UNFULFILLED: COLLABORATIVE ROBOTS AND THE PERSISTENCE OF TOUGH JOBS IN E-COMMERCE WAREHOUSING [1]

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Abstract: This paper investigates workers' experiences with collaborative robots in e-commerce fulfillment centers (FCs). Powered by the latest algorithmic technologies, collaborative robots operate alongside their users rather than independently. They are simultaneously dismissed for their potential to make work worse by reducing worker autonomy and permitting more intrusive means of managerial control and heralded for the possibility that they will enhance job quality by augmenting human capabilities, taking on undesirable tasks, and giving workers more command over their jobs. Yet the actual effects of collaborative robots on work and workers are underexplored. Using data from a survey of more than 1,500 hourly workers employed in 16 FCs operated by a U.S. retailer, I compare job characteristics and worker attitudes across facilities that use one of three main technologies to retrieve customer orders: collaborative robots, conveyors, or hand-pulled carts. The findings show that, compared to the older technologies, collaborative robots are not associated with significantly better jobs. Relative to workers in cart facilities, workers in robotics facilities report lower levels of job satisfaction, decision authority, skill discretion, and supervisor and coworker support, along with increased job insecurity, turnover intentions, and alienation. These levels are similar to those reported in conveyor facilities. In light of these findings, collaborative robots appear to be a refined means of managerial control rather than a liberating departure from past automating technologies. They are likely to impose burdens on growing numbers of workers as the e-commerce industry expands and as they find their way into other sectors.

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Recent advances in automation are poised to transform the workplace. Of late, the advances receiving most attention harness algorithms to dictate how, when, and where work is conducted. These include online platforms, mobile apps, and software systems. What these technologies have in common is that they are digital, existing in an online ecosystem accessible via tablets, smartphones, and computers. Algorithms are not, however, incompatible with physical form. They find a tangible manifestation in collaborative robots, which meld the computing power of artificial intelligence with industrial machinery's capacity to act upon the physical world.[2]

How might collaborative robots reconfigure the way work is accomplished and experienced? To many who study work and organizations, algorithms beget a more pervasive, individualized, and impersonal means of managerial control (Kellogg et al., 2020; Wood, 2021). The ability to transcend space and time in the digital realm undergirds these capacities, making for especially stressful and insecure work (Moore & Robinson, 2016; Wood & Lehdonvirta, 2023). Yet collaborative robots are incapable of such transcendence, with implications running in opposite directions. More positively, they are less intrusive and ever-present than their fully digital counterparts. More negatively, they require users to engage them in the flesh, a key feature of what makes working with older automating technologies so dispiriting. Conveyor belts, machine tools, control panels, these confront workers' persons, acting directly on or with their bodies (Braverman 1974; Noble 1984; Walker & Guest 1952). Technologies that do not impose a particular position, motion, or rhythm on their user may be more amenable than the generations of automating technologies that preceded them (cf. Wood et al., 2019). It is not

[2] Although they cannot be grasped by a worker—or inflict physical injury—the same way a machine can, algorithms can exert control over human bodies. Something that is intangible may still have a material impact or depend on material objects to have its effects (Orlikowski & Scott, 2015).

obvious collaborative robots confer this benefit. What, then, can be said about the work conditions associated with a technology that mixes elements of the old and the new?

Sociologists have paid little mind to the competing possibilities, leaving open important questions about collaborative robots at work. Chief among them is whether this breed of smart machine represents a break from past means of managerial control, leading to a future more compatible with workers' needs, or whether it is one more iteration, however refined, in a long line of industrial automating technologies that minimize worker discretion. Do the algorithmic underpinnings make workers into the controller, rather than the controlled, and do workers also appreciate that this technology can do the heavy lifting? Or are collaborative robots, able to sense and respond to the world around them, even better at directing, evaluating, and disciplining their users?

I address these questions using data on frontline workers in e-commerce fulfillment centers, a critical part of the logistics industry. What is unique about my data is that it covers three phases of automation in one setting, fixing other well-known influences on technological change. It comes from a survey of more than 1,500 hourly workers employed by a U.S. retailer I pseudonymously call Sigma. Respondents perform the same work but are located in 16 facilities that use one of three core technologies to process orders: collaborative robots, conveyors, or hand-pulled carts. With multiple measures of job characteristics and worker attitudes, I show how job quality varies with these technologies. In so doing, I make contributions to ongoing conversations about robotics, algorithms, automation, and the future of work.

Collaborative Robots at Work

Robots have been at work for decades, but wireless sensors, machine learning techniques, and electronic control mechanisms have given them greater dexterity and sharper senses (Pfeiffer, 2016). Paired with increasingly sophisticated algorithms, these capacities have brought robots into a number of non-industrial settings, such as retail and healthcare. Collaborative robots, the most advanced iteration, share the workspace and interact with humans. Examples include surgical assistants, crop monitors, and welding arms. While all robot use has risen, collaborative robot uptake has risen quite quickly: they made up around 10% of robot installations worldwide in 2022, triple the share five years earlier (IFR, 2024).

What the progress in collaborative robotics augurs for workers is, as of yet, unsettled. These robots render work processes "halfway between" manual systems operated by humans and autonomous systems that have little need for people (Kim, 2022). Existing research does not satisfactorily consider this circumstance. Indeed, the few extant sociological studies focus on robots' impact on employment levels (e.g., Dahlin, 2019; Damelang & Otto, 2024), even though there is little consensus on how robots, the collaborative sort included, affect job counts (Lei & Kim, 2024). One reason for conflicting findings is that impact varies by industry, occupation, and technology (Lloyd & Payne, 2023). An even bigger reason is that the labor market consequences of robotization depend on organizational and institutional context (Krzywdzinski, 2017; Lloyd & Payne, 2019).

The complex dynamics influencing automation make it fruitful to move away from debates about job growth and decline and toward investigations of the experience of working with specific technologies (Bailey, 2022; Boyd & Holton, 2018; Fleming, 2019; Moniz & Krings, 2016; Spencer, 2018). Summarizing these sentiments, Spencer (2018) argues that new technology "poses a greater threat to the quality of work than its quantity" (2).

This in mind, in what follows I examine work conditions in the presence of collaborative robots, focusing on job characteristics and worker attitudes. Job characteristics refer to the content and organization of tasks, relationships, and responsibilities associated with a job (Parker et al., 2017). They influence worker well-being, an important outcome of job quality (Munoz De Bustillo et al., 2011). An attitude is a worker's evaluative stance toward her job (Judge & Kammeyer-Mueller, 2012). Attitudes—such as satisfaction and commitment—reveal how workers feel about their jobs' characteristics and predict their well-being and are thus a key correlate of job quality. Automating technologies have been shown to operate on both job characteristics and worker attitudes, though much of this research was conducted in periods when robots and other automating machinery had nowhere near the capacities of today and talk of algorithms was negligible (e.g., De Witte & Steijn, 2000; Fernandez, 2001; Lodahl, 1964; Shepard, 1971; Vallas, 1988).

Implications for Job Quality

The upsides of collaborative robots are hailed by engineers and industry insiders. To them, this breed augments human capabilities and takes on undesirable work (e.g., Daugherty & Wilson, 2018; Major & Shah, 2020; Villani et al., 2018). This optimism is, in part, justified. Like the industrial robots that came before, collaborative robots can perform dirty, dull, and dangerous tasks perhaps ill-suited for humans (Franklin et al., 2020). Unlike their predecessors, their algorithmic capacities inject a new degree of adaptability into automation. Older robots, "separated in space and time" (Guertler et al., 2023), rigidly went about tasks with limited human oversight, often fixed in position and physically caged (Cohen et al., 2022). Collaborative robots, in contrast, inhabit the same space as the workers around them, dynamically responding to users' movements. Friendly interfaces are meant to render the robots programmable so they can operate at workers' behest, facilitating worker command as well as upskilling.

Yet, given their physical form, collaborative robots share similarities with past technologies that sociological scrutiny has shown create challenges for workers. Early research flagged the loss of autonomy accompanying industrial automation devices, including conveyors (Walker & Guest, 1952) and numerical control machines (Braverman, 1974). What transpired with the advent of digitally-enabled devices, such as the computer numerical control machine, was not hopeful either. On the one hand, there were contrasting findings about whether these made work more restricted or less fulfilling (Kelley, 1990; Vallas, 1988). On the other, it was clear these same technologies could open up deeper means of surveillance (Sewell, 1998), demand skills previously expert workers did not have (Zuboff, 1988), and upend status hierarchies (Vallas, 2001).

Today, descendants of this research have turned their sights to the algorithmic technologies pushing automation into new domains. These would seem to be discontinuous with what came before, occasioning a new "contested terrain" of control (Kellogg et al., 2020). A central reason for this break is that algorithms bestow an expansive capacity to direct, discipline, and evaluate workers. Technologies that use them crunch huge amounts of data from their environment, closely tracking workers (Ball, 2022). Algorithms are also opaque, making it hard to grasp the technology's logic and intervene in its decisions (Bucher et al., 2021). Judgments are close to instantaneous as well, leaving managers out of consequential decisions and removing opportunities for workers' emotional appeal (Gray & Suri, 2019). They can restrict choices available to workers (Lee et al., 2015) and make determinations that would otherwise require workers to use their own expertise (Valentine & Hinds, 2022).

Of note, many of the recent pessimistic conclusions hinge on the fact that the control mechanisms algorithms afford are digital. For this reason, software, apps, and platforms have been focal points of research (e.g., Cameron, 2024; Rahman, 2021; Shestakofsky, 2017). Yet collaborative robots are both physically and digitally mediated.

Does this mean the optimistic or the pessimistic view is more apt? Blauner (1964) offers a framework for evaluating this question, arguing that for a technology to improve a job, it must increase a worker's sense of control, meaning, and social connection. Though he proposed this rubric decades ago, the dimensions he emphasized have been shown to influence worker well-being and job quality up to this day (Allan et al., 2019; Nielsen et al., 2017; Wheatley, 2017).

Using this framework, the greatest reason to anticipate a positive outcome is that collaborative robots might favor worker-led control. To the extent they require users to possess more skills, they might also support meaningful work. That said, there are equally compelling reasons to believe collaborative robots are merely a refinement of previous industrial automating technologies. With their added intelligence and versatility, they may paradoxically seem less intelligible to workers granted little access to their decision-making procedures, a circumstance weighing against workers' sense of control and ability to articulate their role in the work process. Furthermore, so long as they do not provide companionship, they should do little to promote socialization and may even hamper it by demanding more focus on the user's part.

