NSF FW-HTF-R:
Preparing Hospitality Workers and Workplaces for the Future of Automation

Economics/Social Science Literature Review

By Deborah M. Figart and Ellen Mutari

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1. Introduction

This targeted review of literature in economics and related social sciences addresses the impact of automation on work in service industries such as hospitality. Particular attention is paid to the role of algorithmic management (AM)—the application of artificial intelligence (AI) to managerial tasks—and new forms robotic assistance that incorporate AI. Rather than focusing broadly on the potential for disemployment—the subject of extensive speculation during the 2010s—this review summarizes recent studies examining how work is being transformed by these emerging technologies in four areas: (1) the types of skills required in service work; (2) whether measurable changes in productivity can be identified; (3) the structure of jobs and career ladders, including occupational segregation by gender, race, and ethnicity; and (4) job quality and satisfaction, including work autonomy and relationships with managers and customers.

This is a fast-changing field with new research being disseminated while this review was in process. Yet, the clearest finding is that many of the answers to these questions are still unknown. The first wave of published work is largely theoretical or predictive rather than empirically grounded. Insights are extrapolated from prior waves of technological development, including automation in manufacturing over the past several decades. However, some of the newer research cited below argues that the development and application of artificial intelligence, especially machine learning, has distinct characteristics that may differ from historical precedent—even from the first wave of digital technology (Herzenberg & Alic, 2019; Autor, 2022; Bailey, 2022; Litwin et al., 2022). Initial empirical work focused on quantitative analysis of macroeconomic data about productivity, wages, and income inequality, leaving a dearth of concrete empirical studies at the level of individual industries, industry segments, or firms.

Such case studies are likely to deepen our understanding of variations in outcomes for worker well-being. A strong conclusion from existing research is that the institutional context in specific industries, industry segments, and workplaces will continue to impact the extent and type of technology adopted and the implications for workers (see, for example, Chui et al., 2016; Litwin et al., 2022). There is increasing consensus that broad generalizations about the trajectory of technological change imply an unwarranted level of determinism (Shestakofsky, 2017; Boyd & Holton, 2018; Herzenberg & Alic, 2019; Howcroft & Rubery, 2019; Rogers, 2020; Bailey, 2022; Howcroft & Taylor, 2022). Technology is not developed or adopted in isolation from society and its institutions. In a survey of emerging workplace technologies, Diane Bailey maintains that "... decisions about which technologies are developed, selected, designed, implemented, and used are not made solely by those with technological objectives, such as engineers and scientists, but in conjunction with powerful others having a variety of organizational, industrial, military, and governmental objectives" (Bailey, 2022, p. 4). The agency of economic actors (including unions) at the microeconomic level and public policy more broadly have important roles to play in shaping technological change.

These conclusions support the importance of the collaborative project in which we are engaged. The key question for this overall project is: Under what circumstances can technological change foster job quality and worker well-being? Under what conditions does technological change undermine these goals? Managerial strategies, particularly whether a firm pursues "high-road" or "low-road" management practices regarding labor, are crucial determinants for worker outcomes (Boushey & Rinz, 2022; IFOW, 2022). According to the University of California at Berkeley Labor Center, "High road firms compete on quality of product and service, achieved through innovation and investment in human capital, and thereby are able to generate family-supporting career-track jobs where workers have agency and voice" (2020, p. 1). These high-road approaches tend to support worker well-being more than low-road strategies where firms compete on the basis of cost and price minimization. The Institute for the Future of Work (IFOW) in the United Kingdom asserts that:

> ...there is a business case for taking a responsible approach to the adoption of technology in the workplace... [and] there are moral, social and economic imperatives to prioritising 'good work', which will see returns at the level of individual, firm and society (2022, p. 4).

In particular, the IFOW summarizes evidence that firm-level productivity is diminished by low-road approaches (including layoffs due to automation).

In the following literature review, we identify important insights into the economic factors influencing the choice of high-road versus low-road managerial strategies. These factors include industry characteristics, such as the degree of concentration, maturation, and/or financialization; these industry characteristics both constrain and provide opportunities for individual firms (Howcroft & Taylor, 2022; Litwin et al., 2022). While financialization can be an impetus for using labor-saving, cost-cutting technologies, for example, the short-term time horizons of financialized companies can also inhibit long-run investments (Howcroft & Rubery, 2019). Product market conditions, especially characteristics of the customer base, also shape managerial strategies (Boyd & Holton, 2018). For example, the salience of quality differences for a firm's target market, as well as their customers' price and income elasticity, will affect whether a firm competes on the basis of price or quality. Labor market conditions, including the availability of cheap (often female) labor, and workplace power relations matter as well (Chui et al., 2016; Howcroft & Rubery, 2019; Qiu et al. 2020; Rogers, 2020; Howcroft & Taylor, 2022). These factors can override the overall financial pressure to adopt low-road approaches (Litwin et al., 2022). Uncertainty about the payoffs from adopting new technologies can also delay implementation (Howcroft & Taylor, 2022). Consequently, firms may have multiple competing objectives affecting their decisions about technology beyond cost minimization through productivity gains.

Finally, the political and social context—especially the regulatory environment and social acceptance—impact the choice of whether and how to adopt emerging technologies (Chui et al., 2016). What is technically feasible may not be economically, politically, or socially viable. Policy advocates concerned about worker well-being are developing proposals for legislation and collective bargaining provisions that could reshape the regulatory environment in order to improve outcomes (see, for example, Herzenberg & Alic, 2019; Kresge, 2020b). Social norms matter too. The International Bar Association (2017, p. 26) provides the example of robotic bartenders. While it has been estimated that it is technically feasible to replace 87 percent of bartenders, resistance by customers (as well as prohibitively high costs) render this estimate unlikely. In the service sector, the experience itself is often the commodity (Mutari & Figart, 2015). Even if the mixed drink were of the same quality, people do not go to bars simply for the drink. All of these economic, social, and political factors play a role in shaping both the process and outcomes when developing and implementing technological change at the workplace.

2. Technology and Skills

Research questions: What effect do robots and algorithmic management have on the types of skills required in service work? Are physical requirements reduced? Is self-direction and organization of work flow increased or decreased? What is the impact on emotional labor skills?

There are two overlapping strands of research regarding the impact of emerging technologies on skill. The first strand analyzes anticipated shifts in the demand for specific skills by employers. This literature attempts to identify which types of tasks are more or less likely to be automated in the near future. The focus on specific skills and tasks was advanced by economists David Autor, Daron Acemoglu, Pascual Restrepo and others. In their task framework, jobs consist of the accomplishment of tasks. Some tasks within occupations (and industries) will be automated and others will not, depending on technical feasibility and other factors. In addition, emerging technologies will generate new tasks to be performed. Analysts estimate net effects of these changes, utilizing existing data about the skill requirements of specific occupations (usually from the Bureau of Labor Statistics' O*NET database) and assumptions about the pace of development of artificial intelligence, machine learning, and other technological alternatives to human labor. The task framework is also used to estimate (based on historical data) and predict (based on anticipated technological change) the impact on productivity (see next section), wages, and income inequality (Autor, 2022).

The second strand of research applies the classic concept of *deskilling* (or "downskilling') initially identified by Braverman (1998 [1974]) almost 50 years ago. Deskilling involves the reorganization of work processes in a way that lowers the skill requirements. Technological change is one way this is accomplished by managers. In the deskilling literature, there are multiple motivations, including both the search for efficiencies that reduce costs and managerial efforts to control the work force. Deskilling reduces the bargaining power of a group of workers since they are more easily replaced. In firms with market power due to concentration, there is less competitive pressure to reduce costs, so control enables businesses to capture a larger share of extranormal profits. While deskilling has its origins in Marxian analysis (Howcroft & Taylor, 2022), mainstream economists acknowledge similar concerns in examining the relationship between income inequality and technological change. Autor, for example, notes that: “The fewer workers that are available to accomplish a given task and the more that employers need that task accomplished by workers (rather than by, for example, machines or algorithms), the higher is the workers’ economic value and thus their potential earnings” (2022, p. 1). Empirical research using this framework examines the impact of automation on bargaining power (Qiu et al., 2020; Leduc & Liu, 2022).

