

Rethinking Robot Ownership: Comparing Public, Corporate, and Private Ownership Models

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Abstract

General-purpose robots, or robots that can autonomously and collaboratively perform a wide range of tasks, are almost universally imagined with a private ownership model throughout the robotics research and development process, in which individual households purchase, own, and maintain their own robots. In this paper, we argue that robot ownership should instead be treated as a central socio-technical design choice that fundamentally shapes who benefits from robotics, how robots are deployed, and which research directions become prioritized. We analyze three ownership models for general-purpose robots: **private ownership**, in which firms retain ownership and provide access through subscriptions, rentals, or per-task fees; **corporate ownership**, in which robots function as community resources or public goods accessed through institutions such as libraries, cooperatives, or community centers. We examine how each ownership model structures access to robots and people's relationships with them along key socio-technical axes including monetization, distribution, repair and maintenance, and liability for harms. We show that the de facto focus on private ownership risks entrenching unequal access to a potentially transformative technology due to its monetary, temporal, and logistical costs. More broadly, we argue that ownership assumptions quietly but powerfully shape robotics research agendas, contributing to hegemonic practices that remain largely invisible in funding, design, and evaluation. We contend that shared ownership is particularly promising for expanding access to robots and improving human-robot interaction, but that realizing this potential requires shifts in both research practices and policy frameworks.

Introduction

Like washing machines and dishwashers before them (Williams 2012), home robots have the potential to be a transformative and beneficial technology. Task-specific robots are already capable of freeing up people's time by automating some chores (Liao et al. 2021; Wedel 2024; Asafa et al. 2018), assisting people with daily tasks (Bhattacharjee et al. 2020; Nanavati et al. 2020), and serving as a tool for fulfilling creative and fun activities. General-purpose robots, while difficult to precisely define, can be thought of as robots which can perform and learn a nearly arbitrary range of tasks

and do so either autonomously or collaboratively with a person. While not yet a realized technology, the development of general-purpose robots is an underlying goal of much robotics research in both academia and industry. Even more so than task-specific robots, such as robot vacuums or autonomous vehicles, general-purpose robots have the potential to be pre-distributive societal equalizers by alleviating unequal chore burdens, actively reducing wealth disparities, and by empowering people to create and carry out unique creative projects, even with limited expertise or time. Although the timeline for developing such robots remains uncertain, policymakers, research funders, academics, and industry can make critical decisions in this early phase of research and development that will shape how general-purpose robots are distributed in society, for what purposes, and who will benefit from their deployment.

The de facto and often implicit assumption in current robot research and development is that these robots will typically exist in a **private ownership** model: consumers will purchase, own, and maintain their own robot. This model has several benefits from a user perspective: the robot is readily available to use in your home at any point and it can learn and adapt to one's preferences over time. Despite these benefits, this model risks leaving much of society behind in terms of access to general-purpose robots due to potential high initial and recurring costs of purchasing and maintaining such a robot. The implications of robot ownership, as well as alternatives to the private ownership model, remain relatively underexplored in robotics research. In this work we define and analyze two alternatives. The **corporate ownership** model entails corporate-owned robots that may be rented out to consumers for specific tasks with per-task fees and/or subscriptions, and this alternative ownership model readily fits into many existing socio-economic infrastructures. The **shared ownership** model instead has robots function as equitably distributed public goods, available freely or cheaply to be used by people of a community at the time of use, with the costs of purchasing and maintenance distributed across the collective. The shared model is relatively idealistic under current political, economic, and industry trends; however, with a focused effort and shift in research and research funding, as well as an explicit and targeted policy effort, the shared model could be a realizable future for general-purpose robots.

In this work, we analyze these three ownership models for general-purpose robots along four different socio-technical dimensions: monetization strategies, distribution, repair and maintenance, and liability for harms. We focus on these dimensions because they are the main ways that ownership models are implemented in practice, shaping the economic, institutional, and legal arrangements around robots and, in turn, who can access them, how they are governed, and how people experience them. Through a horizon scanning exercise, we examine trends in robotics research. We identify how such research is influenced and underpinned by the assumption of private ownership and what directions must change to enable a future of alternate, collective models. Throughout this work, we compare and contrast each model's advantages and disadvantages from both a sociotechnical and end-user perspectives. We also highlight throughout the potential benefits of the shared model in particular. Finally, we conclude by discussing what it would mean for robotics research, funding, and policy to take ownership and access seriously as part of the fairness, accountability, and governance of embodied AI systems. While we focus on general-purpose robots, the analytic approach and many insights extend to task-specific robots and, in some cases, to non-embodied AI systems as well.

Three Models of Robot Ownership

We identify three models for robot ownership, which can overlap in part. Along with each, we provide an illustrative vignette that will be used as a reference in the subsequent sections. The most familiar is **private ownership**, in which an individual or household purchases and owns a robot outright. While seemingly straightforward, private ownership is often complicated by ongoing dependencies on manufacturers, who may retain control through proprietary software updates, licensed drivers, recurring fees, or paywalled capabilities and add-on services. As a result, ownership of the physical artifact does not necessarily entail meaningful control over the robot's functionality or lifecycle.

Vignette private ownership (V.P): Two working parents live with their children in a suburban home. They own a general-purpose "robot butler" that performs daily household chores, assists with meal preparation, helps the children with homework, and carries out outdoor tasks such as taking out the trash or retrieving mail. Over time, the robot adapts to the household's routines and learns new tasks.

The family purchased the robot for a price comparable to a luxury sedan. In addition, they pay a recurring monthly fee for the robot's base software, which combines onboard computation with access to a cloud-based foundation model operated by the manufacturer. Several core capabilities—including collaborative physical tasks, personalized educational assistance, and insurance coverage—are available only through additional subscription packages. Although the family is satisfied with the robot's performance and considers it a worthwhile investment, its continued usefulness remains contingent on ongoing pay-

ments and the manufacturer's software infrastructure.