What insights we have so far, gleaned from management and engineering research, align more closely with the negative outlook. Although collaborative robots promise to work with humans, the latter often serve as "machine tenders," feeding the former work (Weiss et al., 2021). As machine tenders, humans become responsible for addressing malfunctions (Körner et al., 2019). Stress grows when robots' decision-making is indecipherable, making it difficult to predict their next move (Stubbs et al., 2007). By taking on routine manual and mental tasks, robots can make the remaining work more repetitive (Barrett et al., 2012). Narrower jobs provide fewer opportunities to acquire skills that would aid career advancement (Beane, 2018). Collaborative robots can diminish workplace cohesion as well. Altering the division of labor, they create coordination challenges, triggering conflicts over task responsibility, transferring work from one group to another, and disrupting existing norms (Beane & Orlikowski, 2015; Mutlu & Forlizzi, 2008). The algorithms that make collaborative robots so nimble also enhance robots' ability to monitor users, increasing managerial control from a distance (Moore, 2020). When it comes to attitudes, workers do not appear to view robots in a favorable light either. Believing robots to be more productive and less error-prone, robot-exposed workers report higher levels of job insecurity (Dekker et al., 2017; Yam et al., 2023). The existing research thus suggests collaborative robots undermine worker control, meaning, and connection.

These conclusions, nevertheless, are drawn from a mix of studies assessing different outcomes, technologies, and settings. Several limitations arise. First, some studies rely on data generated from a handful workers in one workplace, and others combine responses from workers interacting with different robots in distinct settings. Both approaches make it hard to disentangle whether technology or context primarily influences findings. Second, studies tend to focus on one or a subset of job quality measures, even though effects are likely multifaceted. A robot could increase autonomy while simultaneously degrading other job characteristics; without comparing outcomes holistically, it is unclear if the robot is a net negative. Finally, research tends to show downsides without reference to alternatives. It cannot answer whether collaborative robots make work *relatively* worse than technologies predating them. This is an important limitation because robots could make undesirable jobs comparatively more desirable.

Moving past these limitations, I investigate whether the challenges highlighted above are widespread in a single setting—warehousing—and worse relative to other technologies used to accomplish the same tasks. The value of this approach is that I can hold constant some of what past research has identified as major influences on the use of technologies at work, centering my analysis on collaborative robots' affordances, or the properties framing the possibilities of their application (Hutchby, 2001). Affordances emanate from the interplay between a technology's material features and the social circumstances of its use. Because the social circumstances are largely the same across the warehouses in this study, observed differences in job quality should be tightly entwined with the robots' material features as opposed to organizational and institutional context. Indeed, Leonardi and Barley (2008) argue that an outsized focus on the social dynamics shaping use, as opposed to material features, has confined prior research.[3] They advocate comparing different technologies in the same context, rather than the same technology in different contexts, to highlight material features. By hewing to their suggestions, I move closer to assessing whether collaborative robots' algorithmic underpinnings separate them from other automating technologies in ways that yield distinct job characteristics and worker attitudes.

The Situation in Warehousing

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[3] As an example, the only recent sociological research on job quality and robotics of which I am aware, Findlay et al. (2017), gives next to no description of the robots under study. While offering compelling evidence that job quality can vary across occupations when work is rearranged, the study does little to elaborate technology's role because it cannot say whether the observed changes owe more to managers' choices or features of the robots.

Although present in many industries, collaborative robots loom large in warehousing. Aiming to reduce labor costs while providing near-constant availability, operators have plied investments into automation (Kembro & Norrman, 2025). Accepting, however, that fully-automated “lights out” warehouses are not around the corner (Sgarbossa et al., 2020), the industry has been energized by part-human, part-robot “systems of collaboration” (Pasparakis et al., 2023).

This interest comes at a time when e-commerce has rendered warehousing into a crucial, growing sector. The industry’s workforce has more than tripled in the U.S. in the past 20 years, with 1.8 million people currently laboring to support the distribution of goods and materials (U.S. Bureau of Labor Statistics, 2025). Warehouses also serve as crucial sites of work for the largest companies of the day (e.g., Amazon, Walmart, UPS).

Much of the growth has occurred in fulfillment centers (FCs), warehouses that handle online demand. Human labor is vital to this operation. With fluctuating customer orders arriving at all hours, FC employees face excessive pressures to work quickly and without error. These pressures translate into greater job demands, often at the expense of worker well-being, making FCs home to particularly tough work conditions (Kowalski et al., 2025).

Amidst these circumstances, collaborative robots are seen as integral to helping the industry persist through elevated e-commerce competition and exhaustible labor markets (Jacob et al., 2023). They find their vanguard in two technologies: autonomous mobiles robots (AMRs), and goods-to-person robots (GTPs) (see Fragapane et al. (2021) and Gutelius and Theodore (2019) for reviews).

AMRs. AMRs make self-directed decisions on how to transport and handle materials while engaging human workers. Resembling motorized carts, AMRs typically relay goods from one worker to the next or follow and assist a worker as she completes her tasks. In both cases, the AMR chooses the route, sets the pace, and does the hauling.

GTPs. Most well-known as the low-lying mobile tiles that power Amazon's Kiva system, these robots are found in other companies' warehouses as well. They deliver shelves to workers, confined to work stations, who must retrieve or refill items. They too choose the route, set the pace, and do the hauling.

Both types of robots' ability to navigate the warehouse environment in real-time without collision depends on the intricate menu of algorithms informing their actions. Humans interact with the robots through interfaces carried on their persons, accessible on the robots, or integrated into their work stations. The robots can also monitor productivity and errors, alerting users of mistakes that could lead to counseling for poor performance.

In current use, AMRs and GTPs are met with broad changes in work processes. They directly alter picking and replenishment roles. Picking entails retrieving individual items ordered by customers. Replenishment entails placing new inventory onto shelves. Without robots, these roles require heavy lifting and lots of walking. Workers must also know the warehouse's layout so they can locate items (Guendelsberger, 2019). Robots take on these tasks, potentially offering physical and cognitive relief. Their impact extends beyond these roles, however. For one, they change facility layouts (Azadeh et al., 2019) and hence socialization patterns. They create new traffic flows. They change the hours certain groups work as well as when they take breaks. They can also alter production standards (Sheu & Choi, 2023).

Despite industry hype, the small pool of research shows these robots yield undesirable work conditions similar to those found in the general studies above. In their comparative analysis of eight warehouses, Berkers et al. (2023) find workers depend on robots to dictate the tempo and location of work, reducing their sense of control. Tasks also become more simple and monotonous, yielding less meaningful work. Delfanti's (2021) treatise on Amazon reveals that those who work with the company's Kiva robots are ambivalent: because the robots fetch items, workers trade excessive walking for confinement. They end up mentally depleted, socially isolated, and sore from the circumscribed motions they must make day in, day out. Burtch et al. (2025) show this situation produces elevated rates of repetitive motion injuries. Also examining Amazon, Struna and Reese (2020) highlight the voices of workers, wary of job loss and surveillance, who find it hard to hold conversation across the gulfs separating work stations.

Likely because collaborative robots have only recently been in action in warehouses, the research base does not extend far beyond these studies. And because Amazon is the largest e-commerce employer, it understandably receives much of the attention. No doubt helpful in setting up expectations, this research suffers the limitations of the more general studies of robots. Namely, it either focuses on a single outcome, draws from observation of a single site, or relies on comparisons of different technologies used for different tasks in different settings.

This is not the case in the subsequent analysis. I compare multiple job quality measures across a sample of FCs run by a single company. The products handled inside the warehouses are the same. The roles and standard operating procedures are the same. The sorts of customers are the same. The kinds of managers and workers employed as well as the levels of discretion they enjoy are the same. The institutional environment is the same. What primarily varies across sites is the technology implicated in the order fulfillment process. The cross-site consistency throws the material features of each technology into relief.

Research Setting, Data, and Methods

Automation at Sigma

Robotics are a key element of the logistics strategy at Sigma, a U.S. e-commerce retailer. It operates around 25 FCs across the country, each employing anywhere from 50 to 400 non-union, hourly workers. Seeing a chance to increase productivity and reduce errors, its leaders have deployed AMRs and GTPs.

Both robots replace older picking and replenishment methods. In cart FCs, pickers manually tug boxes throughout the FC. To replenish shelves, workers bring inventory to the appropriate location by hand or using non-robotic equipment. In conveyor FCs, boxes travel on belts to pickers positioned in a set area known as a "zone." Pickers are hemmed in by the conveyor in front and the shelves behind. Replenishment occurs in the system's interstices: a small walkway between shelves allows for restocking.[4]

The technologies likely shape work conditions in unique ways. Hand-pulled carts, the earliest of the lot, are physically onerous. Fully laden, they weigh hundreds of pounds. They give workers jurisdiction over pace and route: users must know where to pilot carts in the cavernous FCs. Though discouraged by management, cart workers find ways to chat on the floor. Conveyors, by contrast, establish buffers between workers, who can only communicate with those beside them. They also create an interdependent and machine-paced workflow. Jams,

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[4] Conveyors rely on algorithms of a different, older sort. Most are centrally controlled, concerned with order allocation rather than responding to the actions of individual workers (McGuire, 2024).

where someone else's idleness leads boxes to pile up, and breakdowns that are no one's fault can slow work down.

Sigma's robots would seem to fall between these two technologies. Like conveyors, they do the hauling. They also isolate workers. GTPs, in particular, restrict the tasks workers must complete as well as the range of motions they must make. Work stations are small, permitting only a few feet's movement. With both robots, workers no longer need to know item locations. A Sigma employee who developed training materials said pickers could be working with robots after an hour of instruction, whereas the other methods took several weeks. Unlike conveyors, the worker who collaborates with either robot is partially in control of the pace: she starts and stops the machine but must wait on it before beginning the next task. There is also less room for socializing, because she must stay within an area others cannot cross. Finally, unlike the other two technologies, the robots inform workers of their productivity in real time.

Importantly, while each technology directly affects picking and replenishment roles, it influences an FC's entire workings. Conveyors, for example, can be several stories tall, relegating workers to different levels and dividing those whose labor at the conveyor from those elsewhere in the building.

