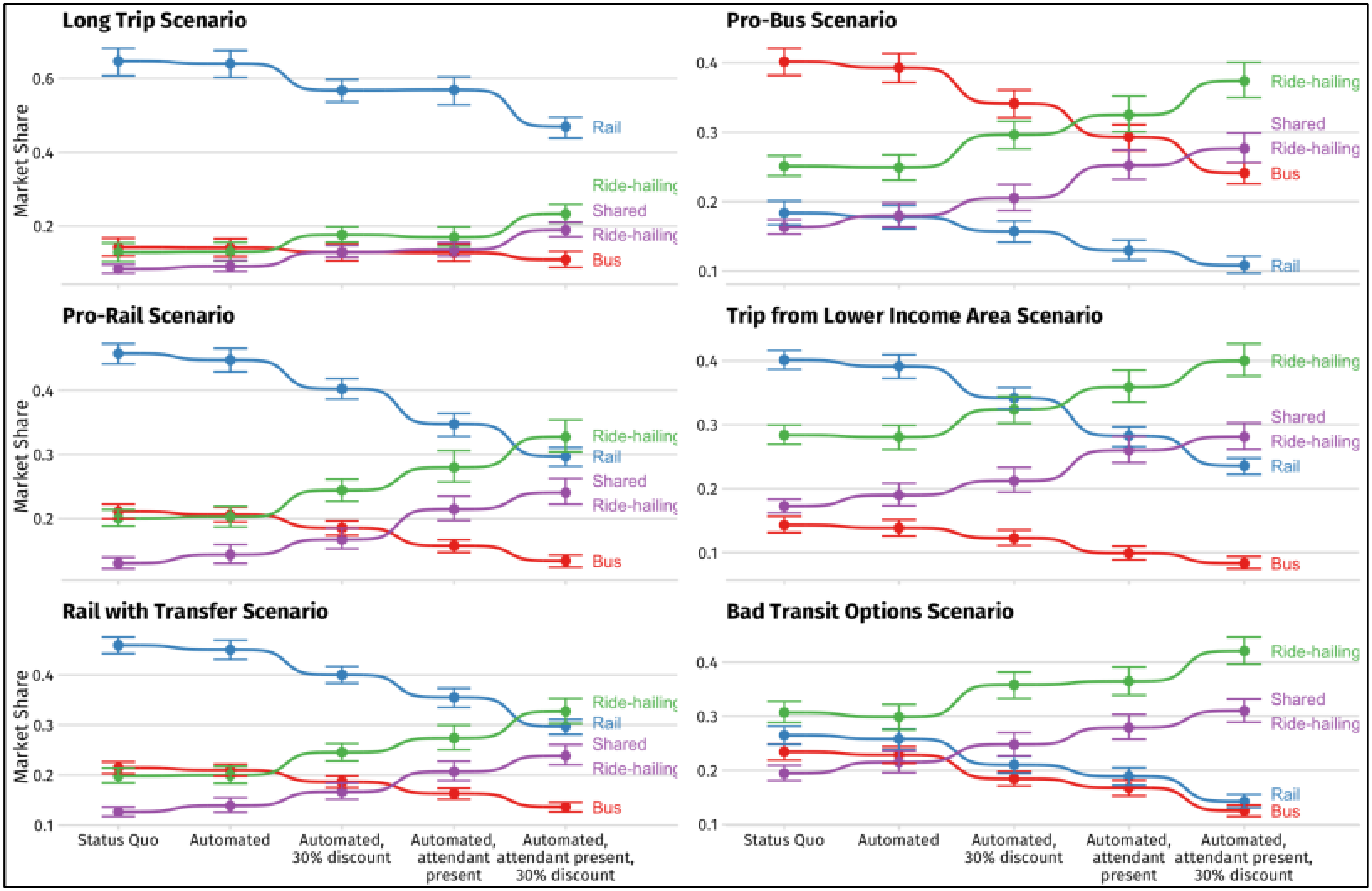



**Figure C.3:** Mean estimated values with 95% confidence interval bars for predicted market share based on introducing automation, an attendant, and price discounts for six trip scenarios.

As one moves left to right across the x-axis, additional features are added to the *ride-hailing* and *shared ride-hailing modes*. “Status Quo” indicates that none of the modes are automated or have an attendant, and that the modes’ prices reflect current prices.

## Appendix C.4 Mode Share of Non-Commute Trips for Regional Core, and Equity Emphasis Areas (EEAs)

**Table C.4:** Mode Share of Non-Commute Trips for Regional Core, and Equity Emphasis Areas (EEAs).
Table Adapted from Joh 2020.

| Non-Commute Mode | Core | Not in EEAs | EEAs |
|---|---|---|---|
| Rail | 6.5 | 2.1 | 4.2 |
| Bus | 4.3 | 0.9 | 4.9 |
| Taxi/Ride-Hail | 2.9 | 0.8 | 1.4 |
| Drive Alone | 24.6 | 36.6 | 31.1 |
| Drive Other and Auto Passenger | 28.6 | 44.2 | 39.4 |
| Walk | 28.3 | 10 | 13.9 |
| Bicycle | 2.9 | 1 | 1.5 |
| School Bus | 1.4 | 4.2 | 3.4 |
| Other | 0.5 | 0.3 | 0.2 |