A second model is **corporate ownership**, in which a private firm owns and operates a fleet of robots that are rented or provided as a service to end users. Although not general-purpose robots, Waymo's autonomous vehicle fleet exemplifies this arrangement. Corporate ownership can offer practical advantages, particularly for immature and fragile technologies: because firms retain ownership, they remain responsible for maintenance, safety updates, and system reliability, lowering barriers to adoption for consumers.

Vignette corporate ownership (V.C): There is an individual living alone in a one-bedroom apartment who needs help assembling a newly delivered bed frame. Since they live in an urban area, they can readily, through an on-demand robot assistant app, request a robot to help. They upload a link to the bed frame and receive an estimated price for the service and an arrival time. Forty-five minutes later, a robot arrives.

Before starting the task, the platform requires the user to create an account and agree to a set of consent forms governing liability, data collection, and service terms. The robot offers optional features such as mapping the apartment and performing a brief onboarding routine to improve collaboration. The user initially declines these additional interactions. The user and the robot assemble the bed together, and the user is satisfied with the outcome. After the task, the final charge is processed, including an additional energy fee calculated based on task duration. Anticipating future use of the service, the user later opts to allow apartment mapping and onboarding, with the resulting data linked to their platform account. The robot then returns to its hub to recharge and serve its next customer.

The third model is **shared ownership**, in which robots are collectively owned and governed by a public or quasi-public institution, such as a library, cooperative, or municipal body. People may borrow, rent, or use these robots for specified periods of time and for little to no cost.

Vignette shared ownership (V.S): Consider a resident who lives together with several roommates and is planning a community event. They want to produce a large number of handmade-style posters with varying designs. After purchasing art supplies, they visit their local library, where they are able to borrow a robot at no cost for one day. As a frequent user of the library's robotics program, they have already completed the required training. For this task, they borrow a modular robot arm housed in a small wheeled unit that accompanies them home. After setting up the materials, they spend about half an hour demonstrating the task, answering a few clarification questions, and then leave the robot to complete the posters independently. The robot finishes the work later that afternoon. Rather than returning the robot immediately, they opt to keep it for an additional day, paying a modest late fee and considering other projects it could assist with (like

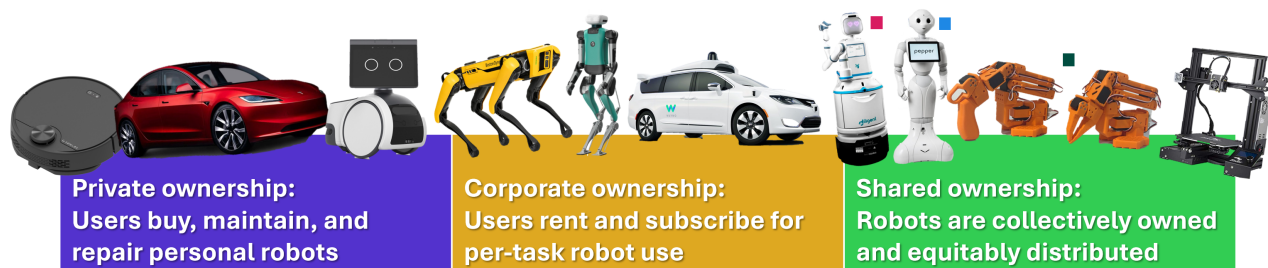


Figure 1: Depicted are existing robots that fall under, or are closely related to, each ownership model. Because few robots are currently deployed under shared ownership, we include robots that illustrate shared or low-cost use: ■ Moxi is a robot that is deployed in hospitals to assist nurses (Jones 2023); ■ Pepper has been used to guide museum tours in a national museum (Smithsonian 2018); ■ SO-101 is a set of open-source 3D printed robot arms from Hugging Face as part of their full-stack open-source robotics initiative LeRobot (Knight et al. 2026; Cadene et al. 2024).

helping them fix up a broken bicycle). When the robot is returned to the library, it is reset and inspected by a staff member for future circulation.

In the following four sections, we analyze these ownership models along four socio-technical axes: monetization, distribution, liability, and maintenance. This analysis illustrates how private and corporate ownership models shape, and in many cases constrain, access to robots and their capabilities, while also showing how shared ownership models could support broader access and different forms of use.

Monetization Strategies

Although general-purpose robots have yet to become available, we can forecast several ways in which they may be monetized either for profit, as in the private and corporate model, or for the means of sustainable upkeep and distribution, as in the case of the shared model. We look to several sources to make predictions about monetization strategies. There are already existing robot companies that sell consumer-facing commercial robots, specialized industrial robots, and robots designed for research purposes. Several robotics start-ups developing general-purpose robots have already publicly released some details of their monetization strategies, and have made forecasts about the value of the general-purpose robot industry more broadly. Finally, we examine strategies used to monetize AI-based software and products and draw parallels to how those strategies might be applied to robotics. As we discuss monetization strategies across different ownership models, we explain how each may affect access to general-purpose robots. We focus on who may benefit and who may be economically excluded.

Private There are several ways in which companies can monetize robot assistants. There is the upfront cost of buying the physical robot, and this upfront price itself may exclude many people from being able to afford one, especially without going into debt or taking out a loan. It is difficult to guess as to what the average price of a robot will be, as existing prices for robots that have a morphology that resembles what could become a general-purpose robot assistants, such as humanoids, vary greatly in their price and capabilities¹.

¹Existing humanoid robots capable of mobile manipulation cost

Even if the price of the robot is as expensive as that of a luxury vehicle, many people could still opt to purchase one, creating a tens- to hundreds of billion dollar market. Depending on the underlying mechanisms of how this happens, the upfront cost of hardware alone risks creating a substantial divide in access to the technology and further reinforcing existing economic inequalities.