2.1 The Task Framework

The task framework research strand dates back to the early 2000s; we review a sample of key studies. One influential article by David Autor was published in the *Journal of Economic Perspectives* in 2015. In this article, the author posed the question, “Why are there still so many jobs?” Autor noted that automation can either substitute for or complement labor. The early phase of automation was more likely to substitute technology for “routine, codifiable tasks.” These tasks involve “precise, well-understood procedures.”

At the same time, this first wave of digital technology was more likely to *complement* tasks that involve abstract reasoning and communication rather than *substitute* for them, resulting in *upskilling*. A report published by IZA World of Labor also observes that “While some low-skill (*sic*.) jobs have been automated, those requiring greater dexterity, teamwork, or interactions with customers have not been widely automated” (Bazylik & Gibbs, 2022, p. 7). These jobs were relatively protected while the first wave of automation displaced mid-level jobs. *Labor market polarization* occurred as what are traditionally labeled “high-skill” jobs benefitted from skill-augmenting information and communication technologies (ICT). David Deming (2021), for example, utilizes data gathered from the text of job advertisements mapped to the Bureau of Labor Statistics’ (BLS’) O*NET classifications, in order to support the *polarization thesis* by tracking the growth of and returns to jobs involving decision-making skills.

At this stage of technological development, humans still had a comparative advantage in tasks involving creativity, flexibility, intuition, and problem-solving. More broadly, Autor uses the term “Polanyi’s paradox” (a nod to the philosopher Michael Polanyi) to characterize tasks that people “tacitly” understand how to perform but cannot clearly explain or codify the procedures. Such skills are harder to automate:

> However, not all tasks that are hard to automate would be classified as high-skill tasks. Tasks such as waiting tables, cleaning rooms, picking and boxing items, or assisting elderly people to perform acts of daily living, require dexterity,

> sightedness, simple communications, and common sense, all of which draw on substantial reservoirs of tacit knowledge. Such tasks are commonly found in personal services jobs, e.g., food service, cleaning, security, entertainment, recreation, and personal care. Computerization has generally not substituted for workers in performing such jobs. But neither has it strongly complemented them (Autor, 2022, p. 9).

Autor provides a specific example: the ability of a guest room attendant to identify the difference between trash and a personal item that has fallen on the floor.

The task framework generated numerous efforts to categorize the vulnerability of specific skills, occupations, and industries to automation.[1] The first wave of studies adopted the distinction between routine, codifiable tasks and those tasks where humans still held a comparative advantage (Autor, 2022). Autor and coauthor David Dorn (2013), for example, proposed a measure of an occupation's Routine Task Intensity (RTI) based on the BLS's *Dictionary of Occupational Titles*. A McKinsey study (Chiu et al., 2016) purporting to estimate the technical potential for automation for specific activities within industries also relies on BLS data. According to their analysis, the technical feasibility of automating the activities that occupy the Accommodations and Food Service Industry is relatively high.

In contrast, an OECD working paper (Marcolin et al., 2016) develops a Routine Intensity Index (RII) using a cross-national survey called the Programme for the International Assessment of Adult Competencies (PIAAC), which is based on individual workers' descriptions of their daily work rather than assessments by outside experts. A higher RII score means that the tasks are more vulnerable to automation. The authors calculate the RII by industry as ranging from a low of 1.99 for Finance up to 2.75 for Food, Beverage, and Tobacco. The Trade and Hotels industry is estimated as having an RII of 2.41 with a relatively high standard deviation of 1.12. Another study (from the Netherlands) that is particularly careful not to misclassify tasks rates the automatability (based on a routine task index) for 427 4-digit occupations); the index of this article presents the full list (Mihaylov & Tijdens, 2019).

This transition from theory to empirical research has not been smooth since the categorization of tasks as codifiable or not codifiable is not self-evident. A recent report by the U.S. Government Accountability Office (U.S. GAO, 2022) concludes that appropriate federal data is not available to predict which jobs will be lost due to automation. Their review of the literature observes that there has been a wide range of predictions in academic studies using various methodologies to generate such predictions. The BLS itself commissioned a study by the Gallup Organization that concludes:

> The primary lesson learned from this report is that researchers and, by extension, policymakers lack the data necessary to fully understand how new technologies impact the labor market. No individual agency or statistical system,

[1] Some of these are discussed in the section on productivity.

in the U.S. or abroad, has developed a comprehensive approach to collecting data on all key constructs needed to assess the impact of AI, automation, and digitization on labor outcomes. These agencies face the challenge of measuring rapidly evolving technologies, as well as the difficulty of parsing a fragmented literature that has thus far not provided clear guidance on what data are needed" (2020, p. 3).

Stephen Herzenberg & John Alic also critique using O*NET/BLS skills data to determine which jobs are most vulnerable. They argue that the BLS methodology utilizes a rigid distinction between what people do (skills) and what they know (knowledge) that does not actually reflect how job analysis is performed. The data are not regularly updated—a problem when dealing with technological change. The taxonomy is very broad so it can be understood by high school students (2019, pp. 46-48; see also Frank et al. 2019).

Social scientists have long noted that low-wage jobs may have hidden characteristics (Rogers, 2020; Zickuhr, 2021a). Jobs may be perceived—by external analysts or even direct managers—as comprised of routine tasks, while the need for judgment, flexibility, and problem-solving are overlooked. In service sector industries such as hospitality, this may affect the quality of the service experience, as explored more fully in the section on deskilling below. Those making decisions about the development, adoption, or implementation of new technologies may have imperfect information about the skill content of particular tasks. This is one reason that integrating worker voice into these processes is so critical.

Finally, the distinction between codifiable and tacitly understood tasks that underlay this empirical work is becoming less and less relevant. Autor asserts that artificial intelligence, especially machine-learning, may enable robotics and other technology to learn tasks that we only tacitly understand (2022, pp. 18-20). Autor emphasizes the uncertainty of how this will unfold. Nevertheless, he still posits that AI will not "rapidly reach deep into the ranks of low-paid service occupations (p. 25)." He views three obstacles:

1. Service robots would have to have the dexterity to navigate a "highly variable human environment."
2. The cost of such machines will probably remain prohibitive (in comparison with the low wages of those employed in these fields) for the foreseeable future.
3. The reality that "personal attention from another human being is intrinsically part of the service" in many instances.

Herzenberg and Alic concur: "AI-enabled automation will remain behind human capabilities for the foreseeable future in work requiring judgment, tacit skills, and common sense—tasks that infuse many parts of most jobs" (2019, p. 2). Bazylik & Gibbs (2022), in contrast, maintain that new advances in artificial intelligence improve robots' mobility and dexterity—key attributes of many low-wage service jobs. In order to minimize further polarization, the authors suggest redirecting technological development: "Much of the research on robotics and AI is aimed at mimicking humans, which biases toward automation. Policymakers should encourage research into how technology can instead augment human creativity and collaboration, particularly in middle- and low-skill jobs (2022, 10).

2.2 The Deskilling Framework

The deskilling framework has been usefully applied to analyze the potential consequences of automation, supported by initial examples based on case studies. In contrast with the early specifications of the task framework, the labor process literature has long noted that the definition of skill is complicated and contested. Ikeler (2016) distills these analyses into a definition of skill based on task complexity and variety as well as worker autonomy. Deskilling can be viewed as the process of reducing the complexity and variety of tasks and/or autonomy in the labor process. From this lens, deskilling involves job redesign. Deskilling can also be viewed as the replacement of workers with higher levels of bargaining power with workers who have less bargaining power. Both can occur simultaneously. For example, a classic study by sociologists Barbara F. Reskin and Patricia A. Roos (1990) found that employers deskilled job content at the same time they hired more women into the positions. Deskilling has also been a useful strategy in response to shortages of skilled labor in industries such as trucking (Litwin et al., 2022).