Each FC utilizes one of these three "core" technologies, which are spread almost evenly across the network. Roughly a third of FCs are robotic, usually employing both AMRs and GTPs; a third, conveyor; and a third, cart. Sigma leadership used multiple criteria to select sites for robot deployment, and it is not clear any one was determinative; different criteria were likely emphasized in each deployment. Managers had different explanations for why their FCs used a particular technology, ranging from building age to order volume to staffing levels. Managers described deployment decisions as top-down, with senior leaders doing little initially to involve teams running the FCs locally. Moreover, none of the selection criteria reflected worker inputs (though managers said they did not lay off workers following robot adoption, which personnel records bear out). Operations data supports these comments, suggesting a diverse set of motives rather than a uniform strategy. First, there was no statistically significant relationship between technology type and building size or headcount. Second, while robots are the latest technology, they have been deployed at different timepoints and in old and new FCs. Third, several U.S. states are home to more than one FC, and the FCs located there use different technologies. Together, the lack of a strong link between FC characteristics and technology type makes it unlikely that Sigma selects FCs for automation using criteria systematically correlated with job characteristics or worker attitudes. As such, a cross-site comparison is well-suited for homing in on the relationship between core technologies and work conditions inside Sigma FCs.

Data Collection

I assessed the work conditions surrounding the core technologies as part of a long-term research partnership with Sigma. Between 2019 and 2021, I was part of a larger research team that met with firm leadership, reviewed administrative records, visited a subset of facilities, and interviewed some 100 frontline workers and supervisors to understand the experiences of laboring inside the company's FCs. Afterward, we administered surveys to evaluate a participative worker voice intervention that we designed and implemented in a select group of FCs.[5] The surveys provide the primary data for this study.

We fielded surveys in 16 Sigma FCs. A third of FCs were surveyed in late 2022; the other two-thirds in the middle of 2023. All hourly workers were eligible as long as they were employed by Sigma during the survey period. (The 10% of workers temporarily employed were not targeted.) Surveys were provided in English and Spanish. Participants could access the survey using a cell phone, research-team provided tablets, or worksite computers, and they could complete the survey on-the-clock or outside of work. For participating, they received a gift card and were entered into site-specific raffles. We obtained response rates of 58% in robotics FCs, 52% in conveyor FCs, and 56% in cart FCs.

The final sample of 1,506 responses includes all hourly production and maintenance workers with complete responses. I excluded workers who had been hired for less than two weeks because they may have not yet worked in the presence of their FC's core technology.

Measures

Independent Variables

With Sigma administrative records, I created a categorical variable, *technology type*, to indicate which of the core technologies an FC used: collaborative robots, conveyors, or hand-pulled carts.

[5] The intervention created joint problem-solving committees in eight sites. Intervention status was randomly assigned to ensure balanced representation across technologies (as well as building sizes).

Dependent Variables

I relied on the surveys to evaluate job characteristics and worker attitudes. The full items are described in Appendix A.

To assess job characteristics, I adapted the scales making up Karasek et al.'s (1998) Job Content Questionnaire (JCQ).[6] The JCQ measures five job characteristics that impact worker well-being (Parker et al., 2017). It has been used in recent studies of automation (Lu et al., 2024; Yang et al., 2025) as well as job quality and well-being, more generally (Moen et al., 2016; Narisada & Schieman, 2022). Following Karasek et al.'s (1998) guidance, I broke decision latitude and social support into two components (decision authority and skill discretion; supervisor support and coworker support). The measures are: *Decision authority*, which tracks control over tasks; *Skill discretion*, which tracks the variety of work encountered on the job; *Psychological job demands*, which tracks the mental toll of work; *Physical job demands*, which tracks work's effects on the body; *Supervisor support*, which tracks the quality of vertical work relationships; *Coworker support*, which tracks the quality of horizontal work relationships; and *Job insecurity*, which tracks the burdens of having to adapt to a dynamic labor market.

[6] The framework informing the JCQ, known as the Job Demands-Control (JDC) Model, is often presented as an alternative to the Job Characteristics Model (JCM) developed by Hackman and Oldham (1975). Both measure job characteristics in similar ways. In fact, Karasek (1979) acknowledged building off the JCM. The distinction is that they are often used to study different outcomes: JDC figures highly in physical and mental health research, whereas JCM is commonly used in job satisfaction and performance research (Parker et al., 2017).

There are numerous worker attitudes, so I focused on three that figure prominently in studies of technological change. *Turnover intentions* tracks job commitment. Appraisals of a redesigned job and concerns technology threatens one's position can lead workers to seek employment elsewhere (Brougham & Haar, 2020; Ren & Chowdhury, 2025). *Job satisfaction* tracks overall sentiment toward a job. Because technologies reconfigure work, satisfaction evolves with automation (Nguyen & Malik, 2022). *Alienation* tracks separation from one's work and coworkers. Classic studies highlighted it as a potential consequence of automation (e.g., Blauner, 1964). In line with newer research, alienation is a composite of four items capturing self-estrangement (Vallas & Kronberg, 2023) and isolation (Glavin et al., 2021).

Because the measures used slightly different scales, I normalized all to range between zero and one. To create multi-item measures, I took the average across each component.

Control Variables

I relied on administrative records to create a set of variables likely associated with job characteristics and worker attitudes. These are the respondent's job tenure; full-time or part-time status; hourly wage; department, which denotes the work group to which a worker is assigned and the tasks they perform; gender; race/ethnicity; and age.

Because the survey was fielded at multiple timepoints, I created an indicator for survey group. This captures the chance that work conditions differed depending on when respondents took the survey.

Finally, I created a variable indicating whether an FC participated in an intervention (unrelated to technology) randomly assigned to half the sites during the survey period.

Estimation Strategy

I use ordinary least squares (OLS) regression to examine the relationship between technology, job characteristics, and worker attitudes. To account for possible correlation among the responses of workers employed in the same warehouse, I cluster standard errors at the level of the FC. I use Bell and McCaffrey bias-corrected cluster-robust standard errors, which are advisable when the number of clusters is small (Cameron & Miller, 2015). I also employ a degrees of freedom adjustment, calculating p-values using $T(G-1)$ degrees of freedom, where G is the number of clusters in the study. As a result, test statistics are based on 15 degrees of freedom.

Findings

Descriptive Statistics

Table 1 presents summary statistics describing the sample. Looking across sites and technology types, most workers were full-time. The majority were in the picking department, the entry point for new hires. Workers averaged around 6.17 years of tenure, though this masks significant variation (SD: 7.16) explained by high turnover among new hires. Wages averaged $21.97 per hour. The mean age was about 40.4 years, again masking significant variation (SD: 13.47). A majority of workers (57%) were recorded as male. A slight plurality was non-Hispanic White (39%), followed by Hispanic (38%), followed by Black (18%).

--- Insert Table 1 about here ---

Distinguishing by technology type, most respondents were located in robotics FCs, followed by conveyor FCs. Across technologies, there were few differences in respondents' observable attributes. Cluster-robust regressions that treat the independent variables in Table 1 as dependent variables to assess their relationship with technology type showed only a significant difference for tenure, with time on the job slightly higher in conveyor buildings than cart ones ($p = 0.033$). These results are not consistent with Sigma implementing technologies in sites based on characteristics of the local workforce or with workers sorting into sites based on technology.

Main Results

I begin by examining job characteristics. Table 2 reports regression results for full models using all controls. Appendix B shows basic models; the results are consistent.

Overall, the three technologies are associated with different work conditions. Compared to workers in cart FCs, workers in robotics FCs report lower levels of decision authority, skill discretion, supervisor support, coworker support, and job security. Psychological job demands are lower too but only at the threshold of significance ($p = 0.120$). A similar pattern is found in conveyor FCs. Compared to cart workers, conveyor workers report lower levels of decision authority, skill discretion, psychological job demands, and job security. Job characteristics do not vary much between robotics and conveyor FCs: Wald tests show no significant differences in effect sizes. Hence, workers report similar conditions under collaborative robots and conveyors.

--- Insert Table 2 about here ---

These outcomes point to lower quality jobs in robotics and conveyor FCs. Workers there are granted less autonomy and subject to greater demands, conditions indicative of a duller job with limited learning opportunities (Karasek et al., 1998).[7] Added to this strain, robotics workers report lower supervisor and coworker support and greater concern with job security. Thus, collaborative robots (and conveyors) do not co-occur with increased control, meaning, or connection.

To see if these differences map onto job assessments, I turn to worker attitudes. Table 3 results show more negative assessments in robotics and conveyor FCs. In robotics FCs, turnover intentions and alienation are greater, and job satisfaction is lower. Conveyor workers report greater alienation and lower satisfaction. Similar to the above results, there are no significance differences between robotics and conveyor workers.

--- Insert Table 3 about here ---

[7] The desirability of high job demands depends on the accompanying levels of job control (Karasek et al., 1998). Surgeons are an example of "active" jobs providing "good stress." They face high demands, spending stretches on risky, time-sensitive tasks, but are also free to choose how to handle each task, giving high control. These circumstances provide greater motivation and learning opportunities and often accord high levels of prestige. By contrast, high demands-low control jobs, such as picking, provide workers little agency or room to grow.

An alternative explanation for these findings could be that Sigma deployed robots and conveyors in sites where job quality was already low or that these technologies attract a more pessimistic set of workers. I assess this alternative in Appendix C. On balance, there is little evidence that pre-existing site differences jointly shaped technology deployment, workforce composition, and job quality.

Working with Robots Directly

Although the preceding results control for job role via department, they represent an average effect across all roles. Yet some workers more directly engage a core technology than others because they must use it to accomplish their jobs. To see if effect sizes depend on engagement, I created a variable tracking core technology exposure. This took a value of one if a worker was in the picking or replenishment departments (i.e., in a direct role) and zero otherwise (i.e., in an indirect role). I then re-ran the full models, interacting this variable with technology type.

To ease interpretability of the interaction terms (Verhagen, 2022), Figure 1 displays predicted value plots derived from the job characteristics models. They show the average change in the predicted outcome associated with a change in exposure, for each technology type. In other words, they provide a counterfactual comparison, indicating the likely outcome were a worker in an indirect role to switch into a direct role without switching technology types (e.g., a bulk worker in a robotics FC were to become a picker). If the plot shows no difference between direct and indirect roles, the corresponding technology's effect is not contingent on whether a worker uses it directly to complete her job.