In addition to the upfront cost of hardware itself, it is likely that companies will heavily monetize software. This is already the case for many existing robots in industry (Bots 2026). *V.P* illustrates an example of how a robot in the home’s software may be monetized. There may be a required subscription to access basic and required features of a robot’s assistance, where “basic and required” are determined by market forces and corporate executives. There will likely then also be tiers of additional functionality one may add on to, as is the case with many LLM based services that improve the robot’s basic functions (Chodak et al. 2025); as well as other subscriptions to more specialized software. In the case of robots, functionality differences can have substantial consequences. While some companies have already implemented relatively benign software-stores for humanoid robots (like the ability to purchase dance-moves (Sinha 2025)), without regulatory oversight, there is little incentive for companies not to paywall many features of the robot, such as its collaborative capabilities (as in *V.P*), or features that may have consequences for its safety, efficiency, and ability to assist users². Such practices are already in place for vehicles, such as Tesla’s self-driving subscription (Price 2024). Throughout the tech stack, additional software costs compound, and even these costs can create differences in economic opportunity among those able to purchase a robot but unable to afford certain software.

Corporate In the case of corporate ownership, consumers pay a fee to rent the robot. This may be a monthly subscription, a per-use fee, or some combination of both. This model is the basis of the “gig-economy” and has seen wide success (and failures) in markets such as food delivery (Melián-

from tens to hundreds of thousands of dollars (Bots 2026).

²Robot speed, for example, is a double-edged sword: it may cost more to be able to have the robot perform tasks quicker under the justification that additional safety software is being used.

González 2022), creative work (Alacovska, Bucher, and Fieseler 2024), and lodging (Guttentag 2019). Most relevant is the application of this model to ride-share and transportation services. Waymo, for example, owns its own fleet of autonomous vehicles which are deployed in certain cities and offer an autonomous alternative to other ride-sharing apps like Uber and Lyft (Melendez and Guerrero 2025). Such a model could also feasibly be applied to robot assistants. As in V.C, there could be service hubs around cities where the robots are stored and maintained; then, if someone is within a certain distance of that hub, a robot could be delivered to their home or picked up. This “gig” model, and robot rentals, have already emerged in the robotics industry (Atharva 2026; Biba 2025). The model offers a promising way of lowering the cost-of-entry to access a robot and thus broadening people’s access to the technology. This may especially be the case for tasks where multiple robots are required (for example, lifting something very heavy or preparing a space in a very short period of time).

As with other products or services, like ride-shares, there may be various dynamic pricing elements to general assistance. The most salient is how cost may change depending on the task that the user wants performed. Task pricing may vary as a function of the amount of time it will take to complete, the amount of compute resources necessary for the robot to either learn or execute the task, and the physical exertion required to complete the task itself. In addition, there may be paid memberships offered that improve the service. Some features that may significantly improve a customer’s experience over time, such as whether the robot has access to information about the user and their home, may be either directly monetized through user payments, or, as in V.C, supplemented by consent to have that data stored and used by the company given how useful it may be (Birch and Cochrane 2022; Jossen 2017).

While the corporate model may lead to more people being able to access and try robot assistants, it is unlikely to provide a sole solution for ensuring equitable access to the technology. The monetization strategies in the corporate model may not enable people to be able to use such a robot for longer periods of time, for more complicated tasks, or for tasks that may pose a risk to the robot. Users may also be hesitant to use these corporate deployed robots due to privacy or data handling concerns, where the company deploying the robot controls all aspects of hardware and software (Axelsson et al. 2025).

Shared Given the nature of shared ownership, robots in this model are likely to be funded as public goods by government entities (local, state, or federal). One approach is to provide access free at the point of use, with costs recovered through taxation rather than direct user fees. This approach could be instantiated through, e.g., public libraries. In the same way people currently borrow power tools from a local library, they may check out a robot; as in V.S, there would likely be additional late fees if the robot is not returned by a certain time. Another approach is to have a fee for borrowing the robot, but that fee would be significantly cheaper than renting a robot under the corporate model. This is analogous to bus fees or tolled roads. There may also be low-cost

subscriptions or additional fees for professional use (such as borrowing a robot to help with a particular business task). The shared ownership model can offer the highest access by eliminating cost barriers by distributing costs. The availability and number of robots, their ease of access, how well they are maintained and updated, and how advanced their capabilities are relative to the state-of-the-art would depend on government funding choices, priorities, and demand.

Distribution

Unlike software or small tools, general-purpose robots are likely to be large or heavy and require specialized transportation. Delivery to homes may differ depending on morphology and ownership model, especially if distribution must fit within existing public infrastructure for the foreseeable future. Here we briefly discuss how distribution methods vary across ownership models and how they shape access to robots and use of shared or community spaces.

Private Under the private-ownership model, there should be few to no access barriers as a result of different approaches to distribution. Robot delivery can exist within the current package delivery ecosystem.

Corporate There are several ways corporate-owned robots may be distributed, all of which have existing analogues. A likely approach is a hub-based setup where there are locations from which people can either go and pick up a robot or, like in V.C, the robot may be delivered to their location. In both cases, the robot will need to be returned to the hub; either by having the user drop them off, them being picked-up by another person or robot, or the robot can autonomously return to the hub if it is close enough. Some similar services that exist today are car rentals with dedicated pick up locations (e.g. Zipcar). Similar to a hub-based approach, there may be several smaller stations with which one can pick up and drop off a robot, as is the case with many shared micro-mobility companies and programs (e.g., CitiBike) (Nacto 2023). Both of these approaches may affect geographical access. In general, there may be a significant divide in availability and quality of service between metropolitan or urban and non-metropolitan or rural areas (as has been the case when technologies are first developed such as the internet (Whitacre and Mills 2007; de Clercq, D’Haese, and Buysse 2023; Jonas 2022), transportation (Wang and Mu 2018; Ansarinejad et al. 2025), and digitized healthcare (Greenberg et al. 2017; Chen et al. 2018)). In the case where robots autonomously navigate to their destination, using sidewalks for example, that deployment may cause accessibility issues for passersby (Han et al. 2024).

Like with existing corporate-owned but shared-use technology, researchers, policymakers and industry will have to work together to ensure robots are both available to people and that their deployment does not disrupt or adversely impact the community they are in. Another aspect of access that may be affected by corporate ownership is the type of tasks that people may use the robot for. Because the robots are used collectively, companies may be more risk averse and may restrict their use and distribution so that the robot may be quickly used by multiple people in succession. Thus,

access in terms of the range of tasks people can use the robot for may be restricted under the corporate ownership model to maximize each robot's use.