Legal scholar Brishen Rogers (2020, p. 542) uses a modern bargaining power framework developed by economist Samuel Bowles that outlines three (possibly overlapping) reasons for employers to adopt a given technology: (1) to increase efficiency or productivity; (2) to deskill work so that less-skilled workers can be hired; and (3) to increase monitoring and surveillance in order to incentivize workers through a threat effect. The first is generally considered socially beneficial, depending on how the benefits of increased productivity are distributed. Rogers views the latter two rationales as power-augmenting for employers. Employers implement technologies that deskill work in order to disempower labor and capture a greater share of profits, even at the potential cost of lower-quality service (p. 536). The relative balance of these motives and outcomes is shaped by labor and employment law, among other factors.

Control over work processes (Rogers' third reason) is one way to convert time into effort. The labor process literature contends that hourly wage employment presents a fundamental challenge for employers—ensuring that the time they are paying for is converted into effort. The rise of gig work is one way of addressing this dilemma. According to a study in the *Academy of Management Annals*, algorithmic control is a new means to accomplish this (Kellogg et al., 2020)—an alternative to technical control mechanisms (e.g., assembly lines) and bureaucratic control mechanisms (workplace rules). The authors identify four potential ways that data-mining, machine-learning, and other algorithms that rely on big data can transform ways employers exert control. Algorithms enable control that is:

1. Comprehensive in monitoring whether employees are adhering to routines, especially with cameras, sensors, accelerometers on smartphones, and other monitoring devices; biometric data; and systems that monitor chats and email
2. Instantaneous in providing feedback and assessment
3. Interactive, through use of platforms and other devices

4. Opaque to workers due to either intentional secrecy or required technical literacy

In addition, algorithmic management entails the “disintermediation” of managers in the work process, meaning that workers have less ability to appeal decisions to another human decision-maker. The authors cite studies that show fewer exceptions are granted to rules, removing empathy, though also the potential for favoritism and bias.

Deskilling facilitates automation because it is more feasible to automate tasks under conditions where the work environment is highly controlled and predictable. Autor (2015), for example, notes that Amazon management restructured the warehouse environment in order to substitute robots for human pickers. Similarly, Lisa Kresge of the Berkeley Labor Center highlights the potential for deskilling as technologies allow jobs to become more controlled and restricted (2020a, p. 41). Deskilling can be a by-product of increasing the routine intensity of a particular set of tasks in order to make them easier to automate. Worker autonomy and flexibility, in this view, is antithetical to automation. In fact, two proponents of automation, Sergei Bazylik and Michael Gibbs, assert that machines are more consistent in their performance of tasks than humans, reducing uncertainty. In their words, “Firms can avoid the complexities of managing employees, including conflict, incentive problems, and absenteeism." (2022, p. 2).

Algorithmic management is a particularly fraught avenue for deskilling because of its implications for worker autonomy. AM intensifies the use of data and algorithms to hire, direct, monitor, schedule, or discipline workers A study for the Joint Research Committee of the European Union (Wood, 2021) contends that algorithmic management is likely to lead to increase standardization of work processes, reduce opportunities for employee discretion, and diminish the ability to utilize intrinsic skills. Though not defined, Wood implies that the skills that are lost involve intrinsic (rather than extrinsic) motivations. The consequences of algorithmic management for some workers will include the reduction of discretion in choosing how to undertake their job as well as limited discretion over the ordering of their day-to-day tasks. Some of the techniques used to control the work process are indirect, involving nudges and penalties as to incentivize particular behavior (Mateescu & Nguyen, 2019).

AM is integrally related to increased surveillance, according to Kathryn Zickuhr’s research (2021a; 2021b) for the Washington Center on Equitable Growth. Greater workplace surveillance incurred by AM enables worker exploitation. Data can be used to allow employers to trim what counts as paid work time, as movements and pauses are tracked, leading to wage theft. Zickuhr also notes the potential of *emotion recognition technologies* to “evaluate workers based on their speech patterns, facial expressions, or tone of voice” in order to more closely regulate emotional labor—despite the unproven validity of the data gathered (2021b, p. 15). Outback Steakhouse restaurants tested a software that analyzes video surveillance to monitor how much time servers spend at a particular table interacting with customers (Kresge, 2020a).

Empirical case studies in specific industries are finding evidence of these deskilling dynamics in service industries (Bernhardt et al., 2021; Litwin et al., 2022). In their study of the warehouse industry for the University of California Labor Center, Beth Gutelius and Nik Theodore (2019) argue that focusing on displacement is misguided. The impact on the content and quality of jobs will be more extensive than job losses. Worker monitoring is becoming more individualized, rather than collecting aggregate data. Sensors and wearables are used to track location, movement (including bending, twisting, etc.) and breaks. In warehouses, as in the hotel industry, these wearables have benefits for workers in monitoring for safety hazards; but are they are also invasive and reduce autonomy. In retail, Karen Levy and Solon Barocas (2017) identify a phenomenon they name *refractive surveillance*—the use of data about retail customers to exert control over workers. These changes constitute “new forms of workplace control, where the technological regulation of workers’ performance is granular, scalable, and relentless” (Gutelius & Theodore, 2019, p. 8).

Reducing labor costs is not the only factor driving the adoption of technologies, according to Gutelius and Theodore. The warehouse industry is experiencing pressure to increase speed of service. Amazon and other e-commerce vendors are shaking up the industry by shaping consumer expectations of a quick turnaround. In addition to automated pickers, warehouses are investing in electronic productivity monitoring to “speed up, control, and streamline human labor” (2019, p. 6). However, because warehouses generally have low profit margins and cost-competition is high, there are countervailing factors slowing the adoption of new technologies. Further, firms may not have clear strategic goals in mind for utilizing all the data they gather, as was found in a case study of retail employers (Litwin et al., 2022).

One question is whether undervalued *emotional labor skills* will be particularly endangered by AI robotics and the speed-ups induced by AM. This question is implicitly addressed in much of the research on the introduction of these technologies in *interactive service work*. Interactive service work involves direct contact with service recipients, including customers, clients, patients, or users; the service is generally inseparable from the experience of this interaction. For example, while the warehouse, shipping, and trucking industries provide services, this is not interactive service work. Many frontline jobs in hotels and casinos—from dealers to cocktail servers to anyone interacting with customers—perform emotional labor (Mutari & Figart, 2015; Bowen & Morosan, 2018; Spektor et al., 2022). Emotional labor comes in two forms: the management and presentation of emotions in the workplace and the tasks involved in the maintenance of relationships. Emotional labor (EL) is usually a crucial (though undervalued) skill in interactive service work.

While AI may foster technologies that are technically able to perform interactive service work, initial evidence implies that there will be skepticism and resistance by customers and employees about automating the emotional labor content of these jobs. Ahmet Vatan & Seden Dogan (2021), for example, conducted semi-structured interviews with 40 Turkish hotel employees at 5-star establishments in two popular Turkish tourist destinations, Istanbul and Antalya. Actual usage of service robots was only in the early stages, so they were primarily gauging employee attitudes about a hypothetical technological change. Employees were largely apprehensive, believing robots will cause unemployment and communication problems with guests. “Sincerity and heartiness” would disappear, according to one employee (p. 6). Others expressed concerns about a lack of empathy and warmth, which they view as important aspects of service. Another qualitative research study interviewing employees in numerous industries (including hospitality) indicated a primary concern with robotics was the loss of "soft skills" or a "human touch" (Bhargava et al., 2021, p. 106).

Two hospitality-based studies (Prentice et al., 2020; Prentice & Nguyen, 2020) explore the role of *emotional intelligence* in both customer loyalty and employee retention. Again, the findings were based on surveys rather that direct measures of customer or employee behavior. Both sets of stakeholders surveyed were skeptical about current AI technologies replicating the service experience provided by human workers. In a study of Bulgarian hotel managers, the managers themselves expressed apprehensions about using service robots for tasks involving social skills and emotional intelligence, fearing service quality would drop. The managers were more receptive to robots performing "repetitive, dull, dirty, and dangerous tasks" (Ivanov et al., 2020, p. 505). Similar conclusions were drawn based on content analysis of existing research: although task-oriented work such as carrying luggage can be effectively assigned to robots, frontline service work with human-oriented dimensions still needs to be delivered by people (Rosete et al., 2020, p. 180; see also Osei & Ragavan, 2020). In the hospitality industry, service generates emotions. Emotions are relevant to customer satisfaction.

