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A Systems Perspective on AI-Driven Labor Transitions: Insights from the Rise of Robotaxis

Abstract

Advances in artificial intelligence (AI) are transforming how automation technologies interact with and change work systems, impacting non-routine manual tasks that have historically remained unaffected. Leveraging an in-depth study of taxi service automation, and drawing on government occupation data, direct observations, semi-structured interviews, and archival data, our analysis focuses on changes in roles and tasks as a "system." In contrast to prior studies which focused exclusively on part of the work system (e.g., driving), we empirically demonstrate that the introduction of AI to a non-routine manual task-oriented work system spurs a significant rebundling of tasks and labor role organization in a way that ripples across the full system. This rebundling occurs via three archetypal patterns of role change: distributing, consolidating, and scaffolding. These patterns highlight system architecting decisions regarding how new and remaining tasks are redistributed and rebundled into roles and how work systems are reorganized. The patterns also suggest refinements for how researchers perform labor impact analyses at the task, role, and sector levels.

Keywords: future of work, artificial intelligence (AI), autonomous vehicles, robotaxis, work systems

1. Introduction

Advances in artificial intelligence (AI) are transforming how automation can interact with and change human labor and work systems. Unlike repetitive physical tasks that have undergone substantial substitution with automation technologies, non-routine manual tasks like driving—which require dexterity, physical skills, and awareness of the physical context—have had limited opportunities for substitution or complementarity with past automation technologies.[1,2] Emerging AI-enabled technologies like autonomous vehicles (AVs) are, however, increasingly capable of performing such tasks.

In light of these advancements, some voices now claim that AI will soon perform all jobs and displace workers across every sector. Past technological revolutions, however, have not eliminated work and workers wholesale but rather have transformed human labor in more nuanced ways.[3] Furthermore, technologies often perform quite differently in constrained development environments compared to how they exist within, shape, and are shaped by actual work systems.[4] This period of AI-enabled technological change calls for careful consideration of how AI is actually transforming work and work systems. As technologies change, moreover, researchers must refine their analytical tools such that they capture the important features of these transitions and their system-level outcomes.

In this study, we empirically 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, drawing on government occupation data, direct observations, semi-structured interviews, and archival data to identify tasks and labor roles for each work system. We then perform a granular mapping of task and role changes. While prior studies have hypothesized about AI-induced rebundling of tasks and labor role reorganization,[5,6] 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: *distributing*, *consolidating*, and *scaffolding*. These patterns highlight the need for a system-level view of the transition as a work system, including dependencies across functions (e.g., driving and maintenance), while providing insights into how they can be anticipated in future transitions. The patterns are grounded in key decisions regarding how new and remaining tasks are assigned and rebundled into roles and how work systems are reorganized, providing a structured way to examine and predict how the reshaping of work systems might unfold in response to AI technology introduction to perform physical work. Moreover, the identified patterns suggest refinements for how researchers perform their labor impact analyses at the task, role, and sector levels. The *scaffolding* pattern in particular emphasizes a critical temporal element of work system changes that traditional labor impact analyses often miss.

2. Prior Literature

Automation and labor analyses are often performed at the task-, role-, sector-, or economy-level. Each of these perspectives captures various elements of interest and all are sensitive to the researchers' selected boundaries of analysis. The selected boundaries often fail to consider the full work system and subsequently incorrectly estimate impacts or miss additional information about how AI-enabled technologies are changing work.

2.1 Task-Level Analysis

At the task level, researchers have sought to define types of tasks. Autor et al.'s[1] 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[7] for a review). Fernández-Macías and Bisello[8] 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. Motivating this effort to categorize tasks is the desire to understand why substitutions of labor with capital might occur[1,9–11] or, more typical within the engineering literature, to develop guidance on what tasks *should* be performed by an automation system.[12,13] Task typologies are also commonly deployed to predict impacts of technology introduction at the role level.

2.2 Role-Level Analysis

Role-level analyses, largely rooted in economics literature and reasoning, 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.[1] Assuming that jobs with more automatable tasks are more likely to be automated, Arntz et al.[14] estimated that 9% of jobs across 21 OECD countries were automatable. Frey and Osborne[15] 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 automation technologies could perform, spurring dramatic conjectures about substitution effects. Huang and Rust,[16] for instance, asserted that AI technologies will eventually perform all types of tasks and present a fundamental threat to human employment.

Some researchers have measured role-level impacts in terms of exposure to AI without equating that exposure to job loss. Felten et al.[17] developed a measure of AI exposure based on occupation-specific abilities. Using that measure, Felten et al.[18] found that highly-skilled, highly-educated white-collar workers are most likely to be exposed to generative AI technologies. Eloundou et al.[19] 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.[6] similarly developed a task-based suitability for machine learning index and found that most occupations include at least some tasks that are suitable for substitution, though few occupations would be fully automatable.