Shared As a collectively owned public resource, these robots should be readily accessible to residents of the communities they serve. These robots may be distributed through local delivery services or public community-facing institutions, akin to the hubs discussed in corporate ownership. An example of an institution that could serve as an access point to borrow general-purpose robots is a public library. Public and university libraries have a longstanding role in empowering society through equitable access to resources and spaces (Scott 2011) in both urban and rural areas alike (DeGuzman, Siegfried, and Leimkuhler 2020). "Libraries of things" are often cooperatives that are a community resource for the borrowing of useful things (Ameli 2017; Claudelin et al. 2022; Things 2026), not unlike makerspaces (Allen et al. 2023). Libraries also increasingly serve as an access point for technologies (Bertot et al. 2011). And, libraries are already adapting AI and robotic technologies to enhance the user experience of library visitors and librarians alike (Hussain 2023; Asemi, Ko, and Nowkarizi 2020). Like in V.S, people may go to their local library, borrow a general-purpose robot for a short period of time, and return it. Having state-of-the-art technology available in a library comes with several logistical and political challenges (Echedom and Okuonghae 2021), and having general-purpose robots available from them would be no different and would require directed policy efforts and time to support this distribution method. Furthermore, because the robot is a shared good, there may be additional training requirements for users to access them, such as obtaining a license to use one.

Liability

As with any technology that interacts with the world, general-purpose robots may cause harms to individuals or property. If those harms are physical or financial, the harmed parties can often seek redress through a civil action in court. Such actions lead to questions about who is held liable for harms caused by robots and how one might insure themselves against the costs of liability. In this section, we will focus on U.S. tort law. Several questions must be answered to determine who, if anyone, can be held liable for a harm caused by a general-purpose robot, including:

- **Who is injured?** The most commonly injured parties will be the user of the robotics system (the person deploying it to complete a task) or a third party.
- **What is the legal claim?** While several claims may be viable, we will focus on two common tort claims: negligence and products liability. In a negligence claim, the plaintiff must show four elements: duty, breach, causation, and injury³ (Legal Information Institute 2023b). In contrast, products liability suits are referred to as "strict

³The duty element requires the plaintiff to show that the defendant owed a legal duty (such as the duty of care) to the plaintiff. The breach element requires the plaintiff to show that the defendant breached that duty. Causation includes both cause-in-fact (that the

liability" claims because no legal duty is required. Instead, a plaintiff must show that they were injured by a product that the defendant sells, the product was defective⁴, and the defect was the cause of the injury (Berke, David 2016).

- **Who are the potential defendants?** The ownership and usage model of the robot will play a key role in determining who might be held liable for injuries caused by the robot. In tort cases, plaintiffs usually cast a wide net in order to be able to recover damages from someone.⁵ The manufacturer, owner, and user of the robots are all potential defendants to the legal claim.

Private Imagine that the family's robot butler injures one of their children. The robot turned to reach for a pencil, and one of its sensors did not detect that the child was in the path of its arm, and as a result it struck the child. The parents seek to recoup some of the medical expenses resulting from the child's emergency room visit. In the private ownership model, this is a case where, for legal purposes, the owner is injured.⁶ Because the injury resulted from a clear defect in the robot's operation, the family is most likely to be successful in a products liability claim. They could bring that claim against both the manufacturer of the robot and the manufacturer of the sensor, and much of the court case would likely involve developing facts to determine where exactly the defect was introduced and thus which company should be held liable. If the parents paid for insurance as part of their subscription services, it is unclear whether insurance would cover these expenses, as it would be more likely to cover the costs of robot repairs. The manufacturer itself, however, likely carries insurance to help offset costs of product liability claims.

Consider instead a scenario wherein a family friend is injured by the robot due to the same failure. In addition to the manufacturer of the sensor and the robot, the injured person could also include the parents themselves as defendants because they own the robot that caused the injury. In this case, the plaintiff would likely sue the family for negligence. The negligence claim is more viable against the owner because the owners owe a duty of care to their visitors (Justia 2025).

In short, under the private ownership model, owners who are injured by the robot are most likely to be successful in a product liability claim against the manufacturer or seller. Other parties who are injured can bring the same product liability claims against manufacturers, but also have the

injury would not have occurred but for defendant's actions) and proximate cause (that the defendant's action not be too attenuated or remote from the final injury). Finally, a legally cognizable injury is required, most often a physical injury, financial loss, or damage to property.

⁴Three types of defects are currently recognized in tort law: design defect, manufacturing defect, and failure to warn.

⁵This is often motivated by the fact that a victory against multiple defendants means that a plaintiff can seek to recover from any one of them (Legal Information Institute 2023a).

⁶Because the child is a minor, the parents would be seeking a legal remedy on the child's behalf, so the parents are considered the plaintiffs.

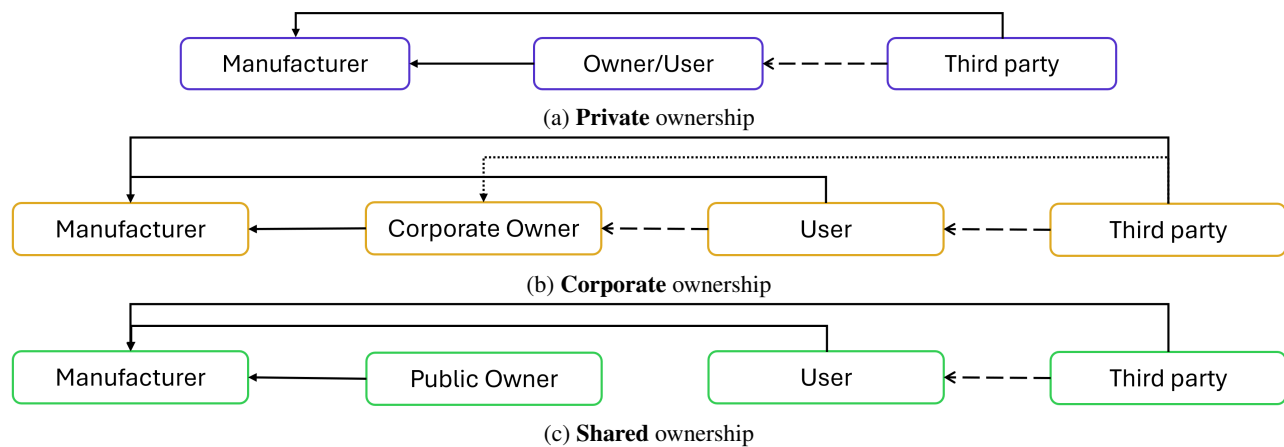


Figure 2: Most likely legal claims to be successful under three robot ownership models: (a) private, (b) corporate, and (c) shared. Solid lines represent product liability claims, while dashed lines represent negligence claims. The dotted line in (b) between the third party and the corporate owner represents a plausible but questionable product liability claim against the owner.

