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The impact of automation and artificial intelligence on worker well-being

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ABSTRACT

Discourse surrounding the future of work often treats technological substitution of workers as a cause for concern, but complementarity as a good. However, while automation and artificial intelligence may improve productivity or wages for those who remain employed, they may also have mixed or negative impacts on worker well-being. This study considers five hypothetical channels through which automation may impact worker well-being: influencing worker freedom, sense of meaning, cognitive load, external monitoring, and insecurity. We apply a measure of automation risk to a set of 402 occupations to assess whether automation predicts impacts on worker well-being along the dimensions of job satisfaction, stress, health, and insecurity. Findings based on a 2002–2018 dataset from the General Social Survey reveal that workers facing automation risk appear to experience less stress, but also worse health, and minimal or negative impacts on job satisfaction. These impacts are more concentrated on workers facing the highest levels of automation risk. This article encourages new research directions by revealing important heterogeneous effects of technological complementarity. We recommend that firms, policymakers, and researchers not conceive of technological complementarity as a uniform good, and instead direct more attention to mixed well-being impacts of automation and artificial intelligence on workers.

1. Introduction

> "There's never been a better time to be a worker with special skills or the right education because these people can use technology to create and capture value."
>
> Brynjolfsson and McAfee [1].

Artificial intelligence (AI) and automation are experiencing a new Spring in the 21st century. While these technologies have engendered discourse on numerous social, ethical, policy, and legal implications, few topics have received more attention than their impacts on the future of work. In public, scholarly, and policy spheres, the potential risk of widespread labor displacement (or substitution) is a subject of great concern [2,3]. While some estimates are less striking, several key studies have estimated that large numbers of workers will find themselves out of a job or needing to make a major transition in the near future due to automation. Muro, Maxim, and Whiton [4,5] estimate, using two separate methodologies, that around 51–52% of U.S. jobs face a high or medium risk of automation. Frey and Osborne [6] project similarly that 47% of US employment is at risk.

On a more international scale, Nedelkoska and Quintini [7] project that around 44 % of jobs in OECD countries face a medium or higher risk of automation, while Manyika and colleagues [54] predict that between 3 and 14% of the global workforce is at risk. Scholars have also begun to emphasize how labor displacement, worker pay, and other associated impacts may play out across demographic groups, such as by race/-ethnicity, gender, region, education level, and industry [8]. In turn, policymakers have begun to outline policy responses in industrial and emerging AI/automation policy strategies, focusing most prominently on the potential of education and training to up-skill or re-skill vulnerable members of the workforce and to create new kinds of jobs [9].

Yet, while many view technological-labor substitution as a significant threat, *technological complementarity*—the use of technology to complement workers—is often viewed as a positive for those workers able to stay in their jobs. In line with traditional labor economic logic reviewed in Section 2, Muro, Maxim, and Whiton ([4]; p. 14) argue that "workplace activity [that] isn't taken over by automation is complemented by it–making each remaining human task more valuable." Autor ([10]; p. 5) suggests similarly that "strong complementarities between automation and labor" can "increase productivity, raise earnings, and augment demand for labor." Beyond wages and productivity, Davenport posits additional benefits for workers, in that "AI will free up

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workers to be more creative and to do more unstructured work" ([11]; p. 4), while Berg, Buffie, and Zanna ([12]; p. 5) argue that automation complements "jobs that place a premium on creativity, flexibility, and abstract reasoning." If these perspectives are accurate, technological complementarity spells positive consequences for worker well-being.

This logic, echoed by scholars and policymakers, is clear: technological substitution may be a bad (even if there is long-term net job gain), but complementarity can be thought of as a good. If we can only educate and up-skill the workforce sufficiently in preparation for future jobs such that workers and automation/AI are complements, then these workers will benefit from the productivity, creativity, and freedom that technological complementarity entails. This begs an important question: will automation and AI have positive impacts on the well-being of complemented workers?

In this paper, we argue that technological complementarity is not a uniform good. While automation and AI may provide some benefit to workers, the history of technological adoption in the workplace and literature on socio-technical systems suggest more complicated and mixed impacts on well-being, including in dimensions such as worker stress, job satisfaction, and overall health [13–16]. We therefore draw on this history as well as the modern understanding of automation to construct a conceptual framework relating automation to worker well-being. Indeed, our framework acknowledges that responsible and sustainable implementation of new technologies like AI requires understanding social, technical, and even biological dynamics in tandem [17].

Our driving research question is: *what are the impacts of automation and AI on worker well-being?* As discussed, some hypotheses suggest that work will become better, for example by increasing worker autonomy, creativity, and freedom. Yet other hypotheses suggest that automation could contribute to negative impacts on workers, for example by inducing a loss of meaning or worker insecurity. We consider five such hypotheses in line with our conceptual framework.