--- Insert Figure 1 about here ---

The plots reveal a complex story. For some outcomes and technologies, exposure makes no significant difference. That is, the relationships in Table 2 persist whether or not one works directly with their building's core technology. For others, the relationship depends on exposure. In robotics FCs, differences emerge for decision authority, skill discretion, and psychological job demands: workers who directly interact with robots report lower readings on these measures. In conveyor FCs, direct roles report lower levels of decision authority, skills discretion, supervisor support, and coworker support. They also report slightly higher physical job demands. Finally, in cart FCs, workers in direct roles report higher physical and psychological demands.

Figure 2 displays predicted value plots for the worker attitude models. Among those who work in robotics FCs, alienation is higher in direct roles. Among those who work in cart FCs, job satisfaction is higher if a worker uses a cart.

--- Insert Figure 2 about here ---

An FC's core technology evidently has a multilayered impact. On the one hand, it can alter operations in broad strokes. Although robots transform picking and replenishment, they also change processes that feed into and on these roles. The job characteristics for which there are no significant differences between direct and indirect roles—job security, coworker support—are likely affected by robot presence alone. A robot may, for instance, be threatening to those who, from afar, see it taking on more responsibility. These same workers may perceive colleagues using the robot as socially inaccessible, for the latter are cordoned off. On the other hand, characteristics that do differ by exposure—decision authority, skill discretion, physical and psychological job demands—are perhaps more tightly linked to the tasks workers must perform such that those who use the technology directly feel the effects most acutely. A similar case can be made for attitudes. Turnover intentions and job satisfaction are likely shaped by what workers see occurring on the floor, even if it affects those in other roles. Alienation, however, is closely linked with work tasks, and so it is less surprising it varies with exposure.

Exposure lends itself to assessing another alternative explanation, namely, that managers adjust their treatment of workers to complement their building's core technology, and this is what actually shapes job quality. If this were so, there should be few differences between directly and indirectly exposed workers in the same FC, after accounting for the common managerial influence. I test this explanation in Appendix D and find persistent technology effects.

Working with Different Robots

The innovations underlying both types of collaborative robots at Sigma are the same, but AMRs and GTPs entail different picking and replenishment processes. The biggest contrast is that GTPs confine users to a set area, whereas AMRs allow movement throughout the FC. To see if job characteristics and worker attitudes vary between these technologies, I restricted my sample to robotics FCs and created a variable indicating whether a respondent worked a) directly with an AMR, b) directly with a GTP, or c) indirectly with either robot. I then regressed each outcome on this measure, along with controls.

Table 4 displays the difference in estimated coefficients for GTPs and AMRs, with cluster-robust Wald tests of significance. Harsher conditions are consistently found with GTPs.

GTP workers report lower skill discretion, supervisor and coworker support, and job security. They report higher physical demands. Turnover intentions and alienation are also higher among this group, and job satisfaction is lower.

--- Insert Table 4 about here ---

Discussion and Conclusion

Despite collaborative robots' profusion, sociologists have provided little evidence showing how these machines affect job quality, leaving us with only a weak grasp on whether the changes spell a more or less hopeful future for workers. At first sight, this technology shares similarities with past machines intended to take on more work, and the negatives accompanying the latter are well known. Yet the consequences of collaborative robots' algorithmic capacities are less certain. To some, algorithms allow robots to eat up undesirable work while submitting to users' wishes, a significant improvement over older pieces of industrial automation (Daugherty & Wilson, 2018; Franklin et al., 2020). To others, algorithms open up more pervasive, restrictive, punitive, and opaque avenues of managerial control (Kellogg et al., 2020; Wood, 2021).

The present study lands somewhere in the middle. At Sigma, collaborative robots have not enhanced work. Relative to the oldest technology, the hand-pulled cart, they coincide with reduced autonomy and similar physical and psychological workloads. They are also associated with greater displacement fears and weakened social support. It is unsurprising, then, that those working with robots report feeling more alienated and inclined to quit. At the same time, robots are not an especially adverse form of automation. Conveyor belts are associated with similar levels of job quality.

What explains workers' tepid stance toward robots? This study emphasizes the material features influencing job characteristics and worker attitudes. The way Sigma's robots have been designed and deployed leaves it biggest mark on autonomy, skill development, and relationships. The robots do little to relieve or intensify physical job demands, which makes sense given that they do the hauling but still require users to retrieve objects. It also makes sense given that they do not induce new performance pressures: analysis of Sigma's productivity standards as well as actual productivity levels shows no significant differences across core technologies. Instead, the difficulties are tied most closely to the robots' tendency to guide the flow of work while permitting little room for human intervention. Workers cannot dictate the machine's pace or route. The interface connecting them to the robot requires little training, shrinking the domain workers must master. The robots also prevent workers from leaving their posts to check in with peers. The contrast between the AMRs and GTPs further underscores what is problematic. GTPs confine users more so than AMRs, reducing decision latitude and chances for socialization. All these features fail to equip Sigma workers with more control, meaning, or connection, ingredients Blauner (1964) argued were vital to emancipatory technologies. On the contrary, they go hand in hand with heightened job strain and decreased well-being.

Stringing these findings together, Sigma's collaborative robots appear as one more means of managerial control, not an automating technology *sui generis*. They reduce worker's scope of action and make for more monotonous, individual jobs, much like prior technologies of mass production. While their algorithmic capacities may set them apart from conveyors and their ilk, these capacities have not been used in truly distinguishing ways. Hence, the hopeful case for collaborative robots is not borne out at Sigma, though there is limited support for the pessimistic view that these algorithmically-powered machines will enable unprecedented managerial control. At present, algorithmic technologies, in their tangible form, resemble their forebears.

Looking forward, it is important to ask if what has occurred at Sigma is likely to occur elsewhere. One concern over whether this study can provide an answer is that its conclusions come from analysis of a single firm. I have argued this confined focus is an asset, reducing the influence of confounders lurking in other studies. I have also presented evidence showing few systematic relationships between core technologies and attributes of Sigma's FCs and workforce. For these reasons, the work conditions associated with each technology are likely due to features of the technologies themselves, features that can be utilized in new settings with presumably similar consequences. Yet the analysis has been correlational rather than causal, and other forces are surely at play (e.g., variation in managerial style, deployment timing, local labor markets), even if their impact is muted. It could also be that Sigma leaders take an approach to automation that activates constraining rather than liberating affordances. Future research could explore this possibility by looking across multiple organizations (and over multiple timepoints), while still taking care to compare the affordances accompanying different stages of automation.

A second, more substantial concern is that it is dubious to expect any technology to have similar effects in different settings, and for good reason. A long line of scholarship has resisted deterministic narratives, arguing that technology is interpretatively flexible, neither good nor bad (Orlikowski, 2000). This study is not incompatible with such an understanding. The affordances that enable particular experiences of collaborative robots are both material and social. In social circumstances different from Sigma's, alternate affordances might be enacted when the same robots get deployed. With this study alone, it is challenging to identify features of Sigma's robots that might allow for more positive outcomes: design and deployment decisions have already been made. To appreciate other trajectories, future research should study what occurs before and after these machines get introduced into an organization, noting closely the relations between workers, managers, and engineers (Thomas, 1994).

As design and deployment processes unfold in other settings, it is undeniable alternative institutional configurations could make for better outcomes than those found at Sigma (Krzywdzinski, 2017). But just because a different outcome is possible does not mean it is likely. As thoughtful perspectives on technological change would have it, the coupling of the material and social depends on who has the power to direct implementation (Bailey, 2022; Leonardi & Barley, 2010; Shaiken, 1986; Thomas, 1994). In the U.S. and many advanced economies, where there are no formal mandates allowing for worker involvement, this responsibility falls primarily to managers (De Stefano, 2019). When it comes to collaborative robots, this does not bode well for workers. Managers have made it clear that adoption rests on efficiency concerns and a desire to replace human labor. This is true across industries (Dornelles et al., 2023). It is true in warehousing, where implementation is seldom driven by concerns for worker well-being but instead by ambitions to increase productivity and reduce labor costs (Berkers et al., 2023). It is also true among designers, who, assuming workers are incapable of learning to direct the machines, engineer workers out of consideration (Michaelis et al., 2020). In these respects, Sigma is no exception. Its leaders invested in robots with little consideration of how it would affect the quality of the jobs they offer. It is probable, then, that Sigma workers' experiences with collaborative robots will be replicated in other firms.

As more firms lean on collaborative robots, unfavorable outcome seems more likely than not in warehousing. This is definitely so at the sector's two largest employers, Amazon and

Walmart, which have made robotics central to their e-commerce strategies. Hence, on top of the litany of challenges that warehouse workers already face, collaborative robots present yet another burden in an already tough work environment.

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Tables and Figures

Tables

Table 1: Summary statistics

	Cart	Robotics	Conveyor
DVs			
Decision authority	3.47 (0.86)	3.26 (0.92)	3.25 (0.96)
Skill discretion	3.83 (0.86)	3.73 (0.89)	3.60 (1.00)
Psychological job demands	3.91 (0.69)	3.84 (0.68)	3.81 (0.71)
Physical job demands	2.66 (1.32)	2.62 (1.40)	2.69 (1.35)
Supervisor support	3.47 (1.16)	3.59 (1.21)	3.35 (1.18)
Coworker support	3.09 (1.25)	3.14 (1.29)	2.98 (1.24)
Job security	3.78 (0.93)	3.58 (1.02)	3.55 (1.07)
Turnover intentions	2.60 (1.12)	2.60 (1.18)	2.51 (1.19)
Job satisfaction	6.84 (2.39)	6.94 (2.40)	6.55 (2.63)
Alienation	1.67 (1.00)	1.66 (1.01)	1.76 (0.97)
IVs			
Hourly wage ($)	21.47 (2.36)	22.31 (2.49)	21.87 (2.08)
Part-time status	33 (11%)	74 (12%)	93 (16%)
Tenure (years)	5.14 (6.26)	5.96 (7.69)	6.94 (6.92)
Department			
Picking	90 (29%)	184 (29%)	231 (40%)
Bulk	41 (13%)	90 (14%)	59 (10%)
Inbound	52 (17%)	85 (14%)	99 (17%)
Replenishment	60 (19%)	128 (21%)	77 (13%)
Shipping	26 (8.4%)	40 (6.4%)	37 (6.5%)
Support	40 (13%)	97 (16%)	70 (12%)
Female	112 (36%)	272 (43%)	269 (47%)
Age (years)	37.35 (13.22)	41.69 (14.06)	40.68 (12.68)
Race/ethnicity			
White	100 (32%)	184 (29%)	309 (54%)
Black	58 (19%)	124 (20%)	86 (15%)
Hispanic	119 (39%)	293 (47%)	160 (28%)
Non-Hispanic Asian/PI/AI/AN	32 (10%)	23 (3.7%)	18 (3.1%)
# Workers	309	624	573
# FCs	5	5	6

Mean and SD in parentheses for continuous variables; frequency and relative frequency in parentheses for categorical variables. Raw values reported for dependent variables.