2.3 Sector-Level Analysis

At the sector or economy-level, researchers have sought to predict impacts to job numbers and worker wages and skills. Acemoglu and Autor[20] 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.[21] identified offshoring as an additional contributor to the trend. Bessen[22] 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.[23]

2.4 Context-Driven Studies

In addition to these more categorical approaches, some researchers have examined the labor impacts of technological change using context-driven work system approaches. These studies have offered additional insights into how technologies and work system co-evolve and have demonstrated that new technologies can alter how work is performed, the division of labor within firms, and the structure of organizations.[24,25] Technology often changes work systems in ways beyond substituting or complementing workers and how these changes unfold can impact job quality and workers' experiences.[4,26,27]

As with prior technology introductions, emerging AI technologies are expected to reshape tasks performed by workers, spur reorganization of jobs, and alter production processes.[5,6,28] Recent context-driven studies have begun to examine the effects of AI technologies on work systems in multiple industries, including hospitality, retail, healthcare, transportation, and warehousing.[4,27,29] Litwin et al.[4] identified a number of cross-cutting themes for emerging technologies' impacts in various industries. 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. Moreover, sociologists and social scientists have identified a number of other limiting factors for AI implementation including the continued importance of tacit knowledge, expertise, and persistent constraints in AI technologies' abilities to perform complex physical, emotional, and cognitive types of work.[30]

2.5 Research Gap

As we enter into "the Era of AI uncertainty,"[28] researchers need to perform cross-level analyses to enhance understandings of AI technology impacts and to refine their measures of such impacts. While some researchers have begun to perform context-driven studies, there is a dearth of empirical analysis of system-level changes. Furthermore, the domain of work systems oriented around a non-routine manual task has been particularly understudied. To that end, this study employs a systems approach to investigate AI impacts on a taxi work system, capturing changes to tasks, roles, and the overall work system, as well as transition states. 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 our understanding of how the introduction of AI-enabled technologies can change tasks and roles in a work system oriented around a non-routine manual task.

3. Methodology

To investigate AI-induced changes to a non-routine manual task-oriented work system, we perform an inductive, comparative analysis of taxi and robotaxi services in the United States. We use an inductive approach as inductive studies are well suited for emergent phenomena that are poorly understood.[31,32]

We select automated driving, and particularly taxi services, as our focus because driving is a quintessentially challenging non-routine manual task which requires dexterity and awareness of the physical context. Furthermore, as a public-facing transportation service, robotaxis offer insights into AI technology deployment in a safety-critical domain which could influence the ways in which risks must be mitigated and communicated to prospective users. Robotaxi services are still developing and our current mixed transportation system 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.

Our research approach involves iterative within-case and between-case analysis, the mapping of how tasks move between roles after the AV technology is introduced, and finally the identification and description of patterns of change that occur. Figure 1 provides a visual depiction of our data collection and analysis process. We further describe this process in the following sections.