Prior studies of the economic factors contributing to the erosion of emotional labor can also provide insights, even those that do not examine technological change. For example, sociologist Peter Ikeler (2016) examines the diminished complexity and autonomy of emotional labor skills in retail department sales positions in a segment of the industry that had shifted towards a discount-oriented business model. His in-depth interviews confirm a contrast in the utilization of emotional labor skills between employees at a service-oriented store (high-road managerial strategy) versus a big-box discount store (low-road managerial strategy). His findings support the hypothesis that the targeted customer base can affect whether an employer emphasizes a high-road or low-road managerial strategy. In contrast, a participant observation study of a San Francisco platform start-up by Benjamin Shestakofsky (2017) provides an example of new emotional labor tasks emerging, as frontline workers were charged with building users' trust in the company's software and services.

3. Technology and Productivity

Research questions: Do robots and algorithmic management increase labor productivity? How is this measured?

Economists prioritize the goal of increased labor productivity. Productivity is defined as output per hour of labor. From a macroeconomic perspective, productivity gains are critical to maintaining economic growth, measured by increases in real gross domestic product per capita. While additions to factors of production (more natural resources, labor, or manufactured capital) can contribute to an economy's productive capacity, qualitative growth rests on improvements in usage of existing resources—especially productivity gains. The primary ways of boosting labor productivity are new technologies and/or increases in human capital (the skills and experience of the labor force). From a microeconomic perspective, productivity gains enable firms to maximize output and minimize costs, increasing profits without price increases. In competitive industries where firms compete on the basis of price, cost-minimization is crucial to profit maximization. In financialized markets, where firms themselves are commodities, cost-minimization sends positive signals to financial markets and generally boosts share prices. Both of these dynamics foster low-road managerial policies.

For these reasons, labor productivity is a closely watched indicator. Yet it is a concept rooted in manufacturing. Measuring productivity in the service sector is more difficult because the "output" is often less tangible. This is particularly true in interactive service work in industries such as hospitality. In interactive service work, the product is inseparable from the experience of providing it. Many of the cautionary alarms about using robotics and algorithmic management in hospitality and related industries stem from concerns about ostensible productivity gains that ignore the diminished quality of the service provided (IFOW, 2022). A collection of studies by Carnegie UK Trust (2020) suggests that current productivity measures over-emphasize the volume out output, mismeasuring the potential benefits of improving job quality.

At this stage, there are more studies of the impact of robotics and algorithmic management on productivity at the macroeconomic level than through microeconomic case studies. This section briefly highlights insights from the macroeconomic approach, then highlights the gaps in evidence from microeconomic studies.

3.1 Macroeconomic studies of technology and productivity

Macroeconomic studies, grounded in the task framework described in the previous section, have attempted to explain a seeming paradox: the expansion of digital technologies has coincided with a period of stagnant productivity and rising income inequality or polarization. One illustrative article by Daron Acemoglu and Pascual Restrepo (2019) notes that historically automation has generated productivity increases. Such automation has often been accelerated by labor scarcity. Wages can actually increase under those conditions. Yet, the story of the past several decades has been different. Productivity measures in the United States and other advanced industrial countries has declined despite the burst of technological innovation.

In order to explain the paradox, Acemoglu and Restrepo (2019) argue that technological change produces both *displacement effects* (job losses) and *productivity effects*. Productivity effects refer to a process where cost reductions from the new technologies increase the demand for workers performing other tasks:

> The productivity effect is simple to understand: automation technologies typically reduce costs and as costs decline, firms have an incentive to expand output, which increases the demand for labour coming from non-automated tasks. Equally, lower costs for automated products increase the demand for

other complementary products, still produced with labour-intensive methods (Acemoglu & Restrepo, 2020, p. 28).

The relative trade-off between these two effects determines the *net employment effect*, meaning whether more jobs are lost through displacement or gained through increases in demand. The net employment effect, in turn, impacts the labor share versus the capital share of national income. In addition, the authors identify a *reinstatement effect* that creates new tasks for labor. This can also help maintain labor's share of national income.

Since 1987, the historical turning point of their analysis, displacement effects have been stronger than productivity or reinstatement effects. Automation (primarily industrial robotics) accelerated job displacement, without offsetting increases in demand for complementary tasks or the creation of new tasks (see also Martens & Tolan, 2018; Rogers & Freeman, 2019). Acemoglu and Restrepo (2019) refer to this kind of technological change as *so-so technologies*—ones that produce only modest productivity gains coupled with large displacement effects. [2] In contrast, an NBER study on the economics of artificial intelligence argues that lags in the development of the most promising AI technologies, particularly machine-learning, explain why productivity has failed to take off (Brynjolfsson, Rock, & Syverson, 2019; see also Atkinson, 2019). This has set up a debate between pessimistic analyses (the so-so thesis) and more optimistic analyses (the lags thesis) (Frank et al., 2019).

The key, for these authors, is to direct resources toward the "right kind" of technologies—ones that enhance productivity and increase broad-based prosperity (Acemoglu and Restrepo, 2020). The authors argue that the right kind of AI is possible, and that developments in AI hold more promise than robotics. They distinguish between automation—whose goal is to replace human labor with cheaper capital—and productivity-enhancing technological change. AI can be used for either purpose. These concepts are analogous to the distinction between high-road and low-road approaches to technology design and adoption.

Society cannot rely on market forces to automatically produce optimal forms of AI, according to Acemoglu and Restrepo (2020). The innovation process is subject to *market failures*, situations where the private sector alone will not generate socially optimal outcomes. These market failures include *path-based dependencies*, the tendency of economic actors to resist changing from one technological paradigm to another (often illustrated by the QWERTY keyboard). Acemoglu and Restrepo also argue that the right kind of AI generates *positive externalities*; this means that third parties who are not directly involved in the firm's decision-making benefit from these technologies. Economists argue that the private sector does not

[2] A contrary position is taken by Georg Graetz and Guy Michaels (2018), who estimate economic contributions of modern industrial robot adoption in 17 countries from 1993 to 2007. The authors find that increased robot use contribute approximately 0.36 percentage points of a mean productivity growth rate of 2.4%. Note that their dependent variable is growth of labor productivity, measured by the ratio of changes in real value added to hours worked. While optimists view these results as supportive evidence, this amounts to only 15% of a small productivity gain (2.4%).

(and is not expected to) factor external costs or benefits into their profit calculations. Market forces do not incentivize these socially beneficial investments. Government, therefore, needs to nurture the right kind of innovation through private-public partnerships (see also Mazzucato, 2015).

Acemoglu and Restrepo are also concerned about political barriers to nurturing optimal technologies: “The wrong kind of AI, primarily focusing on automation, tends to generate benefits for a narrow part of society that is already rich and politically powerful, including highly skilled professionals and companies whose business model is centered on automation and data” (2020, p. 8). Indeed, the authors note that tax policy in the United States and other advanced industrialized countries subsidizes capital investments while taxing employment. Neither market forces nor tax policy are designed to acknowledge social benefits of employment, beyond simply measurable contributions to GDP (see also IFOW, 2022).

The primary insight from this research stream is that we cannot assume that job-displacing technological change is always offset by countervailing forces sparking economic growth. Nor can we assume that the benefits of technological change are broadly shared. Instead, technological innovations can have diverse economic and social impacts.

3.2 Microeconomic studies of technology and productivity

There is far less firm-level or industry-level research investigating the impact of robotics, algorithmic management, and other applications of artificial intelligence technologies on productivity. It is particularly difficult to identify the impact on interactive service work. The first wave of applications were in manufacturing, so the preliminary findings of positive impacts on productivity may have limited applicability (Acemoglu et al., 2020; Aghion et al., 2020).