possibility of bringing a negligence claim against the owners. Manufacturers may carry insurance for product liability claims. Owners are less likely to be insured for injuries to themselves, but may be insured for injuries to third parties, either through their home insurance or specialized insurance that they purchase with their robot. These possibilities are summarized in Figure 2a.

Corporate In the corporate owner model, a new potential defendant is introduced into the mix. In addition to the manufacturer and owner, we also now have a “user,” or the person who has requested the robot from the corporate owner to perform the task. In our previously introduced vignette, the user is the person who needs help assembling a bed frame. Let’s start with a scenario where the user is injured by the robot while the robot is assembling the bed frame. Legally, the user in this case functions similarly to the third party in the private ownership model. The user can sue the manufacturer under a product liability claim, and would have to show that a defect in the robot was the cause of their injury. Similarly, the user can sue the owning company for negligence, as the company owes the user a duty to not injure them with the product that they have leased to them. However, it is unclear whether the user could successfully bring a product liability claim against the corporate owner. One of the requirements of a product liability claim is that the defendant “sells” the product for commercial purposes. The corporate owner would likely argue that they are not engaged in the business of selling robots, but instead creating the software and interface by which users can rent robots. This distinction makes it more difficult for an injured user to bring a product liability claim against the owner.

Now imagine that a friend of the user is the person injured by the robot. Following the pattern above, they are more likely to be successful in a negligence claim against either the user or the owner, or a product liability claim against the manufacturer. Product liability is less likely to be successful against the owner or the user because of the requirement that the defendant be a commercial seller of the product in

question. These relationships are summarized in figure 2b.

Shared In the shared model, we have the same potential defendants as in the corporate model, except that the owner in this case is a public entity instead of a corporation. In the shared ownership vignette, this entity is a local library. Much of the same logic as in the corporate ownership model still applies. The main distinction is that the library is more clearly *not* engaged in the commercial sale of the product, so it is very unlikely that an injured user or third party would be successful in a product liability claim against the library. Similarly, the user does not have the same contractual relationship with the library as with a corporate owner, and therefore the duties owed by the library to the individual who checks out the robot may be different. On top of this, if the library is run by a municipality or state government, sovereign immunity can apply, meaning the injured party will be severely restricted from suing the government.⁷ It is unclear how successful a negligence claim against the library might be as a result. In short, in the shared model, absent very clear modifications or other actions taken by the library that cause the injury, it is unlikely that the owner would be held liable for any injury. Manufacturer and user liability should work similarly to the corporate model, however. These relationships are summarized in figure 2c.

Summary of liability implications The most common legal actions that might be brought when someone is injured by a robot are negligence and product liability claims. In the private ownership model, third parties are likely to be able to hold both owners and manufacturers liable under one or both of these actions. In the corporate ownership model, the corporate owner is less likely to be liable to an injured third party under product liability because of the requirement that the defendant be engaged in the commercial sale of the product. In the shared ownership model, this distinc-

⁷Success depends on whether the government has waived sovereign immunity for tort claims. State laws vary in which claims they allow and under what circumstances. (Mathieson, Wickert, & Lehrner S.C., Attorneys At Law 2022)

tion is even clearer, with both product liability claims and negligence claims unlikely to be successful against the public institution unless there is a very clear action on their part that modifies the robot. This distinction, in some sense, encourages public ownership because institutions like libraries can feel confident about their ability to provide the service without facing significant risk of litigation. At the same time, in the shared ownership model, injured parties have fewer defendants against which they can seek potential legal redress or damages.

Repair and Maintenance

Robots will inevitably need to be repaired, maintained, and stored. Even in the best case where robots can repair and maintain themselves (Islam et al. 2023; Tan et al. 2021; Katz 2026), responsibility for maintenance and repair falls on different stakeholders under different ownership models and can both affect access and alter the meaning of “ownership.”

Private In the private ownership model, like with other computers and appliances, it is generally up to the person(s) who purchased the good to ensure it is maintained and repaired when necessary. The ability to maintain and repair a piece of technology extends its lifespan and can have other benefits such as reducing eco-waste (Bradley and Persson 2022). In the case of repairs, under the private model they will either be done by the person themselves, or a third party. Which one will be a case-by-case basis and depends on several factors such as the owner’s expertise, ease-of-repair, and availability of the necessary parts (Roskladka, Jaegler, and Miragliotta 2023). Maintenance and repairs, however, can be very costly in terms of time, potentially acting as a barrier to those who have less time than others who have persistent access to a robot.

Even having enough space to store and maintain the robot in one’s living space may not be trivial. More so, repairs can be costly, if they can even be performed in the first place. The Right To Repair movement has been a political movement in which consumers advocate for the right to be able to repair broken technologies without negative consequences, such as voided warranties or even facing lawsuits (Montello 2020). This movement advocates for both consumer protections and that companies ensure their product is repairable in the first place. Companies such as Apple and John Deere have historically and famously been anti-Right To Repair by making products that can not be repaired through DIY, legally penalizing those who try, lobbying against Right To Repair legislation, and even arguing that the consumer does not “own” the product in a traditional sense (Montello 2020; FTC 2025; Perzanowski 2022) (but rather they have rented it for its lifetime). In efforts to ensure people can maintain and repair the technology, every US state has at least filed (Pirg 2025) and the EU (European Parliament 2024) has passed Right To Repair legislation. Assuming repairs and maintenance are somewhat affordable in terms of time and money and that consumers are protected for doing so, there are several potential benefits to the private ownership model.