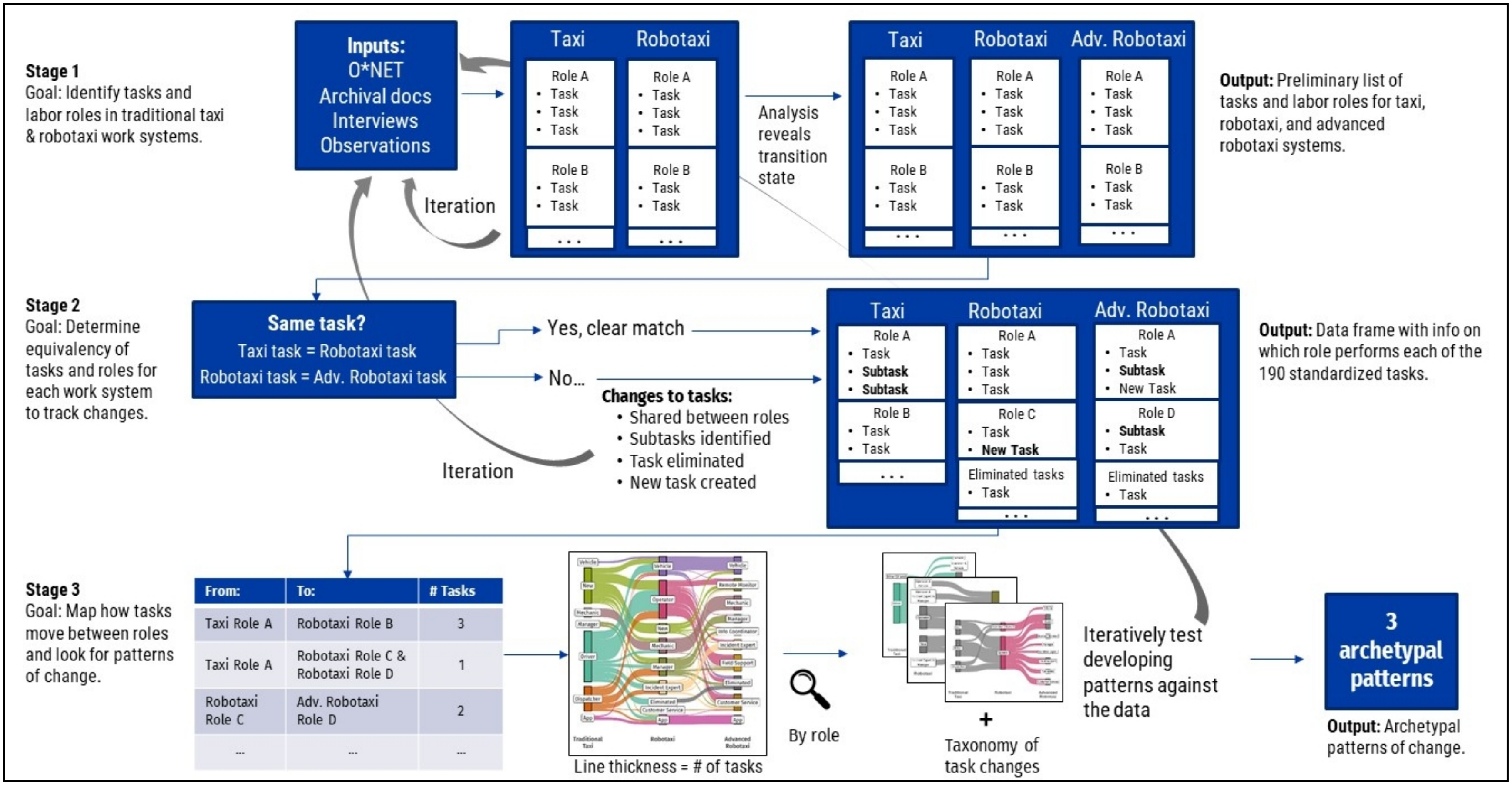

Figure 1. Data collection and analysis process

3.1 Research Setting: Taxi Services

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. An alternative comparison is ride-hailing firms like Uber and Lyft, otherwise known as Transportation Network Companies (TNCs). While taxi firms and TNCs both facilitate transportation as a service, they have substantially different work systems. TNC work systems are oriented around developing and maintaining software platforms, and core functions such as data science and algorithm optimization are not present in a traditional taxi work system. Also, TNCs do not own, manage, or maintain large fleets of vehicle—functions that are required for robotaxi firms (at least for the time being).[1] TNCs classify themselves as *technology* companies rather than *transportation* companies as their core function is to provide the technology needed to match riders to drivers that are providing transportation as a service with their own, privately-owned vehicles via an app.[34] These differences influence the tasks and roles associated with the respective work systems of taxis and TNCs. Although consideration of ride-hailing jobs is important for understanding the potential future overall labor impacts of robotaxis, ride-hailing work systems are not suitable as a direct comparison with robotaxi work systems for now. We thus adopt taxis services as our basis of comparison.

Though far from the level of ubiquity promised by AV firms a few years ago, robotaxi services are publicly available in multiple cities in the U.S. and China. 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).

[1] The robotaxi landscape is changing rapidly and Uber recently partnered with Lucid Group and Nuro to deploy 20,000 robotaxis on Uber's platform.[33] Nonetheless, TNCs have historically be asset-light organizations and thus we feel that taxi firms are the more appropriate basis of comparison for this study.

For each city in which they operate, robotaxi firms have a depot where the AVs are stored and maintained. Some depots include automotive machine shop equipment so that the firms' mechanics can perform in-house vehicle repairs.[35] Robotaxi firms also have central command centers that oversee fleet operations across multiple cities. These command centers house workers that monitor and assist the AVs in a manner similar to air traffic controllers.[36,37] 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 these remote monitors.[38–40] Little is known about other types of workers who directly support these services, and how the overall taxi work system might be changing.

3.2 Unit of Analysis

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.[41] 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.