Many early studies used aggregated statistics (by industry or country) and focused on robots rather than AI or AM. The problem is the scarcity of data. According to one review of possible data sources, the McKinsey Global Institute has the only comprehensive data on AI, but it is not available to the public or academic community. The International Federation of Robotics gathers robot shipping data that has been utilized. However, it includes only a narrow set of robots and is difficult to integrate with other data sources. The European Manufacturing Survey is a better source, but is limited in both geographic and industrial scope (Seamans & Manav, 2018).

One interesting regression analysis of aggregated data finds that AI has a statistically significant, positive effect on labor productivity (Damioli, Van Roy, & Vertesy, 2021). The research goal was to move beyond the debates between the optimists and pessimists interpreting macroeconomic productivity data. The study’s authors use a sample of 5257 companies worldwide that filed at least one AI patent between 2000 and 2016. These firms were concentrated in Asia. Their dependent variable is the natural log of firm labor productivity, defined as *inventory turnover divided by the number of employees*. This variable defines output as how many times total inventory was sold and replaced during a given period of time. The AI proxy (independent variable) was measured by the number, value, and quality of AI patents. When analyzed by industry, the service sector has particularly strong results for the latter period studied (2009-2016). The authors acknowledge several limitations to generalizing from their results. By sampling only firms with AI patents, it is not surprising to find higher productivity gains; this method does not address the macroeconomic concerns over whether the productivity gains generate broad-based benefits. Further, their AI proxy may not represent the full range of AI applications, missing firms that simply purchase off-the-shelf hardware, software, and/or platforms. The labor productivity measure is also unusual.

A systematic literature review on robotics in travel, tourism & hospitality industries, published in 2019, surveyed 131 publications since 1993 (Ivanov et al., 2019) found no research on firm performance and competitive advantage due to the adoption of emerging technologies. Another review found that the initial capital investments for hospitality robots was costly. However, it was unclear whether the investments resulted in lowering labor costs (Yang et al., 2020).

More research is clearly needed on the factors that may influence whether hospitality employers pursue high-road or low road approaches to technology adoption. Financial considerations are important, though not the only factors. The state of research about the costs and benefits for hospitality firms is well summarized in one review article (Osei et al., 2020). The authors note that the aim of emerging technologies is to improve resource management effectiveness and competitiveness and enhance the guest experience. The authors identify the following benefits:

+ Reduced labor costs
+ Solution to seasonal employment and labor turnover
+ Operational and employee efficiency, especially reducing time spent on tedious and repetitive tasks
+ Better evidence-based decisions through data collection
+ Supply chain efficiency (for example, through mobile apps for booking)
+ Creation of new jobs through digitalization

They also note the following limitations:

- Financial costs of initial investments and maintenance
- Costs due to the need to hire specialists
- Job losses
- Costs due to the need to rewrite job descriptions, training, and operations manuals
- Resistance by employees

Given data limitations and the sparsity of existing research, firm-level case studies are an important starting point. An NBER analysis by Robert Seamans and Raj Manav emphasizes the need for more studies using firm-level data to address important questions:

> Firm-level data on the use of robotics and AI would allow researchers to address a host of questions, including but not limited to: the extent to which, and under what conditions, robots and AI complement or substitute for labor; how robots and AI affect firm- or establishment-level productivity; which types of firms are more or less likely to invest in robots and AI; how market structure affects a firm's incentives to invest in robots and AI; and how adoption is effecting firm strategies (2018, p. 7).

Further, firm-level data would also allow for studies of effects on firms of different sizes, the impact on managers, entrepreneurs and innovators, and the effect on regional economies. Firm-level research is also the best way to address questions about worker well-being. Seamans and Manav suggest that "Without an understanding of the changes in worker experience resulting from technology adoption, it will be difficult to craft appropriate worker education, job training, and re-training programs. Further, issues related to inequality could be examined, particularly with relation to the "digital divide" and the effects of technology adoption on different demographics" (2018, p. 7). In sum, the need for such research at the industry and firm level is another reason why our NSF-funded project fills important gaps in the literature.

4. Technology and the Structure of Jobs

Research questions: What effect do robots and algorithmic management have on the structure of jobs? The internal organization's career ladder or internal labor market? Occupational segregation of jobs by gender, race, and ethnicity?

Research on job structures examines the interrelationship among positions in a firm's hierarchy. Transforming the skills and tasks involved in a given job necessarily has implications for the structure of career ladders and whether companies use internal labor markets for higher-level positions. Worker well-being could be improved by training employees in new technology-related skills and/or valuing the skills of working with the new technologies to develop new career ladders: *upskilling* (Green, 2020; Litwin et al., 2022). In contrast, as described below, emerging technologies are likely to accelerate the process of *fissuring*—the outsourcing of work instead of the hiring and nurturance of a stable workforce. (The term was introduced by management professor David Weil in his 2014 book *The Fissured Workplace*.) Fissuring allegedly creates barriers to the development of internal labor markets and career ladders. Research thus far does not confirm that this is occurring in practice. Nor are there good models of upskilling in response to emerging technologies.

Because particular skills are often gendered and racialized, researchers also focus on *occupational segregation*, the distribution of positions among different demographic groups.

Most of the discussion so far centers on whether occupational segregation leaves disadvantaged groups more vulnerable to displacement or deskilling. There is less evidence of how gendered or racialized occupational labels might evolve over time as emerging technologies are implemented in workplaces.

The task framework and the deskilling framework, discussed in the previous sections, both influence analyses of changes in job structure. The task framework emphasizes that technological change can spark the creation of new tasks that lead to new skills, responsibilities, and even occupations. In an overview of "How is New Technology Changing Job Design?," Sergei Bazylik and Michael Gibbs note that, "New technology raises relative employee productivity in some tasks, creates new tasks, and replaces employees in other tasks. Firms respond by changing job design—the mix of tasks assigned to workers—and subsequently their demand for workers with different skills" (2022, p. 2). The deskilling framework focuses on comparing the labor process (job design) before and after changes in managerial strategies and/or the introduction of new technology. According to Kresge, "Workforce management algorithms focus on directing workers to complete a work task – they delineate what task needs to be done, how the task should be done, and in what order tasks should be completed" (2020a, p. 34). AM simultaneously deskills the aspects of the work process that used to be under the worker's control while shifting some managerial tasks from supervisors to algorithms. Algorithmic management is therefore transformative in its impact on job structure (see also Mateescu & Nguyen, 2019).

While the task framework posits a clear distinction between technologies that complement existing tasks and those that displace them, the deskilling framework complicates this narrative. For example, one proposed benefit of robotics as a complementary technology is their ability to improve worker health and safety by taking on physical labor. They may improve diversity by enabling the disabled to work in positions that previously posed barriers (IBA, 2017). Yet even supposedly complementary technologies designed to assist workers with physical labor may ultimately deskill them. Kresge provides the example of janitorial robots developed for Walmart. This supposedly "autonomous" floor cleaner is not fully autonomous. Employees assist with mapping the route and preparing the area to be cleaned, riding along with the device. The relationship is actually flipped: "... as intelligent machines move along the continuum toward more fully autonomous machines, the relationship between the worker and the machine shifts from the machine assisting the worker to the worker assisting the machine" (2020a, p. 39). This process reduces the worker's autonomy and control over the work process in a manner similar to assembly line production.

In the absence of participatory design or other processes that include worker voice in shaping emergent technologies, changes in job structures have tended to take the low road. While upskilling and retraining have been suggested as alternative, high-road approaches, effective models of these practices have yet to be identified. This is another potential outcome of this NSF-funded project (Spektor et al., 2022).

4.1 Impact of emerging technologies on workplace fissuring

Many AM systems originated in the platform economy. These systems are being adapted to almost all sectors of the U.S. economy, reshaping employment relations (Mateescu & Nguyen, 2019; IFOW, 2021; Jarrahi et al., 2021; Nguyen, 2021; Wood 2021). Such developments may portend the further fissuring of the workplace. Fissuring entails three strategies: (1) classifying (or misclassifying) workers as independent contractors rather than employees; (2) subcontracting functions (tasks) to temporary agencies or other firms where workers have less employment stability; or (3) franchising the brand or product line to independent businesses (Rogers, 2020, p. 570). Fissured workplaces rely less upon internal labor markets for hiring and promotions. Many functions are performed by external workers, creating barriers to the development of internal career ladders.