Table 2: Relationship between technology and job characteristics

	Decision authority	**Skill discretion**	**Psychological job demands**	**Physical job demands**	**Supervisor support**	**Coworker support**	**Job security**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Robotics	-0.066**	-0.059***	-0.032	0.031	-0.035+	-0.048**	-0.069*
	(0.019)	(0.010)	(0.020)	(0.027)	(0.017)	(0.015)	(0.026)
Conveyor	-0.068*	-0.064***	-0.037+	0.032	-0.034	-0.034	-0.067+
	(0.027)	(0.013)	(0.019)	(0.019)	(0.027)	(0.022)	(0.037)
N	1,506	1,506	1,506	1,506	1,506	1,506	1,506

All models include full set of controls. Complete regression results available in Appendix Table B1. Reference category for technology is cart. Cluster-robust standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Relationship between technology and worker attitudes

	Turnover intentions	**Job satisfaction**	**Alienation**
	(1)	**(2)**	**(3)**
Robotics	0.080**	-0.062***	0.060**
	(0.026)	(0.013)	(0.015)
Conveyor	0.055	-0.064**	0.041*
	(0.033)	(0.020)	(0.019)
N	1,506	1,506	1,506

All models include full set of controls. Complete regression results available in Appendix Table B2. Reference category for technology is cart. Cluster-robust standard errors in parentheses.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Difference in effects by robot type

	GTP – AMR coefficients
Decision authority	-0.030
Skill discretion	-0.084+
Psychological job demands	-0.009
Physical job demands	0.078*
Supervisor support	-0.040**
Coworker support	-0.068*
Job security	-0.080**
Turnover intentions	0.065+
Job satisfaction	-0.097+
Alienation	0.053*

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Figures

Figure 1: Predicted job characteristics by technology exposure

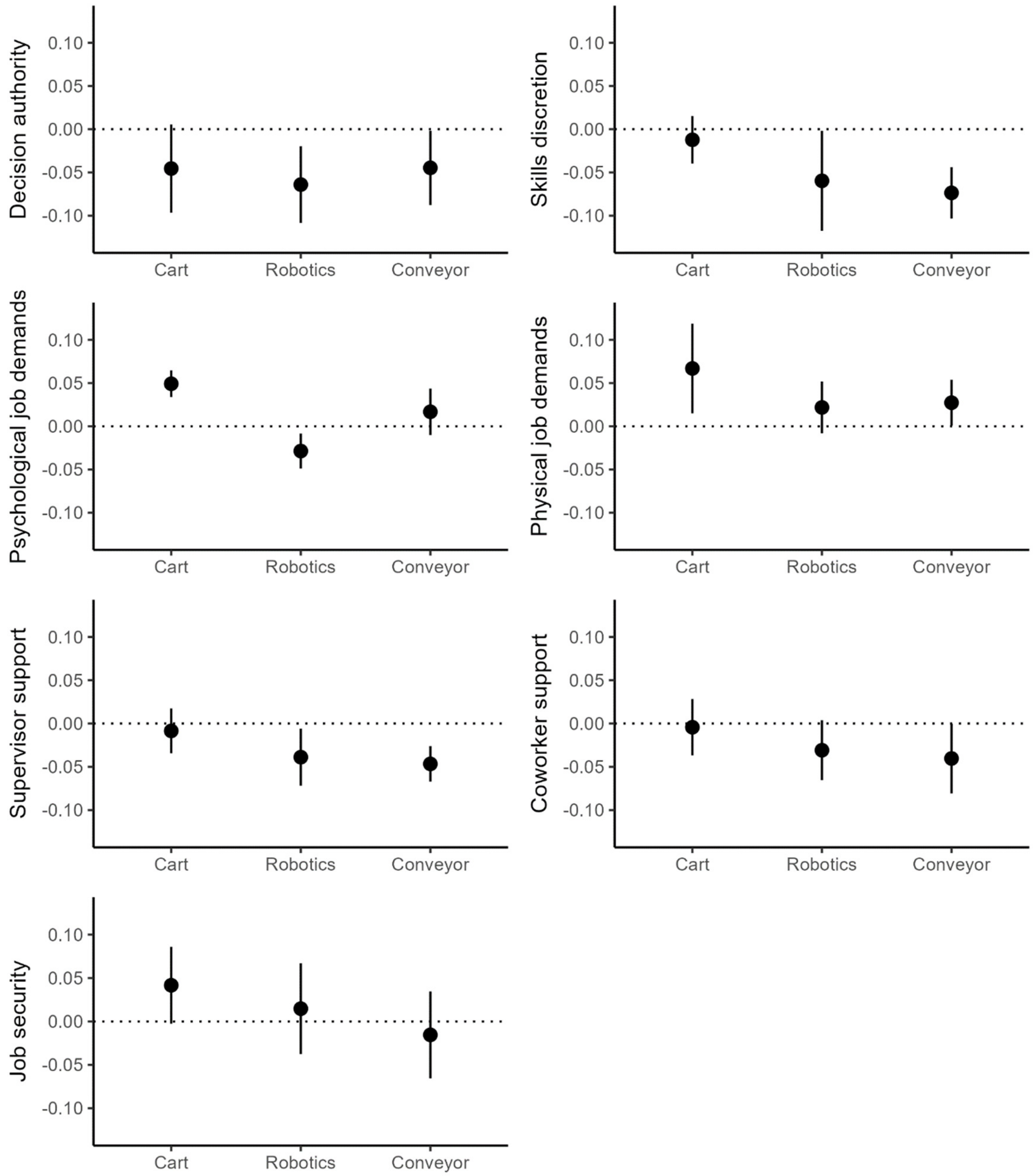

Figure shows difference between predicted values for direct and indirect exposure. Reference category is indirect exposure.

Figure 2: Predicted worker attitudes by technology exposure

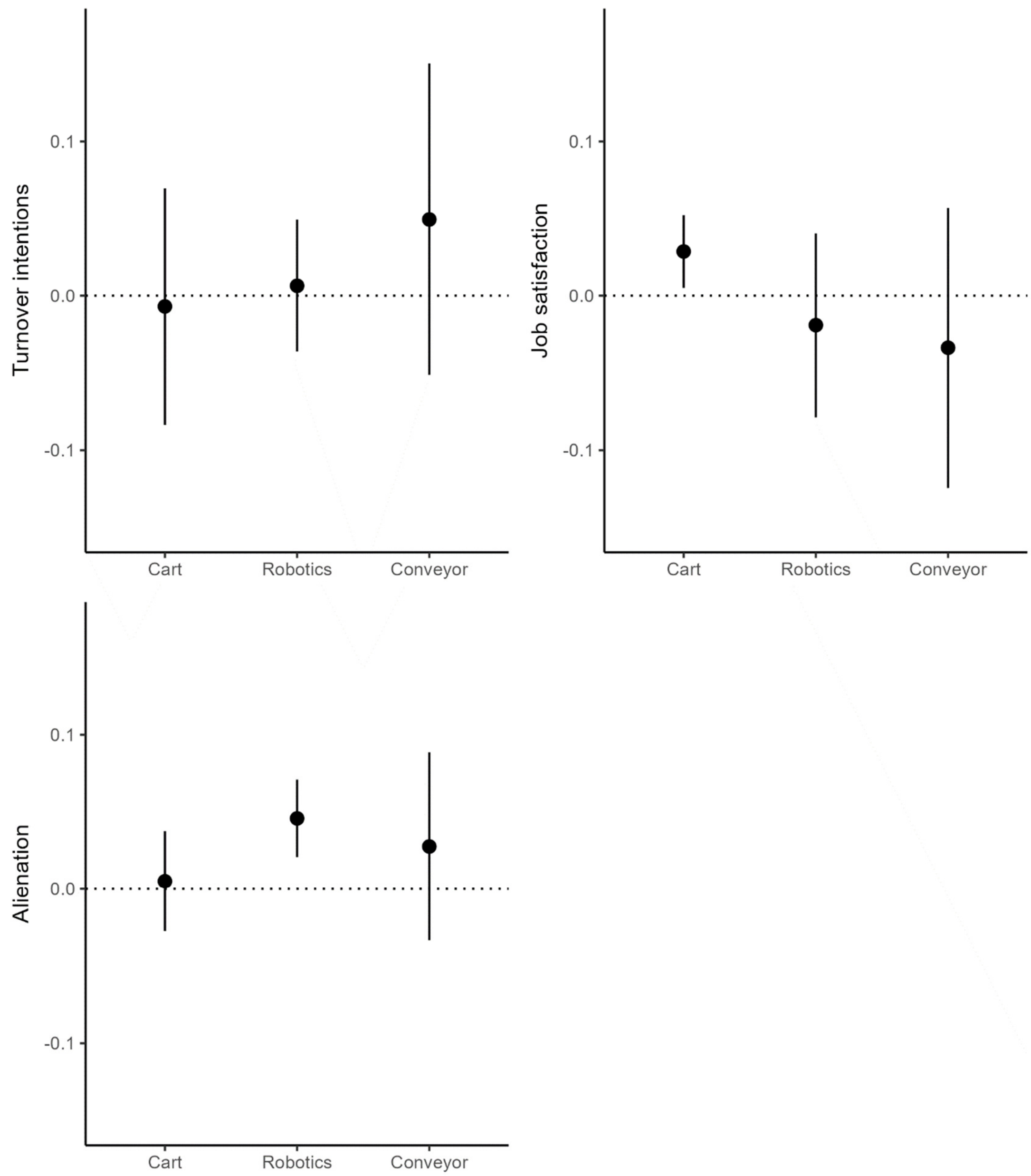

Figure shows difference between predicted values for direct and indirect exposure. Reference category is indirect exposure.