3.3 Data Collection

To develop our taxi and robotaxi system 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.[42] 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.[2,6,17–19,43] Taxi occupations are well-established and both O*NET and academic literature[34,44] offer detailed descriptions of taxi system tasks and roles on which we can draw to develop our taxi system representation. 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.

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 1 for a summary of our data sources, additional details provided in Appendices A-C). 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 systems (e.g., image labeling).

Table 1. Summary of data sources

<table>
<tr><td rowspan="9">O*NET Data & Archival Documents</td><td colspan="3">Document Type</td><td>Number of Items</td></tr>
<tr><td colspan="3">O*NET Occupation Information</td><td>4</td></tr>
<tr><td colspan="3">U.S. Bureau of Labor Statistics Data on Occupations</td><td>3</td></tr>
<tr><td colspan="3">News Articles Mentioning Frontline Robotaxi Roles</td><td>7</td></tr>
<tr><td colspan="3">AV Firm Public Reports and Petitions</td><td>5</td></tr>
<tr><td colspan="3">Job Postings for Frontline Robotaxi Roles</td><td>24</td></tr>
<tr><td colspan="3">Reports about AV Regulations</td><td>4</td></tr>
<tr><td colspan="3">Supplementary Responses and Documents from Interviewees</td><td>4</td></tr>
<tr><td colspan="3">Total:</td><td>51</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 (hours)</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.

3.4 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 firms are 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.

3.4.1 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 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 (see Appendix A for details). To fill in the gaps of potentially missed roles, collect additional task information for identified roles, and to 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. 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. Interviewees were selected via purposive sampling to capture the different types of frontline roles involved in robotaxi services and cover different perspectives.[31] 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).[32,41] In addition to semi-structured interviews and observations, the lead researcher attended academic, regulatory, and industry conferences about autonomous vehicle deployment.

We triangulate our findings[45] 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.

We use our collected data to construct standardized task and role entries akin to those in O*NET for the robotaxi and advanced robotaxi roles.[2] 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. Appendix D presents one example of our translation process. Preliminary analysis reveals that a transition point exists that significantly impacts what roles exist in the taxi 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 – *Robotaxi*, and 3) AI technology capabilities expanded (onboard operator removed)

[2] 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.

– *Advanced Robotaxi*. For some tasks and roles, it is not immediately apparent whether they existed prior to, or arose during, the *Advanced Robotaxi* phase. We check these items with our interviewees to determine proper allocation of tasks and roles for each of the three different phases.

3.4.2 Taxi System Tasks and Roles

Social, economic, and regulatory forces have changed the structures of taxi firms over time.[34,46] 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.[44,47] We assume a centralized taxi firm structure since robotaxi firm structures more closely mirror those of a centralized firm and leverage O*NET data to define tasks for roles in our taxi system representation.

3.5 Stage 2: Determining equivalency of tasks and roles to track changes

We 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 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).

The matching process also surfaces tasks that are not included in the O*NET data. If through additional interviews or data sources we find that 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. Appendix D 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.

3.6 Stage 3: Mapping how tasks move between roles and identifying patterns

We use the R programming language[48] and the *ggsankey* package[49] to create Sankey diagrams that map and visually depict 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) 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. 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.[41]

4. Results

4.1 Automation of Driving Changes Much More than Driving

Figure 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, 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.