The hospitality industry already exemplifies fissuring (Rogers, 2020; Spektor et al., 2022). Hotels operate on a franchise model, while some services are subcontracted. Outsourced functions can be performed by employees at these firms or further outsourced to contingent workers, including gig workers obtained through platform technologies. The stated purpose is to allow companies to focus on their "core competencies" (IBA, 2017). This fissuring is likely to accelerate, at least in some segments of the industry. An analysis of the future of hospitality employment posits an increased reliance on gig workers (El Hajal & Rowson, 2021). The Covid-19 pandemic and consequent labor shortages are accelerating a shift to increased reliance on contingent forms of labor in the industry. Some hospitality jobs may be permanently lost. The authors of this study suggest that outsourcing coupled with AM shifts the structure of compensation. Workers can be remunerated on the basis of productivity measures rather than simply time at work.[3]

This work reorganization can have negative consequences for worker well-being. Outsourcing shifts risk from the employer to the worker, and blurs the line between employees and independent contractors (IBA, 2017). Some analysts suggest that workers are misclassified as independent contractors or "networked users" of a platform, uncovered by important labor market regulations. Tasks may also be outsourced from unionized workplaces to nonunion employers, reducing employment security as well as compensation (Mateescu & Nguyen, 2019; Green, 2020; Litwin et al., 2022). Coupled with the *employment-at-will principle* in current law, increased productivity monitoring can diminish employment security (Ajunwa et al., 2016).

AM is being designed and implemented in ways that foster this broader shift in the structure of work. In particular, fissuring is facilitated by algorithmic controls over work processes, surveillance, and data collection: "Worker monitoring is part of a cycle of fractured work arrangements through which firms de-skill work and misclassify employees, allowing them to pay workers less, sidestep worker protections, and undermine workers' bargaining ability, ultimately increasing economic inequality and distorting economic growth" (Zickuhr, 2021b p. 3). Kate Bahn, Chief Economist at the Washington Center for Equitable Growth, agrees,

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[3] Fissuring through algorithmic management thus represents a solution to the problem of converting time into labor because workers are compensated for output.

highlighting research indicating that fissuring has contributed to both lower wages and lower job quality (2019).

In particular, AM facilitates a shift toward performance-based (or success-based) remuneration (IBA, 2017). Some workers may appreciate the flexibility this presents, and this may reduce the pressure on employees to log in hours simply to appear productive. However, more accurate productivity measures could depress wages. Rogers (2020), for example, alleges that more accurate monitoring may obviate the need for *efficiency* wages. Efficiency wage theory explains above-average wage levels in some firms as a response to uncertainty about productivity (again, the conversion of time into effort). According to the theory, employers raise wages above the market level in order to induce employee loyalty and effort. Efficiency wage theory is supportive of high-road employment practices.

4.2 Impact of emerging technologies on occupational segregation

Occupational segregation by race and gender has clustered disadvantaged groups in jobs with routine tasks, according to several studies outlined below. This has left women and people of color more vulnerable to job displacement. At the same time, these studies find that women's segregation into interactive service professions has sheltered them during the first waves of automation. While instructive, these studies may not be generalizable to emerging technologies based on AI. As discussed in the section on skills, distinctions based on whether jobs consist of routine tasks may be less applicable to emerging AI technologies.

Briefly, a study for the Brookings Institution (Cortes & Pan, 2019) uses regression analysis to evaluate how technological changes from 1980 to 2017 affected men's and women's employment and occupational allocation. The authors adopted Autor and Dorn's RTI measure of occupations with risk of automation. They find that routine tasks are prevalent in female-dominated occupations (female share higher than 89 percent) but also in occupations with a very low percent female. However, men and women adapted differently to declining job opportunities in middle-skill, routine-intensive occupations. Women disproportionately pursued higher education and entered high-skill occupations, while men were displaced into "low-skill" occupations. A report for the Institute for Women's Policy Research (IWPR) using digitalization scores from Brookings, concurs that women are more likely than men to be in occupations with both the lowest and the highest risk of technological substitution (Hegewisch et al., 2019). Women make up 47 percent of the workforce, but 58 percent of the workers at the highest risk of automation. The risk of job displacement is even higher for Hispanic women, according to IWPR's research (see also Ajunwa, 2021). A more forward-looking analysis by the McKinsey Global Institute (2019) predicts that women's concentration in jobs utilizing social and emotional labor skills may continue to shelter them from employment disruptions.

Debra Howcroft and Jill Rubery (2019) go beyond these routine skills measures to deepen the discussion of gender and workplace technologies. They note that the cost incentive to automate is reduced if the workforce consists of low-paid, non-union labor. Yet they also warn that the potential for gender bias in emerging technologies needs to be confronted. The oligopolistic companies currently dominating technology development tend to be male dominated and have a history of coding in bias. The work culture also reflects gendered norms. The reorganization of work time that some portray as offering female caregivers more flexibility may, in fact, increase work intensity and infringe on caring responsibilities. They view participatory design, co-determination, and collective bargaining as means of redressing these potential problems (see also Green, 2020). Similar concerns have been identified with the potential for intersectional biases (Howcroft & Taylor, 2022). In particular, technology advocates tend to assume that processes such as machine learning are scientific and therefore neutral and bias-free. Instead, proactive auditing is critical to ensure equality and inclusion. The Institute for the Future of Work, for example, has created tools for auditing AI hiring systems for bias (IFOW, 2020).

While traditional approaches to occupational segregation presume that the bundling of tasks into jobs is a neutral process, and that discrimination occurs when jobs are allocated, more recent work in history and the social sciences challenges this assumption. Job characteristics, in the modern view, are shaped by employers' expectations about potential job-holders. Gendered and racialized attributes are clustered and embedded in occupations (Mutari & Figart, 2015). Yet these designations can change in response to social, economic, political, or technological forces. For example, clerical work evolved from a male domain to a female domain in the late nineteenth century, partly because girls from farm families were more likely to finish high school. Consequently, the new technology of typewriters became identified with manual dexterity (a feminized skill).

Emerging workplace technologies therefore prompt important unanswered questions (Ajunwa et al., 2016; Howcroft & Rubery, 2019; Green, 2020; Kresge, 2020a):

- How might the alleviation of physical demands in jobs facilitate occupational integration by gender? Or might the reduction of physical demands feminize jobs?
- Will service robots replicate and reinforce the gender and racial labels on particular tasks and jobs? For example, are masculine or feminine voices, body types, or other aspects of gender performance incorporated into the technologies in ways that align with traditional patterns of occupational segregation?
- How will increased surveillance and productivity data impact different groups of workers? Will bias be encoded or reduced?
- What is the impact of emerging technologies on the allocation of caregiving responsibilities?

Because of the high representation of women, racial minorities, and immigrants in the hospitality workforce (Spektor et al. 2022), these issues have particular salience for this NSF-funded project.

5. Technology and Job Quality/Satisfaction

Research questions: What effect do robots and algorithmic management have on job satisfaction? On freedom of choice in arranging one's work tasks? On the worker-manager relationship? On the worker-customer interactions?

Modern economic theory and policy are in the process of shifting the goals for a good economy from material living standards (macroeconomics) and maximizing utility (microeconomics), toward broader definitions of well-being grounded in the concept of capabilities. One representation of this shift is the adoption of broader definitions of job quality. Traditionally, economic studies defined job quality primarily in terms of pay and benefits. Since labor economic theory defined paid employment as providing *disutility* (diminishing satisfaction), remuneration was assumed to be the primary motivation for labor force participation (Mutari & Figart, 2015, pp. 5-8). Contemporary definitions of job quality increasingly recognize that workers are motivated by aspects of the work experience, including whether their work provides a sense of purpose and dignity; their relationships with coworkers, managers, and customers; the degree of their control over hours, schedules, and work processes; job security; physical and mental well-being; and whether their job supports other aspects of their identity and life. In our previous work, for example, we defined a good job as one that helps the worker build a life and reinforces a positive sense of identity (Mutari & Figart, 2015, p. 19).