Appendix

Appendix A

In this study, job characteristics do not map one-to-one onto control, meaning, and social connection but instead share points of overlap and so provide an overall indicator of all three. The measures are:

Decision authority includes two questions: “My job allows me to make a lot of decisions on my own,” and “I have a lot of say about what happens on my job” (1 = strongly disagree to 5 = strongly agree).

Skill discretion includes two questions: “I get to do a variety of things in my job,” and “My job requires that I learn new things” (1 = strongly disagree to 5 = strongly agree).

Psychological job demands includes two questions: “My job requires working very hard,” and “I have enough time to get the job done” (1 = strongly disagree to 5 = strongly agree).

Physical job demands includes one question: “After I leave work, I have enough energy to do the things I want or need to do” (0 = never to 5 = always).

Supervisor support includes one question: “I feel supported by my supervisor” (0 = never to 5 = always).

Coworker support includes one question: "I feel supported by my coworkers" (0 = never to 5 = always).

Job insecurity includes one question: "I feel my job is secure" (1 = strongly disagree to 5 = strongly agree).

The worker attitude measures covered in this study are related but conceptually and empirically distinct (Chiaburu et al., 2014). The measures are:

Job satisfaction is adapted from VanderWeele (2017). It includes one question: "Overall, how satisfied are you with your job as a whole these days?" (0 = not at all to 10 = completely).

Turnover intentions is adopted from Lawler et al. (2013). It includes one question: "I will probably look for a new job in the next year" (1 = strongly disagree to 5 = strongly agree).

Alienation is a composite index (alpha = 0.77) made up of four questions: "At work, my mind is focused on my job," "My job is boring" (reverse coded), "My work gives me a sense of purpose," and "At work, I feel like I belong" (0 = never to 5 = always). The first three questions are similar to the self-estrangement items proposed by Mottaz (1981) and Shantz et al. (2015), and the last question is similar to Glavin et al.'s (2021) isolation item. The composite measure is reversed so higher values correspond to higher levels of alienation. Confirmatory factory analysis showed this index met standard assessments of good fit.

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Appendix B

Tables B1 and B2 show complete results for Tables 2 and 3.

Table B1: Relationship between technology and job characteristics

	Decision authority		Skill discretion		Psychological job demands		Physical job demands		Supervisor support		Coworker support		Job security	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Robotics	-0.068**	-0.066**	-0.056**	-0.059***	-0.025	-0.032	0.030	0.031	-0.021	-0.035+	-0.036+	-0.048**	-0.057+	-0.069*
	(0.020)	(0.019)	(0.014)	(0.010)	(0.027)	(0.020)	(0.019)	(0.027)	(0.023)	(0.017)	(0.020)	(0.015)	(0.031)	(0.026)
Conveyor	-0.069*	-0.068*	-0.069***	-0.064***	-0.032	-0.037+	0.034+	0.032	-0.044	-0.034	-0.038	-0.034	-0.060	-0.067+
	(0.027)	(0.027)	(0.010)	(0.013)	(0.026)	(0.019)	(0.018)	(0.019)	(0.027)	(0.027)	(0.024)	(0.022)	(0.041)	(0.037)
Hourly wage ($)		0.007+		0.012**		0.003*		0.002		0.003		0.012**		0.011*
		(0.004)		(0.004)		(0.001)		(0.004)		(0.004)		(0.003)		(0.005)
Part-time status		-0.006		-0.051*		-0.042*		-0.076*		0.032*		0.001		-0.049**
		(0.010)		(0.022)		(0.020)		(0.027)		(0.012)		(0.018)		(0.015)
Tenure: First 90 days		0.023		0.069**		0.037		-0.017		0.128***		0.077**		0.076*
		(0.026)		(0.018)		(0.027)		(0.044)		(0.023)		(0.026)		(0.027)
90 days to 1 year		0.018		0.033		0.024		-0.015		0.064**		0.074**		0.052+
		(0.017)		(0.023)		(0.021)		(0.024)		(0.021)		(0.022)		(0.025)
2nd year		-0.007		0.059*		-0.029		-0.018		0.004		0.008		0.009
		(0.025)		(0.027)		(0.029)		(0.021)		(0.020)		(0.031)		(0.033)
3rd year		-0.009		0.051+		-0.019		-0.013		0.027		0.015		-0.001
		(0.030)		(0.028)		(0.027)		(0.031)		(0.023)		(0.031)		(0.033)
4th year		0.022		0.015		0.006		-0.031		-0.015		0.026		-0.028
		(0.035)		(0.042)		(0.031)		(0.029)		(0.034)		(0.033)		(0.047)
5th year and beyond		-0.005		0.003		-0.011		-0.009		-0.038+		-0.030		-0.021
		(0.016)		(0.022)		(0.020)		(0.020)		(0.019)		(0.032)		(0.025)
Department: Bulk		0.049**		0.022		0.028+		-0.014		0.035+		0.045*		-0.014
		(0.014)		(0.028)		(0.014)		(0.025)		(0.017)		(0.021)		(0.026)
Inbound		0.031		0.030		-0.051**		-0.041		-0.001		-0.006		-0.041
		(0.029)		(0.025)		(0.017)		(0.025)		(0.024)		(0.021)		(0.027)
Replenishment		-0.012		-0.038		-0.018		0.010		-0.028*		-0.023		-0.027
		(0.020)		(0.029)		(0.015)		(0.028)		(0.013)		(0.018)		(0.021)
Shipping		0.056*		-0.010		0.014		0.004		0.021		0.002		0.003
		(0.023)		(0.016)		(0.024)		(0.035)		(0.026)		(0.029)		(0.028)
Support		0.068**		0.116***		-0.031+		-0.059+		0.048*		0.036		-0.021
		(0.021)		(0.022)		(0.016)		(0.028)		(0.020)		(0.027)		(0.018)
Gender: Female		-0.014		-0.005		0.014		0.063**		-0.002		0.001		0.020
		(0.013)		(0.012)		(0.012)		(0.018)		(0.013)		(0.010)		(0.019)
Race/ethnicity: Hisp.		-0.038*		-0.011		-0.042**		-0.035+		-0.005		-0.032*		-0.041*
		(0.015)		(0.015)		(0.012)		(0.018)		(0.019)		(0.014)		(0.018)
Black		-0.018		-0.005		-0.025+		-0.021		0.004		-0.008		-0.047
		(0.025)		(0.018)		(0.012)		(0.025)		(0.018)		(0.018)		(0.027)
Non-Hisp. APIAIAN		-0.026		-0.018		-0.042		-0.044		-0.002		0.035		-0.044
		(0.030)		(0.019)		(0.026)		(0.030)		(0.034)		(0.037)		(0.046)
Age (years)		-0.001*		-0.001**		-0.001*		-0.004***		0.001		0.001+		-0.001+
		(0.000)		(0.000)		(0.000)		(0.001)		(0.001)		(0.000)		(0.001)
N	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506
R-squared	0.014	0.056	0.016	0.104	0.004	0.059	0.012	0.072	0.024	0.075	0.017	0.057	0.009	0.041

All regressions control for survey group and intervention status. The reference category for technology is cart; for race/ethnicity, non-Hispanic White; for department, it is breakpack. Cluster-robust standard errors in parentheses.
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table O2: Relationship between technology and worker attitudes

	Turnover intentions		Job satisfaction		Alienation	
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics	0.047	0.080**	-0.041**	-0.062***	0.040*	0.060**
	(0.030)	(0.026)	(0.013)	(0.013)	(0.016)	(0.015)
Conveyor	0.011	0.055	-0.059**	-0.064**	0.039*	0.041*
	(0.043)	(0.033)	(0.019)	(0.020)	(0.016)	(0.019)
Hourly wage ($)		-0.010*		0.008		-0.011***
		(0.004)		(0.004)		(0.003)
Part-time status		-0.011		0.027		0.000
		(0.016)		(0.018)		(0.011)
Tenure: First 90 days		-0.068		0.082*		-0.049*
		(0.049)		(0.029)		(0.022)
90 days to 1 year		-0.033		0.031		-0.046*
		(0.037)		(0.027)		(0.019)
2nd year		-0.005		0.004		-0.009
		(0.028)		(0.029)		(0.021)
3rd year		0.042		-0.032		-0.007
		(0.042)		(0.037)		(0.025)
4th year		0.020		-0.015		-0.021
		(0.049)		(0.042)		(0.027)
5th year and beyond		0.013		-0.040		0.024
		(0.031)		(0.033)		(0.024)
Department: Bulk		-0.001		0.016		-0.043*
		(0.023)		(0.023)		(0.017)
Inbound		0.017		-0.050		0.000
		(0.036)		(0.035)		(0.018)
Replenishment		0.040		-0.059*		0.017
		(0.024)		(0.023)		(0.017)
Shipping		-0.001		-0.005		-0.014
		(0.031)		(0.033)		(0.020)
Support		-0.037		0.004		-0.039+
		(0.030)		(0.025)		(0.019)
Gender: Female		-0.071**		0.019		-0.039***
		(0.018)		(0.017)		(0.010)
Race/ethnicity: Hisp.		0.063*		0.013		-0.030*
		(0.022)		(0.016)		(0.012)
Black		0.047*		0.012		-0.026+
		(0.020)		(0.021)		(0.015)
Non-Hisp. APIAIAN		0.133**		0.003		-0.039
		(0.037)		(0.029)		(0.026)
Age (years)		-0.004***		0.003***		-0.004***
		(0.001)		(0.000)		(0.000)
N	1,506	1,506	1,506	1,506	1,506	1,506
R-squared	0.013	0.099	0.023	0.068	0.020	0.109

All regressions control for survey group and intervention status. The reference category for technology is cart; for race/ethnicity, non-Hispanic White; for department, it is breakpack. Cluster-robust standard errors in parentheses.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix C

One alternative explanation for the main results could be that pre-existing FC differences jointly influenced technology selection, workforce composition, and job quality. In other words, Sigma leadership may have implemented certain technologies in FCs that disproportionately employed a particular kind of worker (e.g., those who exhibited poor performance or hostility toward management), or a certain kind of worker might be attracted to FCs that use a particular technology (e.g., workers who prefer a heavy workload or limited pressures to socialize with coworkers). If either were the case, workers in a given FC could be disposed to report certain job characteristics or attitudes, and this would not be due to the building's technology *per se*.