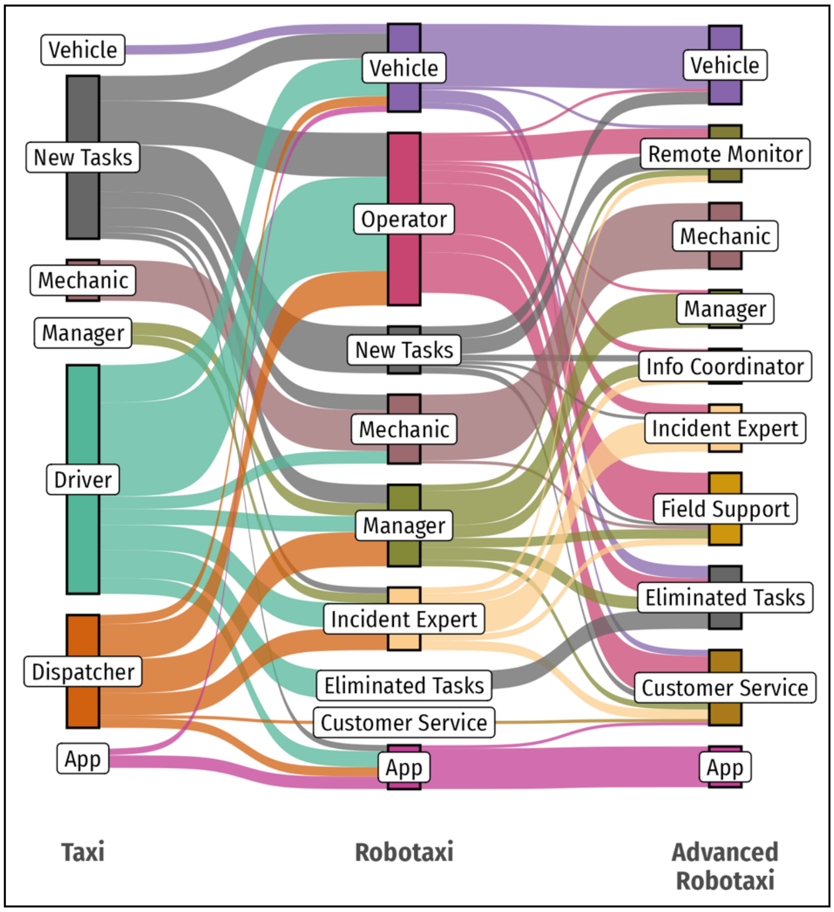

Figure 2. Tracing of tasks between roles across three phases of a taxi work system

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. As evident in Figure 2, the number of roles increases as the system transitions from taxi to robotaxi and from robotaxi to advanced robotaxi. This increase occurs in large part because the driver—and later the operator—role is subdivided in multiple other roles. Though the number of roles is increasing, the total number of jobs is likely to decrease over time because fewer workers are capable of managing a greater number of vehicles.[50]

4.2 What Types of New Roles are Created?

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 briefly describe these roles below (see [name removed to protect anonymity][51(p34)] for detailed descriptions).

The mechanic and manager roles are similar in the taxi and robotaxi systems. Robotaxi mechanics perform typical vehicle repairs and maintenance and also need expertise in software and computing systems to maintain the AV sensors and computing equipment. 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 (e.g., providing guidance on when onboard operators should takeover and manually navigate the vehicle through a situation versus allow the vehicle to handle the situation independently).

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. Operators play an active role in evaluating AVs' performance, taking notes on their areas of failure and carry out many of the vehicle- and passenger-support tasks previously performed by taxi drivers like refilling the gas and answering rider questions.

Remote monitors, customer service agents, and information coordinators are all centralized roles. Remote monitors perform real-time, though not continuous, monitoring of the autonomous vehicles. They can provide secondary verifications for the AVs and perform a limited number of vehicle maneuvers remotely but do not remotely drive the vehicles. Another remote support role, customer service agent, has adopted many of the service tasks that taxi drivers and dispatchers previously performed, including answering rider questions, issuing safety reminders (e.g., buckle your seatbelt), and managing rider behavior. Customer service agents serve 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. The creation of multiple new distinct but interconnected roles introduces greater complexity and information processing requirements into the robotaxi system. 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.

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 once the operator role is eliminated. Incident experts are also involved in 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. In a typical taxi firm, dispatchers and managers perform these functions. Robotaxi firms are also subject to a number of federal and state reporting requirements. 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.

4.3 Patterns of Change for How Roles Respond to the Introduction of AI

Figure 2 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 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 occurs 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. These changes often arise from firms' decisions on how to allocate work between capital and labor. Alternative decompositions and architectures are also possible.

Robotaxi firms could, for instance, keep drivers onboard the AV[3] to perform all remaining non-driving tasks. The following sections further describe these patterns.