One fieldwork study of the introduction of new technologies in handicraft (mostly male) and garment production (mostly female) in India found that workers are more likely to cooperate with workplace changes that protect and fortify their pre-existing sources of identification with their job. Identification, according to the author, means valuing one's work as an end in itself. This can include identification with one's occupation, the organization and its mission, or the work itself (Ranganathan, 2021).

Once again, there is a gap in available empirical findings. Studies that operationalize a broad concept of job quality and investigate changes due to technology are scarce. There is progress, however, in operationalizing job quality as a first step. A Great Jobs Demonstration Survey conducted by Gallup and other collaborating institutions created a job quality index based on the job characteristics valued by a large sample of workers. One interesting characteristic (in addition to pay, benefits, purpose, schedules, etc.) is "Having the power to change things about your job that you're not satisfied with." The survey also found that only 40 percent of U.S. workers were currently employed in what they define as good jobs, while 44 percent were in mediocre jobs and 16 percent were in bad jobs (Rothwell & Crabtree, 2019). Future reports from this project will focus on how technology and skills relate to job quality (p. 35).

Another good model for investigating job quality comes from the Institute for the Future of Work (in the U.K.). Their Good Work Charter identifies ten dimensions of "good work" (2022, p. 5). IFOW argues that all of these dimensions should be considered when designing or deploying new technologies in the workplace. Their recent report, *The Case for Importance*, synthesizes existing evidence on the benefits of a high-road approach to each dimension, as well as the economic and social risks of going down the low road. For example, they note that autonomy and voice play a larger role than pay in determining job satisfaction, and all are correlated with higher levels of productivity.

An interesting approach to job satisfaction in hospitality jobs utilizes *sentiment analysis*. Sentiment analysis identifies the emotional content in text by examining meaningful patterns and frequently used words. Technology was not addressed in the study. The authors evaluated employee comments from an annual employee job satisfaction survey at a U.S. hospitality organization. The survey was available in English and Spanish (Young & Gavade, 2018). The sentiment analysis found that the most prevalent emotion was joy, implying that the hospitality employees have job satisfaction. However, the surveys in Spanish expressed more sadness and anger about their jobs. Spanish-speaking employees in particular expressed anger toward male supervisors. Whether the distinction by language was attributable to occupational segregation into particular jobs was unclear from the researchers' description of the findings.

Only a few studies examine the relationship between technology and measured job satisfaction. Based on their interviews with workers across industries, one study concluded that job satisfaction only increased when organizations collaborated with workers on how to best utilize technology to improve business practices. Input meant that employees perceived the new technology as an opportunity, not a threat. AI and robotic technologies were seen as eliminating low-value, routine, menial, boring, and strenuous tasks. Employees reported increased productivity and accuracy (Bhargava et al., 2021, p. 111). A cross-national study entitled "Don't Fear the Robots," identifies a robust and statistically significant **negative** correlation between a worker's job satisfaction and the automatability (routine intensity) of the job's tasks. Based on their model specifications, the authors find that automatable jobs are viewed as monotonous or uninteresting by employees. The authors conclude that technology is eliminating low-satisfaction jobs—raising job satisfaction through a composition effect. Although they recognize that this transition implies a period of unemployment ("labor market frictions"), they believe that the end result could be "a more satisfied workforce" (Gorny & Woodard, 2020, p. 3).

A study for the Joint Center for Political and Economic Studies (White & Contractor, 2019) summarizes a survey of U.S. workers' attitudes toward technology in the workplace, disaggregated by race and ethnicity. Unfortunately, the study does not differentiate by occupation or industry, making the quantitative results of questionable use for understanding the specific dynamics within industries or occupations. While 38 percent workers surveyed noted an increased use of technology in their workplaces, few reported experiencing automation. The authors report their findings as suggesting positive attitudes toward technology; however, the survey data is less persuasive. Only 41 percent of Asian Americans indicated they had experienced increased opportunities as a result. This was higher than other racial and ethnic groups: 24 percent of African Americans, 31 percent of Latinos, and 28 percent of Whites concurred that technology improved their opportunities. Similarly, a minority of each group agreed with the assertion that technology had increased efficiencies at their workplace. Workers from all of these groups expressed a degree of interest in acquiring more technological training. Financial constraints were a barrier to additional training for approximately half of respondents, in all racial categories.

5.1 Impact on Autonomy and Work Intensity

There are numerous reports that highlight the potential impact of robotics and AM on key dimensions of job quality. Most draw upon qualitative evidence to support their analysis. One of the most commonly raised concerns is the impact of AM on autonomy and work intensity (see, for example, Mateescu & Nguyen, 2019; Bernhardt et al., 2021; Nguyen, 2021; TUC, 2021). Autonomy, control, and manageable stress levels are important dimensions of job quality according to both the Great Jobs Demonstration and the Good Work Charter.

Kresge (2020a) distinguishes between AM that *directs* workers and AM that *manipulates* workers. Both forms of AM reduce qualities that workers value in their jobs. Directing workers involves prescribing actions and ensuring they are done in a specific way. This form of direction restricts workers' discretion in physical or digital space through real-time oversight and task direction. Manipulating workers influences workers behavior through incentives (nudges) and/or penalties, incorporating insights from behavioral economics and organizational psychology. These behavior modification techniques, imported from platform-based gig work, are leading to a process called *gamification*. Gamification can also include competitive rankings of workers in order to incentivize effort. Gamification can have positive effects. In one study, some of the garment workers in routinized jobs welcomed gamification following introduction of RFID (radio frequency identification) technology as a new challenge that provided a sense of workplace identity. Those in jobs with more complex tasks were more likely to be resistant (Ranganathan, 2021).

The rewards and penalties in gamification and other manipulative forms of AM are coded to reflect managerial goals, usually either increasing productivity or service quality. Most examples, however, point to the use of AM for *work intensification*—speedups to increase productivity. For example, a collection of case studies (Litwin et al., 2022) found that technologically induced changes in hiring, scheduling, task direction, monitoring, evaluation, and discipline or dismissal—especially for workers at lower end of pay scale—led to work intensification and diminished job satisfaction. Constant monitoring increases stress, undermining physical and mental well-being. Speedups can also contribute to physical injuries (Gutelius & Theodore, 2019; Kellogg et al., 2020; Kresge, 2020a). Wearable technologies and other productivity monitoring techniques pose problems for workers' privacy rights (Ajunwa et al., 2016; Ajunwa, 2018; Bernhardt et al., 2021; Nguyen, 2021).

Several reports refer to evidence about the use of AM to supervise guest room attendants (GRAs). These workers are frustrated by the opaqueness of systems that nudge or prompt them to do tasks in a certain order or restrict them from altering the pattern, especially when it violates their own understanding of the work process (Kellogg et al., 2020). The algorithm does not know when a guest has left a room, unlike a worker with localized responsibility for a wing or floor. Guests still expect rooms to be cleaned in location order and complain to the GRAs when their room is “skipped.” Workers wind up carrying cleaning equipment or pushing heavy carts over longer distances, resulting in more wear and tear on the body (Mateescu & Nguyen, 2019). In an Atlantic City casino, the TIDY program routed guest room attendants to prioritized rooms rather than focusing on a section. The result was to reduce autonomy and judgment, as well as the loss of contact with regulars (Mutari & Figart, 2015). In the same casino, the work of cocktail servers was restructured to respond to drinks ordered through an app. This reduced their responsibility for managing the liquor consumption of customers, and also reduced the positive interactions that led to higher tips.

5.2 Impact on Worker-Management Relations

Robotics and AM systems impact worker-management relations in two ways. First, AM adds an intermediary between managers and those they supervise (Kellogg et al., 2020). Second, AM systems generate enormous amount of data. In fact, the collection of data seems to be outstripping the ability of managers and human resource specialists to effectively utilize it (Litwin et al., 2022).