By owning their own robot, people will be able to perform DIY repairs to hardware and customize and update software. This presents possibilities for the rapidly growing

open-source robotics community (Macenski et al. 2022; Cadene et al. 2024; Quigley et al. 2010), to continue to lead to the development of low-cost robotics hardware and open-source robot models and datasets (Etukuru et al. 2024; Chi et al. 2025; Collaboration et al. 2024; Khazatsky et al. 2024; Belkhale and Sadigh 2024). Having this added control over one’s robot can be both beneficial from a usability and interaction perspective (Sheidlower et al. 2024), but also potentially allow people to adapt the robot to their needs if they are not already met.

Corporate Under corporate ownership, the companies distributing the robots will generally be responsible for repair, maintenance, and storage. This alleviates the burden on the consumer but gives companies full control over maintenance and software. While this may be beneficial, it may also lead to asymmetrical and problematic distributions of power over how the robots behave, akin to issues in the generative AI space where companies have disproportionate control of models and data (Rehak 2025; Widder, West, and Whittaker 2023; DeVrio, Eslami, and Holstein 2024), and where there remain unsolved challenges in incorporating meaningful participation of different stakeholders during model development and deployment (Suresh et al. 2024).

Shared Like the corporate ownership model, users will generally not be responsible for repair and maintenance.

Ownership Models Shape Robotics Research

As robot capabilities and autonomy improve, the settings in which they can be deployed expands. Despite this rapid evolution, much robotics research is still implicitly organized around a single, largely unquestioned goal: the development of privately owned robots. This assumption shapes what problems are studied, how results are framed, and which research directions are funded and amplified. In this section, we examine how core research priorities change when alternative ownership models are taken seriously. We ask what normative assumptions are embedded in today’s research agendas and how those agendas might change if the assumption of private ownership were reconsidered. A primary distinction that emerges is the timescales of interaction: privately owned robots are deployed for long periods of time, enabling long-term interactions with users; whereas in corporate and shared ownership, robots are used across many people and for shorter periods of time. At a high level, this difference implies a greater tolerance for imperfections in collaborative capabilities under private ownership, since users and robots can gradually adapt to one another. Many research directions remain broadly valuable across ownership models, and advances in core robotics technologies benefit all three. Nevertheless, the aim of this section is to highlight how ownership assumptions influence which directions receive greater emphasis, attention, and resources.

Personalization and Continual Learning

Personalization has emerged as a central objective across contemporary robotics and AI research. Personalization is often considered uncritically: as a robot learns about a user over time, the better aligned, more efficient, and more useful

this robot will inevitably become (Lee et al. 2012; Irfan et al. 2019). However, this framing of personalization often implicitly assumes the private ownership model in which there is a sustained, long-term interaction with the same people.

The private ownership model implies that robots have ample recurring opportunities to observe routines, solicit feedback, and incrementally adapt. In this setting, personalization is supported by a large potential budget for interaction: the repeated exposure to the same users, tasks, and environments allows the robot to build rich internal models of these users' preferences and norms. Much existing work on continual and life-long learning tacitly relies on this ownership assumption, treating data accumulation and persistent user modeling as both technically feasible and socially acceptable. In contrast, corporate and shared ownership models substantially compress this interaction budget. Robots in these settings encounter users episodically, often for short, task-bounded interactions, and may be redeployed across many households, environments, or even varying physical embodiments. This raises a fundamental research question: what does personalization mean when interactions are neither long-term nor exclusive? Techniques designed for gradual, individualized adaptation may fail or produce misleading or inappropriate behavior under these constraints.

Shared ownership, in particular, introduces a novel tension between individual personalization and collective learning. A shared robot may interact with hundreds or thousands of users over its lifetime. Some data or feedback may be broadly useful, improving the robot's general competence or safety across contexts. Other information may be highly personal, context-specific, or sensitive, and thus inappropriate to retain or transfer between users. Deciding which experiences should inform the shared robot system's performance and which should be treated as ephemeral or user-scoped is both a technical and governance challenge. It requires criteria for relevance, consent, retention, and deletion.

Finally, these ownership models complicate assumptions about persistent identity and personality in robots. Many personalized systems implicitly maintain a stable personality or behavioral style over time, reinforcing the sense of continuity that supports user trust and predictability. Yet when robots are shared across users or even instantiated across different physical morphologies, this persistence can become unsettling. A robot that appears to remember past interactions in ways that are opaque or misaligned with the current user may evoke an uncanny sense of inappropriate familiarity. This suggests an underexplored design space: how to manage partial, bounded, or deliberately decayed personalization so that robots remain competent without implying a continuity of identity that exceeds their social role.

Social Design Considerations and Data Privacy

Similar to the ability to personalize, robots will need to behave appropriately in different social contexts and potentially perform non-physical assistive tasks (such as providing wellbeing (Spitale, Axelsson, and Gunes 2023; Rasouli, Ghafurian, and Dautenhahn 2025; Spitale, Axelsson, and Gunes 2025; Kaushik et al. 2025; Winkle et al. 2020) or educational support (Belpaeme et al. 2018; Williams et al.

2024; Park et al. 2019; Miranda, Castellano, and Winkle 2024)); and do so while respecting people's rights and privacy. Much research in social and privacy-sensitive robotics assumes a private ownership model (e.g. long term social adaptation (Matheus et al. 2025; Di Napoli, Ercolano, and Rossi 2023; Graaf, Allouch, and Dijk 2016; Cagiltay et al. 2020)), a corporate ownership model (e.g. human-AI interaction in transactional situations such as assisting customers in a store (Niemelä et al. 2019; Kanda et al. 2009; Song et al. 2022)), or is relatively agnostic to ownership type (e.g. privacy-preserving robot sensing (Eick and Antón 2020; Vitale et al. 2018; Grabler and Koeszegi 2024; Zhou et al. 2023; Lau, Zimmerman, and Schaub 2018; Sullivan and Mutlu 2025)).