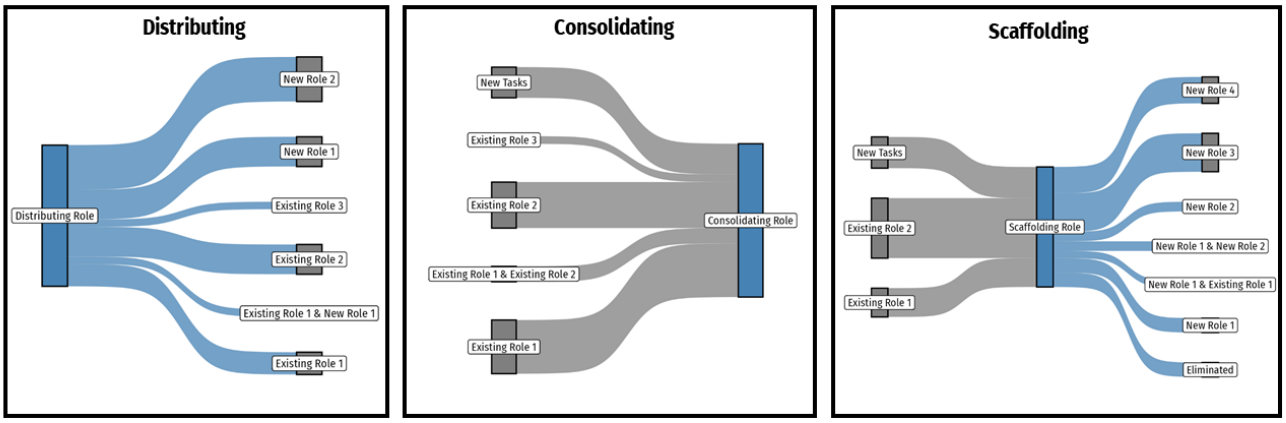

Figure 3. The three archetypal patterns

4.3.1 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's[55] *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.,[4] or excluded from the capabilities of the system. Offloading of tasks is distinct from outsourcing a task beyond the boundary of the firm. Our model does not distinguish between

[3] 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.[52–54]

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.[56,57] 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.[25]

Figure 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.

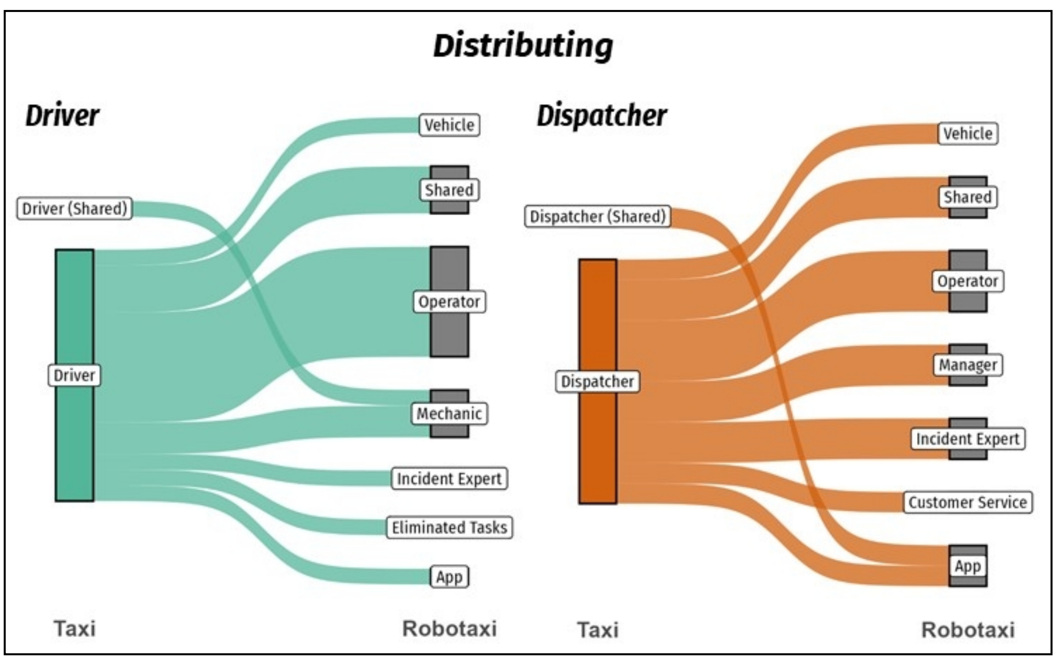

Figure 4. The *distributing* pattern

4.3.2 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,[3] 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.[10]

Figure 5a 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 5b). 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.