A report by Data & Society (Jarrahi et al., 2021) observes that AM reshapes power dynamics between workers and managers, shifting power to managers to exercise control over workers. AM can also decrease middle manager power and agency, automating many of the tasks that they perform. The data gathered through AM can be used for decisions about retention, promotions, raises, or other human resources assessments. On the one hand, this data, if used properly, could be a means of avoiding bias and favoritism. However, as discussed previously, they can also remove empathy and discretion (Kellogg et al., 2020). Furthermore, it is at least as plausible that bias can be coded into algorithms, which are, ultimately human constructs (Howcroft & Rubery, 2019). Based on interviews with low-wage and hourly workers, Aiha Nguyen asserts that “The chief concern about extensive data collection is not the collection of the data itself, but what it augurs for changes in workplace conditions and work standards. According to one participant at a Data & Society workshop on worker surveillance and privacy, ‘the problem happens not when the data is collected, but after’” (2021, p. 15). These concerns circle back to the issues of autonomy and privacy discussed above.

Another concern is that many workers, especially in low-wage work, lack of familiarity with technology and big data. A lack competency with the tools of their jobs can reduce workers’ sense of autonomy. This also shifts power from employees to managers. Transparency is key. Technology must, at minimum, be explainable. Even better, workers should be consulted before AM is introduced to build trust and increase likelihood of implementation going well. Ideally, this process also addresses the question of who owns and has access to the data generated during the work process (TUC, 2021).

In sum, worker well-being (and thus job satisfaction) is strongly correlated with perceptions of managerial fairness by direct supervisors and others in positions of authority. Yet workers’ own criteria for fairness, especially the balance among principles of equality, equity, and need, can vary. Based on these insights, one experiment in participatory algorithmic management (Lee et al., 2021) sought worker input on both their own shift work schedule preferences and their views of managerial fairness. While not implemented in a specific workplace, the study provides a model for how worker voice can be solicited during the development and implementation of algorithms used in the workplace.

5.3 Impact on worker-customer interactions

As noted by several studies in the discussion of emotional labor, there is apprehension among employees about the ability of AI robotics to replicate emotional labor skills. The applications of AM in housekeeping and cocktail service indicate concerns about lack of autonomy, deskilling, and increased work intensity. An unexplored question is the implication of work intensification on remuneration of tipped employees. If the quality of these interactions is diminished, does this impact them financially? If so, are there ways to minimize the impact?

One study investigates the customer experience in more depth. A survey of customers who had experience with AI applications at Australian hotels compared the impact of the AI and employee interactions on customer engagement and loyalty (Prentice et al., 2020). These applications included chatbots, concierge robots, digital assistance, voice-activated services, and travel experience enhancers. The authors' regression analysis found that high-quality interactions with both AI and employees enhanced both customer engagement and customer loyalty. Nevertheless, high-quality employee service had a greater positive impact. Employees' reliability, empathy, and assurance were the qualities that had the greatest positive impact in model specifications without the AI variables.

In fact, the authors found that customers have different expectations from their digital versus human interactions. It should be noted that the appendix listing questions indicates that different questions were asked about each type of interaction, with minimal investigation of AI's ability to perform emotional labor. Another limitation is that the study focused on whether a customer's emotional intelligence impacted their interactions, rather than indicating the institutional characteristics that made customer-AI interactions better or worse.

Emerging technologies also shift tasks between workers and customers, with consequences for their interactions. On the one hand, people are now paid to do things that customers used to do for themselves (e.g., shopping). On the other hand, some tasks are off-loaded onto customers, lowering costs for the firm (e.g., cashierless checkouts). Even when shifted to customers, new tasks are often created for workers. In Shestakofsky's (2017) study, the newly created tasks were often centered on training and assisting users (those offering and purchasing services through the platform). In the reorganized labor process within grocery stores, employees now monitor multiple self-checkout stations, rather than interacting with a variety of customers in one station. The work now consists of trouble-shooting for frustrated customers when their interaction with the technology fails—a more stressful task than the one that was replaced. While productivity "supposedly" increases, the quality of both the customer's and the worker's experience is diminished (Litwin et al., 2022).

6. Discussion

Research question: To what extent do any of these questions have notable observations in the hospitality industry?

These findings (the answer to this research question) have been integrated throughout the literature review. There have been a few empirical studies of the impact of technology in hospitality, primarily hotels. Most gauge the attitudes of workers, managers, or customers toward the possible use of service robots, rather than investigating the actual impact during or after their adoption. The particular example of guest room attendants has been used to forecast the impact of algorithmic management on autonomy and other dimensions of job quality. However, these are preliminary observations (often drawn from news articles), not systematic case studies. There are clearly many gaps in the literature about the best way to proceed with technological change in hospitality workplaces.

That said, the salient takeaways for the hospitality industry from the studies and reports in this literature review are:

- The task framework has been utilized to estimate the routine task content of specific occupations and industries in order to determine automatability. Industries such as hospitality/hotels receive medium to high automatability ratings in some estimates. However, the validity of these methods is increasingly questioned, especially with the advent of machine learning, leading to increased uncertainty about the future of automation.
- The high cost of service robots coupled with the limits of the technology will limit the speed of their adoption. AI-enabled automation has a long way to go to effectively perform soft skills and emotional labor. This means that firms will face significant trade-offs between cost and service quality. Depending on market conditions, they may have to choose whether to compete over quality or cost.
- Even once the technology improves, technical feasibility will have to overcome resistance by various stakeholders, as demonstrated in several studies by industry analysts. Instead, researchers recommend developing and adopting AI technologies that augment human skills rather than mimic and replace them. Emphasis also should be placed on physical tasks where robotics can improve worker well-being. Hotel employees, managers, and customers are far more open to these complementary technologies. Yet there are still concerns about whether complementary technologies (such as Walmart's janitorial robots) can also be deskilling. Directing innovation in the appropriate direction may require the involvement of government and other stakeholders such as labor unions.
- Algorithmic management is a fraught area for deskilling and routinizing work. The tacit skills and emotional intelligence embedded in interactive service work may be overlooked by programmers developing such algorithms. The example of guest

room attendants is frequently used. Most of this research, however, is based on other industries, including platform-based gig work. Such studies indicate that AM, as implemented thus far, has contributed to speedups and work intensification that undermine worker well-being. In interactive service work (retail, for example, as opposed to warehouses), service quality is diminished. There are also open questions about the use of the data gathered by these technologies, including worker privacy rights and transparency.

- Macroeconomic analyses of technology and productivity offer a cautionary paradox. The first wave of digital automation coincided with declines in labor productivity. These findings indicate that any small gains in productivity at the firm level did not generate broad-based prosperity or a rapid take-off in growth. There are still few studies of the extent of productivity gains from service robot or AM at the firm level, especially in hospitality. Two literature reviews focused on the industry (Ivanov et al., 2019; Yang et al., 2020) find little evidence on this question. This is a ripe area for future studies.
- The hospitality industry is already somewhat fissured, with functions such as property management and food service outsourced by ownership. One study (El Hajal & Rowson, 2021) predicts that this pattern will accelerate, with increased reliance on contingent labor. AM is also shifting some hospitality jobs to productivity-based compensation systems, according to the same study. Outsourcing and fissuring are associated with diminished job quality including compensation.
- Hospitality industries such as hotels exhibit occupational segregation, with women and people of color clustered in low-wage jobs. There are many unanswered questions about whether and how technological change might lead to greater integration or feminization. There are also unanswered questions about whether bias will be coded into technology by developers.
- Broad definitions of job quality remind us that worker well-being depends on more than the pay and benefits that determine workers' living standards. Several possible threats to hospitality job quality are highlighted by existing research on emerging technologies: compensation, autonomy, skills/engagement, and relations with managers and customers. These problems are best address by introducing mechanisms for voice and participation into technological development and implementation.

The empirical work being conducted by the NSF project participants will contribute strongly to filling these identified gaps in understanding how emerging technologies are impacting the industry and worker well-being. We also suggest that a latter stage of the project include another literature survey of the proposed solutions to identified problems. In the process of writing this review, we identified extensive work being done on collective bargaining strategies. We believe that it would be useful to summarize these proposals as the project shifts into developing participatory methods for design and training.

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