Closely related to this work, work by Axelsson et al. (Axelsson et al. 2025) investigated how underrepresented communities in computer science, including women at a computer science conference and humanities researchers, view the design and deployment of robot wellbeing coaches. Their study revealed that participants are actively concerned about "who owns the robot and the data?" largely due to uncertainty about how their data will be used by the owner of the robot. These concerns are not unique to embodied AI (Bodó and Janssen 2022; European Parliament 2016; Parliament 2024) but must be uniquely addressed in the context of HRI. For example how robots communicate both verbally and non-verbally (Urakami and Seaborn 2023; Saunderson and Nejat 2019; Kim, Lee, and Mutlu 2024), what its limitations are, and to obtain user consent for interactions (Saporito et al. 2024; Sarathy, Arnold, and Scheutz 2019; Rakova, Shelby, and Ma 2023). While these functions will be required for any robot, how they manifest may depend explicitly on who owns the robot and user awareness of that. Although there is some early work that accounts for ownership when assessing user acceptance of robots (Roesler, Rudolph, and Siebert 2024), there is, to the best of our knowledge, little work on how robots are used differently and how their design can be improved based off of interactions with deployed robots.

People Teaching and Learning from Robots

Robots must be able to learn from end users. Even for highly capable robots, the ability to learn leads to better user experiences and greater task efficiency. A prototypical example is cleaning a living room, which requires knowing where items belong and what level of cleanliness is expected; more complex or unique tasks may also require teaching the robot low-level actions. Research that seeks to enable users to teach robots new tasks is referred to as human-in-the-loop (interactive) robot learning (HIRL) (Baraka et al. 2025), and is the focus of much robotics research. Whereas "personalization" research tends to focus on a robot adapting to a user's preferences, HIRL focuses on the ability of people to directly teach robots new behaviors and tasks.

Teaching a robot requires (1) interfaces for user instruction and feedback (e.g., language, physical input, or GUIs), (2) algorithms that interpret this feedback to update task models, and (3) verification mechanisms through which the robot communicates its understanding. Learning from

demonstration, wherein people demonstrate to the robot how to do a task, often by directly teleoperating the robot, has recently seen much success (Zare et al. 2023; Zhao et al. 2023; Chi et al. 2024). Other common modalities include providing corrections (Luo et al. 2025; Spencer et al. 2020), pairwise-preferences (Christiano et al. 2017), and evaluative feedback (often through language or by providing a scalar-value rating) (Bradley Knox and Stone 2008; Arzate Cruz and Igarashi 2020; Sheidlower, Moore, and Short 2022). Most HIRL research develops algorithms that learn from a single feedback modality, largely due to easier development and evaluation. However, this design choice is implicitly tied to the private ownership setting. When a robot is deployed for an extended period in a home, users can adapt to the robot’s preferred teaching modality, and the robot can continue to improve autonomously through interaction with its environment even without supervision (Kessler Faulkner et al. 2019; Lee, Smith, and Abbeel 2021).

This dynamic changes significantly under the corporate and shared ownership models wherein the robot must learn how to perform a task satisfactorily in a short amount of time and with feedback from potentially inexperienced users. People naturally teach both robots and other people with multiple feedback modalities and with a great degree of variation (Huang et al. 2024; Huang, Aronson, and Short 2024; Georgiou et al. 2025). Although there is much emergent work towards learning from multiple feedback modalities (Bryk et al. 2022; Fitzgerald et al. 2022; Hindemith et al. 2023; Yuan et al. 2024), it is still relatively under-researched. Algorithms that can learn from multiple feedback modalities are both more accessible to a broad population, someone may find providing evaluations very intuitive but corrections very difficult, and have the potential to be more efficient: as one provides a demonstration they could be simultaneously explaining why they are or are not doing certain things in the task. Ensuring people can efficiently teach the robot in a natural and comfortable way is useful for all robots, but is especially important when a robot does not have the chance or time to explore and learn on its own. Briefly, additional design choices affected by limited interaction time and diverse users include modeling human error and bias (Knox et al. 2024; Ghosal et al. 2023), as well as the role of algorithmic transparency in interaction (e.g., communicating internal state) (Brawer et al. 2023; Hu et al. 2024).

The evaluation of HIRL systems also changes. Current evaluations emphasize task success over repeated trials in a fully-autonomous setting without human collaboration, where the teaching data typically comes from expert users or synthetic oracles (Huang, Aronson, and Short 2024) (other AI agents trained to perform the task, typically with added noise to try and mimic human suboptimality; not unlike how some LLM evaluation processes are automated (Gu et al. 2025; Tao et al. 2024)). Evaluations with real-people and real-robots is costly, and evaluations outside of a lab setting even more so, both in terms of time, recruitment effort and various logistical hurdles, especially in public spaces (Dey et al. 2025; Bu, Fischer, and Ju 2025). Such evaluations, however, are necessary, and the burden can be lessened with targeted funding efforts that support such research endeav-

ors, despite slower publishing rates and a less direct connection to the private ownership model. To ensure these systems can work with a wide variety of people, they must be evaluated with a wide variety of people, lest risk leaving certain groups behind in their ability to teach robots new tasks.

Foundation Model Approaches to Robotics

Foundation models will likely be central to robot software. LLMs and VLMs have already been used to enable open-ended dialogue with users and improve robot perception (Kim, Lee, and Mutlu 2024; Han et al. 2026). Many important issues associated with generative AI, including factual inaccuracies (Huang et al. 2025), biased and unfair behavior (Navigli, Conia, and Ross 2023; DeVrio, Eslami, and Holstein 2024; Truong, Zimmermann, and Heidari 2025), and the under- or misrepresentation of vulnerable populations (Lee, Montgomery, and Lai 2024), may therefore also manifest in robots. Here, however, we focus on robot-specific behavioral foundation models, which generate actions for task completion. These relatively recent models offer a promising pathway toward performing diverse manipulation tasks across varied environments. They are typically trained end-to-end on large corpora of robot demonstrations containing videos of task execution, proprioceptive states such as joint configurations, and natural-language instructions, using an LLM or VLM backbone to embed language instructions, visual observations, or both (Kim et al. 2024; Black et al. 2024). Current work sensibly prioritizes basic functionality: enabling robots to autonomously complete tasks in home- or office-like settings.