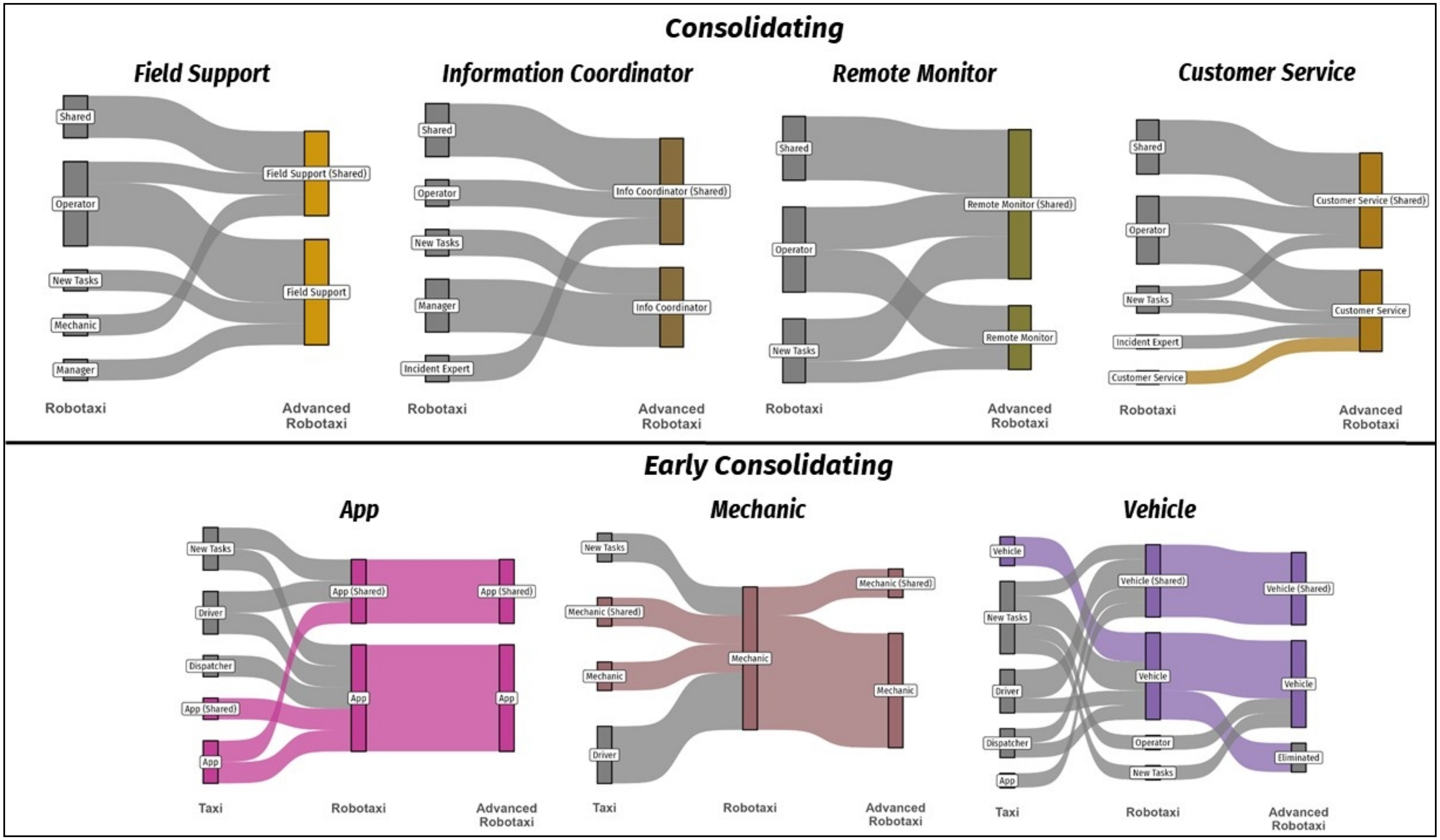

Figure 5. The *consolidating* and *early consolidating* patterns

4.3.3 Scaffolding

Firms introducing AI technologies to their work systems may undergo transitional phases during which they further develop the 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.

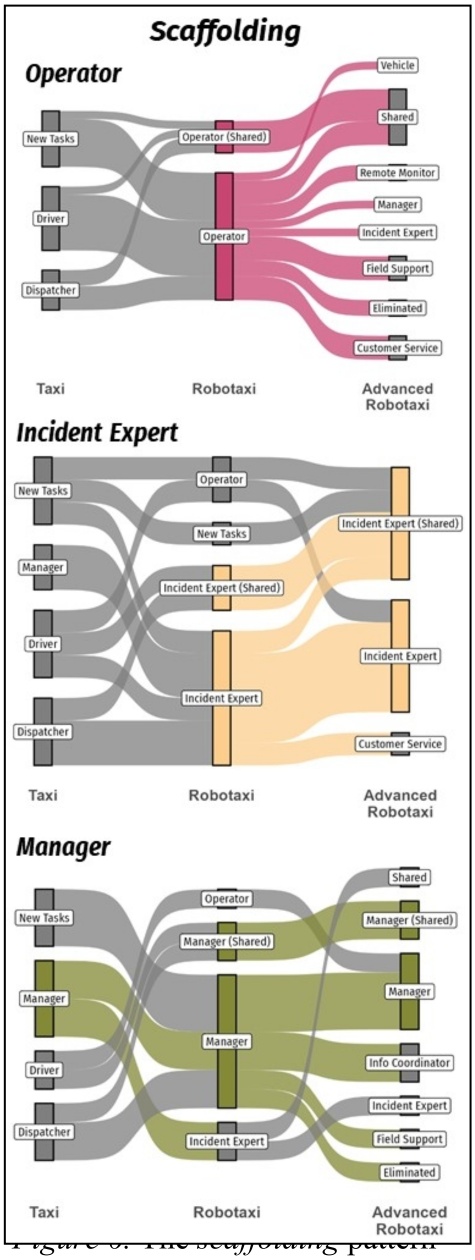

Figure 6. The scaffolding pattern

Figure 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 the operator's diagram.