Site selection and worker sorting do not likely to explain variation in this sample, given scant correlation between FC technology and observable building and workforce characteristics. Another detail weighing against selection bias stems from the high rates of turnover typical in warehouse work. In this sample, only 34% of those employed in robotics FCs were there before robots were introduced. Hence, if Sigma leadership opted to institute robots based on an FC's workforce, most of the workers who informed this decision were no longer present. Sorting concerns also seem to have limited merit, as conversations with workers revealed that many chose their jobs based on pay levels or location, not a familiarity with the way their prospective employer arranged work.

Nevertheless, I took several steps to offer an additional counterweight to these concerns. First, I re-ran the main models using a sample that excluded workers in robotics buildings who were present before adoption, and the same conclusions held. These respondents could not have caused Sigma to implement robots in their FC. Second, I regressed a variable indicating whether a worker was present before robot adoption on the control variables, using a sample that contained only those who work in robotics FCs. Apart from tenure, which was to be expected, no other variable predicted that a worker was present before adoption. This suggests that FCs did not attract a different kind of worker after they had implemented robots. Finally, I created an alternate *technology type* variable indicating whether a worker was present before or after her site's core technology was adopted and re-ran the above models using the full sample.[8] The results, reported in Tables C1 and C2, line up with the main analysis; in the full models, there are no significant differences between the effect sizes for those present before and after adoption.

Taken together, there is little evidence that pre-existing site differences jointly shaped the choice of core technology and job quality outcomes in each FC or that each core technology has attracted particular kinds of workers.

[8] I do not have comprehensive data on whether and when the other sites adopted carts or conveyors; if any sites did switch core technologies, this likely occurred decades ago and so only a very small fraction of survey respondents, if any, could have experienced the transition. As a result, there were only four possible values for this variable: present after carts; present after conveyors; present before robotics; present after robotics.

Table C1: Relationship between technology and job characteristics, accounting for worker pre-robot presence

	Decision authority		Skill discretion		Psychological job demands		Physical job demands		Supervisor support		Coworker support		Job security	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Robotics (Pre-adoption)	-0.068*	-0.064**	-0.058*	-0.056**	-0.017	-0.036	0.044*	0.034	0.007	-0.025	-0.024	-0.048*	-0.044	-0.068*
	(0.024)	(0.021)	(0.024)	(0.016)	(0.027)	(0.023)	(0.018)	(0.023)	(0.021)	(0.016)	(0.018)	(0.019)	(0.031)	(0.031)
Robotics (Post-adoption)	-0.068*	-0.069*	-0.053**	-0.065**	-0.039	-0.025	0.005	0.025	-0.074**	-0.054*	-0.059+	-0.047+	-0.081*	-0.071**
	(0.031)	(0.027)	(0.017)	(0.021)	(0.032)	(0.021)	(0.025)	(0.040)	(0.024)	(0.022)	(0.031)	(0.027)	(0.033)	(0.022)
Conveyor	-0.069*	-0.068*	-0.069***	-0.064***	-0.031	-0.037+	0.036+	0.031	-0.042	-0.035	-0.037	-0.034	-0.059	-0.067+
	(0.027)	(0.027)	(0.011)	(0.013)	(0.026)	(0.020)	(0.018)	(0.019)	(0.027)	(0.027)	(0.024)	(0.022)	(0.041)	(0.037)
Hourly wage ($)		0.007+		0.012**		0.003*		0.002		0.003		0.012**		0.011*
		(0.004)		(0.004)		(0.001)		(0.004)		(0.004)		(0.004)		(0.005)
Part-time status		-0.006		-0.051*		-0.041*		-0.077*		0.030*		0.001		-0.049**
		(0.011)		(0.022)		(0.019)		(0.027)		(0.011)		(0.018)		(0.016)
Tenure: First 90 days		0.023		0.068**		0.038		-0.018		0.125***		0.077**		0.076*
		(0.026)		(0.018)		(0.027)		(0.044)		(0.023)		(0.024)		(0.027)
90 days to 1 year		0.018		0.033		0.025		-0.016		0.062**		0.074**		0.052+
		(0.017)		(0.023)		(0.021)		(0.024)		(0.021)		(0.022)		(0.025)
2nd year		-0.007		0.059*		-0.029		-0.018		0.005		0.008		0.009
		(0.025)		(0.027)		(0.029)		(0.021)		(0.020)		(0.031)		(0.033)
3rd year		-0.009		0.052+		-0.020		-0.012		0.029		0.015		-0.001
		(0.030)		(0.027)		(0.027)		(0.031)		(0.024)		(0.032)		(0.034)
4th year		0.022		0.016		0.005		-0.030		-0.011		0.025		-0.028
		(0.035)		(0.043)		(0.031)		(0.027)		(0.035)		(0.035)		(0.048)
5th year and beyond		-0.004		0.006		-0.015		-0.005		-0.027		-0.031		-0.020
		(0.018)		(0.024)		(0.018)		(0.021)		(0.022)		(0.039)		(0.029)
Department: Bulk		0.049**		0.022		0.028+		-0.014		0.035+		0.045*		-0.014
		(0.014)		(0.028)		(0.014)		(0.026)		(0.017)		(0.021)		(0.026)
Inbound		0.031		0.030		-0.050**		-0.042		-0.001		-0.005		-0.041
		(0.029)		(0.025)		(0.017)		(0.025)		(0.024)		(0.021)		(0.027)
Replenishment		-0.012		-0.038		-0.017		0.009		-0.029*		-0.023		-0.028
		(0.020)		(0.029)		(0.015)		(0.028)		(0.013)		(0.018)		(0.021)
Shipping		0.056*		-0.010		0.015		0.003		0.021		0.002		0.003
		(0.023)		(0.016)		(0.024)		(0.035)		(0.026)		(0.029)		(0.028)
Support		0.068**		0.116***		-0.031+		-0.059*		0.048*		0.036		-0.021
		(0.021)		(0.022)		(0.016)		(0.028)		(0.020)		(0.027)		(0.018)
Gender: Female		-0.014		-0.005		0.014		0.063**		-0.002		0.001		0.020
		(0.013)		(0.012)		(0.012)		(0.018)		(0.013)		(0.010)		(0.019)
Race/ethnicity: Hisp.		-0.038*		-0.011		-0.042**		-0.035+		-0.004		-0.032*		-0.041*
		(0.015)		(0.015)		(0.012)		(0.018)		(0.019)		(0.014)		(0.018)
Black		-0.018		-0.005		-0.024+		-0.021		0.003		-0.008		-0.047
		(0.025)		(0.017)		(0.012)		(0.025)		(0.017)		(0.018)		(0.028)
Non-Hisp. APIAIAN		-0.026		-0.019		-0.042		-0.045		-0.003		0.035		-0.044
		(0.030)		(0.019)		(0.026)		(0.029)		(0.033)		(0.037)		(0.046)
Age (years)		-0.001*		-0.001**		-0.001*		-0.004***		0.001		0.001		-0.001+
		(0.000)		(0.000)		(0.000)		(0.001)		(0.001)		(0.000)		(0.001)
N	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506	1,506
R-squared	0.014	0.056	0.016	0.104	0.005	0.059	0.014	0.072	0.036	0.076	0.018	0.057	0.010	0.041

All regressions include controls for survey group and intervention status. The reference category for technology is cart; for race/ethnicity, non-Hispanic White; for department, it is breakpack. Cluster-robust standard errors in parentheses. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table C2: Relationship between technology and worker attitudes, accounting for worker pre-robot presence

	Turnover intentions		Job satisfaction		Alienation	
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics (Pre-adoption)	0.064+	0.080*	-0.038*	-0.068***	0.050*	0.068**
	(0.031)	(0.032)	(0.014)	(0.016)	(0.018)	(0.020)
Robotics (Post-adoption)	0.015	0.080*	-0.046*	-0.051+	0.020	0.045*
	(0.042)	(0.037)	(0.020)	(0.028)	(0.015)	(0.018)
Conveyor	0.013	0.055	-0.059**	-0.064**	0.040*	0.040*
	(0.043)	(0.033)	(0.019)	(0.020)	(0.016)	(0.018)
Hourly wage ($)		-0.010*		0.008+		-0.011***
		(0.004)		(0.004)		(0.002)
Part-time status		-0.011		0.028		-0.001
		(0.016)		(0.017)		(0.010)
Tenure: First 90 days		-0.068		0.083**		-0.050*
		(0.049)		(0.028)		(0.021)
90 days to 1 year		-0.033		0.032		-0.047*
		(0.037)		(0.027)		(0.019)
2nd year		-0.005		0.003		-0.009
		(0.028)		(0.029)		(0.022)
3rd year		0.042		-0.034		-0.005
		(0.043)		(0.037)		(0.026)
4th year		0.020		-0.017		-0.018
		(0.047)		(0.043)		(0.028)
5th year and beyond		0.013		-0.046		0.032
		(0.028)		(0.034)		(0.027)
Department: Bulk		-0.001		0.016		-0.043*
		(0.023)		(0.023)		(0.017)
Inbound		0.017		-0.049		-0.001
		(0.037)		(0.035)		(0.018)
Replenishment		0.040		-0.058*		0.016
		(0.025)		(0.023)		(0.017)
Shipping		-0.001		-0.004		-0.015
		(0.031)		(0.033)		(0.019)
Support		-0.037		0.004		-0.039+
		(0.030)		(0.025)		(0.018)
Gender: Female		-0.071**		0.019		-0.039***
		(0.018)		(0.017)		(0.010)
Race/ethnicity: Hisp.		0.063*		0.013		-0.029*
		(0.022)		(0.016)		(0.012)
Black		0.047*		0.013		-0.027+
		(0.020)		(0.021)		(0.015)
Non-Hisp. APIAIAN		0.133**		0.004		-0.039
		(0.037)		(0.029)		(0.026)
Age (years)		-0.004***		0.003***		-0.004***
		(0.001)		(0.000)		(0.000)
N	1,506	1,506	1,506	1,506	1,506	1,506
R-squared	0.016	0.099	0.023	0.068	0.022	0.109

All regressions include controls for survey group and intervention status. The reference category for technology is cart; for race/ethnicity, non-Hispanic White; for department, it is breakpack. Cluster-robust standard errors in parentheses. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix D

Another alternative explanation for the results could be that the way FC managers treat their workers depends on their building's core technology. Were this the case, job quality and worker attitudes would actually reflect managers' behavior toward their workers rather than the core technology in use.