However, several additional research directions will be important for ensuring these models succeed in corporate and shared ownership settings. Prior work has shown that robot foundation models may exhibit different performance depending on the race of an observed person in a scene (Hundt et al. 2022). Although this work predates modern LLMs and VLMs, its implications remain relevant. Ensuring consistent performance across users, alongside transparent access to information about robot capabilities, is particularly important when time for adaptation is limited. Similar to HIRL, dataset diversity may also shape styles of motion, behavior, and instruction interpretation, potentially leading to mis-specified tasks or behavior users find uncomfortable (Mckenna et al. 2024; Sebo, Krishnamurthi, and Scassellati 2019; Karli, Cao, and Huang 2023). Another important direction, particularly for shared ownership, is enabling human-robot collaborative task completion, which is often overlooked when models are designed primarily for autonomous task execution.

Research Funding

Robotics research is shaped at a fundamental level by its funding apparatus. Compared to most subfields of computer science, robotics is unusually capital-intensive: embodied systems require specialized hardware and long development cycles, with time horizons from research to deployment often measured in decades rather than years. In the United States, this has made large-scale robotics research heav-

ily dependent on federal funding, especially from defense-oriented agencies such as DARPA. For much of the field's history, Department of Defense programs, including the DARPA Grand Challenge and the DARPA Robotics Challenge, have played an outsized role in setting research priorities and have channeled hundreds of millions of dollars into autonomous vehicles and disaster-response robots (International Federation of Robotics 2025; Sofge 2015). These programs accelerated technical progress while at the same time normalizing a particular ownership and deployment imaginary: robots as state-owned, centrally controlled assets built for military use and emergency-response.

Over the past few years, this landscape has begun to shift. As robots become cheaper and advances in machine learning expand the space of commercially viable applications, private capital and industrial labs have moved into domains once dominated by government-sponsored research. Investment is increasingly concentrated in service robots, warehouse automation, domestic robots, and humanoid platforms (Goldman Sachs 2024), with U.S. robotics startups alone raising \$2.2 billion in the first quarter of 2025 (Marion Street Capital 2025). This shift is a sign of commercialization, but it also marks a change in the way private ownership models are treated as default design targets. When research is funded and evaluated primarily in terms of privately owned or subscription-based systems, it is unsurprising that the commensurate research agendas tilt toward individually deployable, scalable, and monetizable robots. If shared or public ownership models are to take root, funding institutions must explicitly support the technical, infrastructural, and governance questions those models raise.

The Case to Focus on Shared Ownership

The private-ownership model alone will lead to inequitable access to general-purpose robots, largely because of the financial burden of purchasing and maintaining them. While the corporate model lowers that financial barrier to some extent, it also potentially increases people's reliance on the companies that produce the robot, concentrating power over the robot in the company rather than the users, and may disempower people from using robots frequently or in the ways they want. The shared ownership model offers several advantages. In the shared model, the cost of the robot is distributed across many people, e.g. as a public good funded by governments. The cost to use the robots can be minimal. This alone can lead to people having access to robots who might not otherwise be able to, freeing up their time and allowing them to accomplish tasks they need assistance with. In addition, the shared model also particularly incentivizes equitable distribution of robots, making location less of a potential barrier than under the corporate model. Like the corporate model, the shared model removes potential burdens of repair, maintenance, and storage from the user to an external party. Unlike the corporate model, however, there is greater potential for user participation in how the robot is maintained, updated, and behaves, because each user has some degree of ownership over the robot.

The shared model is not perfect; it is undeniable that a robot always being in one's home is most convenient, and

a shared model may pose more legal difficulties for users or third parties to hold liable institutions accountable for harms. However, we hope to have made clear that it offers several benefits of both private and corporate ownership with few of the drawbacks. For shared ownership to be realized, and be a viable model in the future, whether as the sole model or alongside both private and corporate ownership, ownership models need to become an explicit part of robot policy and research funding going forward, with an emphasis on the unique challenges that arise from a shared model.

Limitations and Conclusions

This paper offers a broad, exploratory account of how different models of robot ownership shape both socio-technical outcomes and research agendas in robotics and HRI. Each of the themes we discuss, from liability and learning paradigms to deployment and institutional incentives, warrants further research in its own right. Here, we map the terrain and begin to unravel the consequences of the normative assumptions about ownership that currently structure much of the field.

At the same time, many important aspects of robot ownership fall outside the scope of this analysis, including how ownership relates to the democratization of technology and AI, how robots may be used for harmful or extractive purposes, and the ethical questions raised when robots perform sensitive or consequential tasks. Robots are also highly composite systems, consisting of interdependent hardware and software components that may be owned by different actors and governed under different ownership paradigms (Moon and Rhim 2024). These layered ownership arrangements may have downstream consequences across many of the dimensions discussed in this paper. Similar complexities already exist in AI and algorithmic supply chains, where multiple actors may own or control different parts of a system in ways that shape its use and governance (Cobbe, Veale, and Singh 2023; Hopkins et al. 2025). We largely abstracted ownership into distinct categories, allowing us to broadly examine its implications across domains. However, understanding robot ownership as a more multi-faceted and overlapping phenomenon, including how and when the different models may coexist, remains an important direction for future work. We also note that robots that primarily serve medical or assistive functions are outside the scope of this work.

This paper is written with an eye toward those who shape research priorities and funding landscapes, including funding agencies and policymakers. Shifts in how general-purpose robots are imagined and supported will inevitably intersect with political, institutional, and economic constraints; in the United States in particular, corporate funding plays a large role in steering research toward private and corporate ownership models. Making these influences visible is important: ownership assumptions are technical and conceptual, and also reinforced through concrete funding structures and incentive regimes. Finally, while our analysis is grounded primarily in the U.S. and reflects a broadly Western framing of ownership, the underlying questions are not confined to these contexts. We hope this work motivates parallel examinations of how ownership assumptions shape robotics research in other national and economic contexts.

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