5. Discussion

The identified patterns offer insights into how tasks and roles are being reshaped for AI-impacted work systems oriented around a non-routine manual task. The patterns highlight critical system-architecting decisions that occur, as well as the potential for alternative transition pathways that could influence impacts to affected workers. Moreover, the identified patterns highlight the need for a systems perspective to study AI and labor.

5.1 Consideration of Work System Transition States

Our identified patterns emphasize the importance of focusing on the decision-making processes by which work system changes are occurring rather than merely on end-states. Referring to a role as "substituted" implies that an AI technology is performing all of that role's tasks. In reality, the *distributing* pattern reveals that many of a "substituted" role's tasks are redistributed to multiple labor roles. Similarly, the *consolidating* pattern demonstrates that multiple roles can emerge from the introduction of AI, some of which do not directly interface with the technology.

As previously noted, the final system design following the introduction of an AI technology is not predetermined but rather involves system-level decisions regarding how existing tasks, newly-identified subtasks, and newly-created tasks are allocated to roles. Depending on the types of system designers engaged (e.g., AI experts, workers, members of the public), alternative preferred architectures may emerge. Prior research has shown that such engagement can yield improved, innovative complex work system designs.[58] The optimal system architecture also depends on who is performing the work. Business models within the AV industry continue to evolve, with AV firms like Waymo partnering with fleet management companies like AutoNation[57] and TNCs like Uber striking deals with various AV developers.[59] System architectures will need to continue to adapt to these evolving organizational systems.

Alternative architectures not only influence impacts to workers but also ongoing operational requirements for firms. Labor roles exhibiting the *distributing* and *consolidating* patterns may have different wages, education requirements, training needs, etc. depending on how system architecting decisions are made and how new roles are created. By making assumptions about the end-states of roles, system designers miss many of the important decisions that shape work system design throughout that process of change. Our identified patterns draw attention to these decision points. Previously, designers may have asked:

- Should a firm choose to adopt a technology to perform a task?
- Should a firm choose to eliminate the role associated with that task (substitution) or use the technology to help perform that task (complementarity)?

Our patterns open investigation of alternative paths of inquiry such as:

- How might a firm choose to bundle an eliminated role's tasks (i.e., how might *consolidating* take place)? Will workers likely have higher skill levels and wages as a result of *distributing* or *consolidating*?

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 considering *scaffolding* roles, system designers can map out alternative transition strategies and explore tradeoffs of alternative strategies using existing tools, such as Szajnfarber et al.'s Evolvability Analysis Framework.[60] Such tools can help firms develop and consider approaches that strive toward optimal outcomes for firms and workers.

5.2 Refining AI Impact Analyses

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.[11] 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[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[61] 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.

Our patterns also 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.[43,62] 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."[63] 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[64] 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). Drivers more 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.

This study used robotaxis as a domain in which to explore AI-induced changes to work systems oriented a non-routine manual task. As both a public-facing service and part of a safety-critical domain, robotaxi services have unique characteristics that may influence some elements of our findings. In particular, current and future regulation of robotaxis by both federal agencies like the National Highway Traffic Safety Administration and state or local governments may influence how tasks are redistributed and what roles remain in ways that may not apply to less regulated domains.

6. 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 work system outcomes.

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Appendices

Appendix A. Detailed summary of semi-structured interviews

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

Appendix A (cont.)

Num.	Category	Org.	Position	# of Interviews	Total Length of Interview (min)	Date	Location	Recorded and Transcribed
17	Pilot Program or Government -Run Deployment	Government	Operations Management	1	55	19-Oct-22	Zoom	Yes
18		Government	Operations Management	1	63	18-Oct-22	Zoom	Yes
19		Government	Operations Management	1	64**	11-Oct-22	Zoom	Yes
20		Government	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	Research er's 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 B. 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 C. 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 C. (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 C. (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 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 D. Examples of data analysis processes

Process(es)	O*NET Task	Open-coding Task(s)	Quotes	Firm	Role
Task and role identification from data. (Task performed by different role in Robotaxi and Advanced Robotaxi systems). 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, dividing O*NET task (task split at ellipses), and 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)	Government-run deployment	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
Identifying new task	N/A	Perform pre- and post-trip	"They [field support agents] have a checklist, as simple as you can think of where they're walking around the	Firm A	Field Support

		systems checks	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)		
			"…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.