To evaluate this research question and our set of hypotheses, we apply the measure of automation risk created by Frey and Osborne [6] to a longitudinal data set from the General Social Survey (GSS) covering the years 2002–2018. We perform a series of regression analyses to evaluate the impact of automation on four dimensions of well-being: job satisfaction, stress, insecurity, and overall health, using a variety of alternative specifications and covariates that incorporate aspects of the working environment. We additionally assess changes over time and pay special attention to workers facing the highest levels of automation risk. Combined, these analyses help us to evaluate the multidimensional impacts of automation and AI on worker well-being, and to consider the hypotheses proposed to explain any such effects.

This study contributes foremost by presenting a conceptual framework to expand the sophistication of our understanding of worker well-being, and by surfacing important related findings that we believe are not adequately reflected in public, scholarly, or policy discourse. In short, *our findings suggest that technological complementarity with workers is not a uniform good*: Indeed, there is persuasive evidence of negative effects on some dimensions of well-being. The results are at times surprising and dynamic and paint a more complex picture of the recent history and likely future of automation and AI in the workforce.

In Section 2, we provide a background on recent technological development, the literature on skill-biased technological change, and prior studies addressing technology's impacts on worker well-being before proposing our own conceptual framework and hypotheses. Section 3 introduces our data and empirical strategy, the results of which are presented in Section 4. Finally, Section 5 reflects on the key takeaways of our study and Section 6 concludes.

2. Background and conceptual framework

2.1. Changes and continuities in technological development

Numerous scholars and increasingly private and governmental entities have argued that current technological developments related to AI and automation represent a turning point in human history.[1] According to these interested parties, automating technologies have capacity to transform the private and public sectors, both leading to radically new possibilities as well as increasing the possibility of social, ethical, and security harms [18–20]. Reflecting the dual-edged nature of these innovations, discourse has considered issues ranging from the impact of automation on labor and economic growth [21,22] to how AI can be governed to safeguard human rights and promote equity [23,24]. These general purpose technologies are thus thought to represent a revolution which will profoundly affect economies, societies, and human life [25, 26].

As an expression of this urgency, dozens of countries have begun developing national policy strategies to address automation and AI [27]. These strategies indicate that national governments, along with firms and intergovernmental bodies like the EU, are eager to capitalize on AI's innovative potential yet worried about labor disruption and other social and ethical risks [28–30]. In turn, a wide range of industry actors have begun incorporating AI into their products, services, and management practices [31–33]. According to Schwab [34]; we are witnessing the first steps of a Fourth Industrial Revolution, or Industry 4.0.

Yet regardless of how we ultimately classify this moment in history, an examination of the processes of change reveals that slower-moving organizational dynamics and overall socio-technical adaptation characterize even the most novel innovations [35]. In relation to the adoption of information and communication technologies (ICTs) and the internet, scholars have convincingly argued that even these profound revolutions have been a product of cumulative technical advances over time, of available complementary technologies, and slower-moving innovations in organizational culture and capacity [39,40]. More recently, in explaining the lack of aggregate productivity growth which appears to contradict high expectations surrounding AI, some scholars point similarly to implementation and restructuring lags [41,42].

By not treating the present advances in technology as a decisive breakpoint, forecasters and analysts can instead focus on continuities with the past; these continuities may provide useful lessons for those wishing to anticipate future impacts of technology. They can help scholars to avoid simplistic assumptions of technological determinism by instead evaluating technologies in their specific socio-technical context (rather than as external, randomly arriving variables) [43]. For example, one such continuity following the emergence of a technology with potentially large impacts is the corresponding rise of utopian and dystopian thinking [44–46]. A second recurrence is concern about human labor, and the subsequent tension between advocates and resistors of technology-induced reforms [47–49]. Today, these debates seem awkwardly familiar.

Another task of forecasters of AI and automation is to assess possible *differences* and novelties related to automating technologies that may be relevant to future impacts [46]. Differences may appear in the forms of adaptation to technology via organizational processes and management, in the broader social and economic context, and in the nature of the technologies themselves [50]. For example, even more so than in the case of previous automating technologies, AI is characterized technically

[1] AI is defined by the OECD [36] as "a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments." One can distinguish AI from automation, identifying the former most commonly today with machine learning and the latter with robotic process automation and industrial robotics [37]. For a more detailed discussion of definitions, see Krafft et al. [38].

by its ability to learn or adapt to its environment, and to do so semi-independently of human control [36] while other more heuristic definitions emphasize simulation of human thinking or behavior [51]. Both types of definitions have clear relevance to human labor. Arguably the most important distinguishing characteristic of AI then, in the context of human work, is its potential to simulate or computerize human tasks and capacities (including cognitive and social-emotional ones) previously thought unique to humans.