One virtue of looking within an organization as I have done here is that some of what guides management practice—firm strategy, performance metrics, performance pressures, HR policies, and standard operating procedures (SOPs)—is largely stable across sites, meaning that these factors should play only a limited role in explaining outcome variability. Sigma also does not appear to tailor its management structure to local technologies: across the technologies, there is no significant difference in managerial span of control, as measured by the ratio of the number of workers to managers in an FC.

That said, my own research has documented notable differences in managerial styles across the FCs (Kowalski 2022). These differences would be an issue for the present analysis if the styles varied systematically with core technologies, which my prior research did not find.

As an added check, I performed an exploratory analysis aimed at disentangling managers from the technology used in their buildings. To do this, I re-ran the technology exposure analyses with an added fixed effect for FC, which allowed me to partial out the influences on job quality common to a workplace. While this move required the exclusion of variables that do not vary within the FCs, I could still estimate the interaction between technology type and exposure. To the extent that managers in an FC have a shared approach to overseeing their subordinates, it should be broadly felt across the building, independent of a worker's role and technology exposure, and thus absorbed by the fixed effect. If differences between direct and indirect exposure disappear upon inclusion of the fixed effect, this would suggest that job characteristics and worker attitudes are more tightly linked with FC-level influences, including managerial style and practice, than with technology. The results, displayed as predicted value plots in Figures D1 and D2, suggest otherwise. They are nearly identical to the patterns shown in Figures 1 and 2 in the main text. The inclusion of FC fixed effects indicates that even when workers are subject to a common managerial influence, their experiences differ according to the kinds of technology they use to complete their primary tasks.

References

Kowalski, A. M. (2022). *Terrible timing: The causes and consequences of problematic work schedules* [Dissertation]. Massachusetts Institute of Technology.

Figure D1: Predicted job characteristics by technology exposure, with FC fixed effects

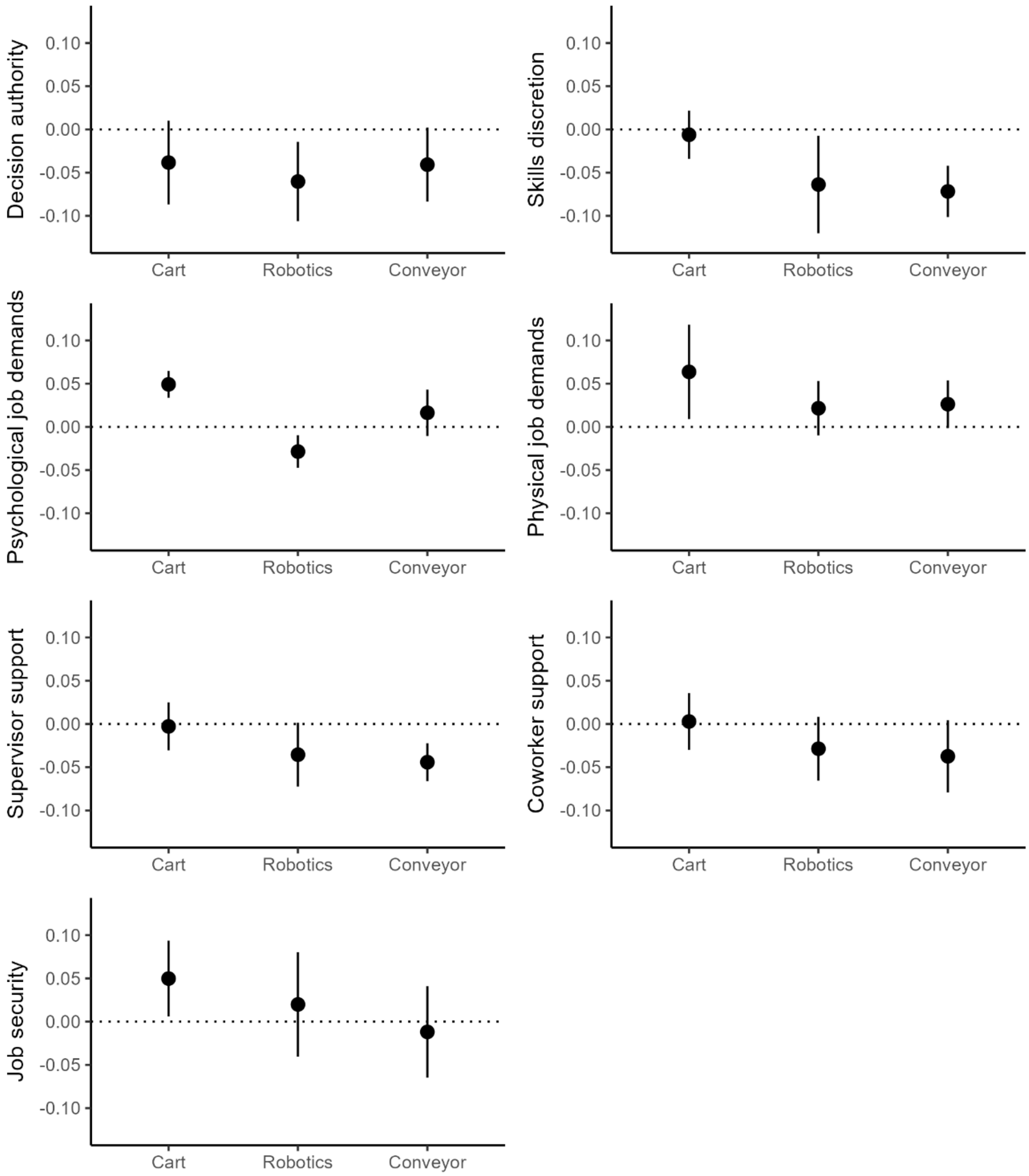

Figure shows difference between predicted values for direct and indirect exposure. Values come from regressions of each outcome on technology type, technology exposure, technology type x technology exposure, hourly wage, full-time status, tenure, gender, race/ethnicity, and age, including a fixed effect for FC. Reference category is indirect exposure.

Figure D2: Predicted worker attitudes by technology exposure, with FC fixed effects

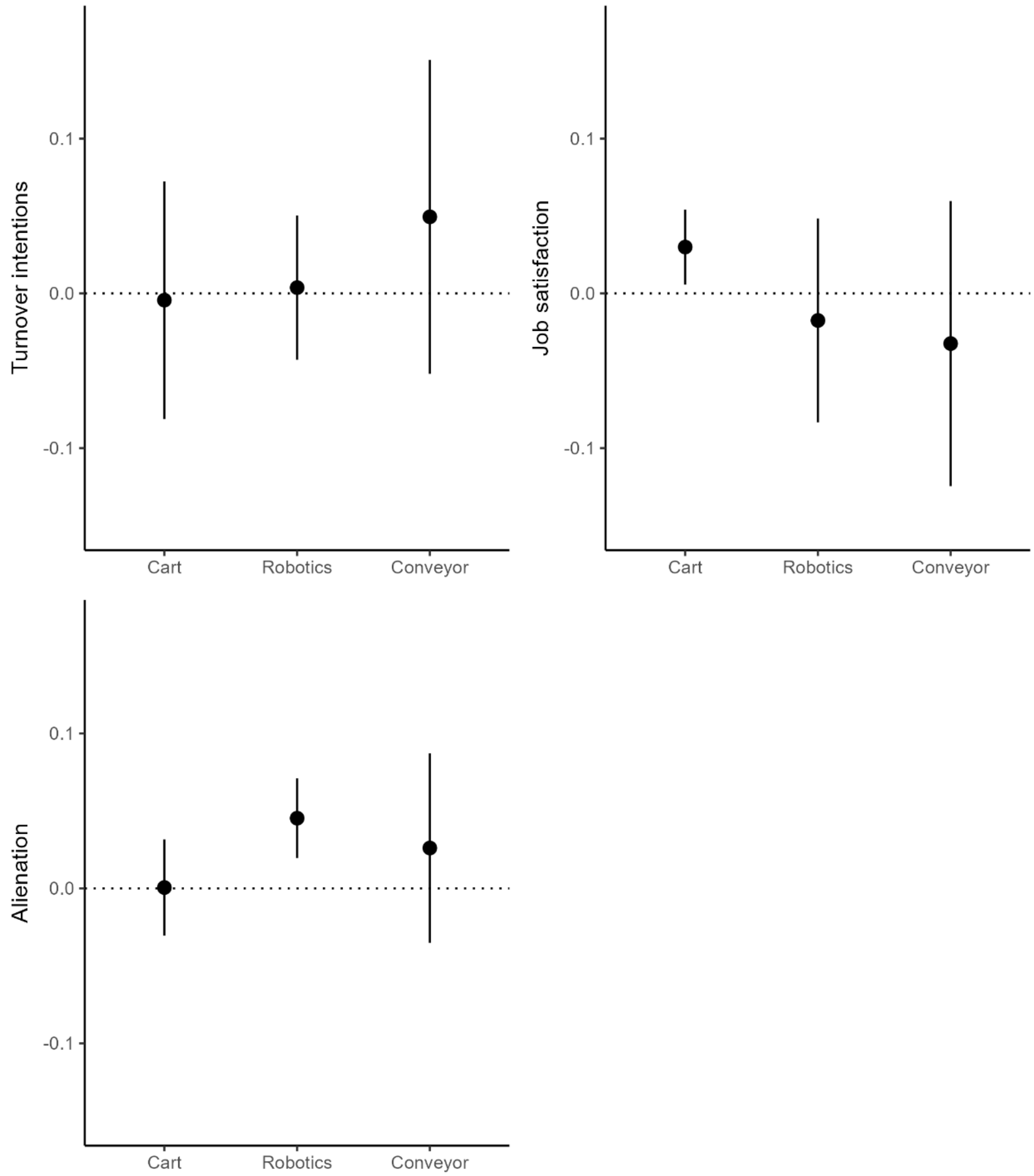

Figure shows difference between predicted values for direct and indirect exposure. Values come from regressions of each outcome on technology type, technology exposure, technology type x technology exposure, hourly wage, full-time status, tenure, gender, race/ethnicity, and age, including a fixed effect for FC. Reference category is indirect exposure.