Unsurprisingly, significant current debate addresses whether automating technologies will lead to net job loss or gain via a fruitful but fraught process of creative destruction [52]. Yet even optimistic estimates anticipate significant labor disruption for vulnerable groups and regions with potentially negative consequences for political and social cohesion [53]. Moreover, to mitigate disproportionate impacts and ease adaptation, research and discourse to-date emphasizes proactive education, training, and even social welfare policies [54]. However, the prospect that ongoing automation and AI-based innovation is pursued aggressively—while ameliorative social policies remain mere recommendations—threatens the viability of optimistic projections [55].

One potential result of this modern technological development is that workers may find themselves unemployed and without recourse. Another is that *even those workers who remain employed* may find work environments and skill expectations change too rapidly beneath their feet, leading to a range of possible harms. The prospect of negative impacts seems especially likely if the Fourth Industrial Revolution is overly driven by a techno-utopian and economic logic which pursues innovation without considering impacts on workers who remain on the job. In the worst case, these changes would risk exacerbating harms caused by labor deregulation and globalization, which have contributed to polarization between good and bad jobs and increased job precarity and insecurity across the board [56–58].

In the next section, we present one of the most successful theories in recent history that helped to explain automation's effects on employment following the computer and internet revolution. This theory serves as a jumping off point for how AI and automation may impact working environments and worker well-being going forward.

2.2. Technological substitution and complementarity

In a seminal paper in the skill-biased technological change literature, Autor, Levy, and Murnane [59] (henceforth ALM) developed a theoretical model to explain the relationship between technology and the workplace, focusing on the content of *tasks* performed in various jobs. Until that point, scholarly literature had instead emphasized skill levels, noting a correlation between decreasing costs enabled by computers and an increase of highly-educated (or skilled) workers. This correlation suggested that low-skill workers and technology were substitutes, whereas workers with high levels of skill (or education) were complements of technology [60].

The shift from examining skill levels/education to disaggregating occupations by tasks represented an important refinement. This newer perspective, the "task model," draws on knowledge of what tasks computers perform and how these capabilities may complement or substitute for human skills needed to perform those tasks:

> "The simple observations that undergird our analysis are (1) that computer capital substitutes for workers in carrying out a limited and well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules (what we term "routine tasks"); and (2) that computer capital complements workers in carrying out problem-solving and complex communication activities ("nonroutine" tasks)." ([59]; p. 1280)

ALM showed that, in a four-decade period starting from the 1960s, as computers became cheaper, the prevalence of routine tasks decreased consistently, while the proportion of jobs centered on nonroutine tasks grew. Further, as both routine cognitive (i.e., "high-skill") and routine manual ("low-skill") tasks were affected by technology, it became clear that the prior understanding of labor impacts in terms of skill levels was an oversimplification of a more complex reality. In fact, most of the jobs that disappeared following the computer revolution were in the middle of the skills distribution, rather than at the bottom. The task model therefore revealed an important distinction between tasks and skills which has been used extensively by subsequent literature [61–63].

As discussed, however, recent technological developments in AI and machine learning in particular have challenged what we understand as what computers cannot do [64], making it necessary to revisit the original task model. Frey and Osborne [6] (henceforth FO) led this endeavor by developing a forward-looking measure of occupational susceptibility to computerization. Their measure of computerization risk—a probability—incorporates new premises regarding what computers can do or will be able to do soon. With the help of a team of subject experts, the authors identified three types of tasks as current engineering bottlenecks (i.e., tasks that computers cannot effectively replace given the current technological frontier): 1) perception and manipulation involving fine motor tasks, especially in unstructured work environments, 2) creative intelligence, and 3) social intelligence. Their methodology assumed that any task other than these could be replaced by a computer in the near future (i.e., the next decade or two). The susceptibility to computerization measure was then estimated based on the prevalence of hypothesized engineering bottlenecks in each occupation, according to an occupation-level inventory of tasks (discussed in detail in Section 3.1).

Interestingly, FO found a strong and negative correlation between levels of education and susceptibility to automation, in line with the pre-ALM predictions of technological impact. Moreover, high-risk occupations (which they defined as susceptibility at or above 70%) should feel impacts in a relatively short time horizon, defined as the next ten to twenty years. That is, in contrast to recent fears that white-collar jobs are among the most exposed to AI [5], FO projected that low-skill occupations will be the most affected as automating technologies become scalable to the market. Examples of these vulnerable occupations include transportation, logistics, office and administrative support, and service occupations. If confirmed, such a trend contrasts with the displacement of middle-skill workers in prior decades and has immediate policy implications for what types of workers should be the focus of labor, education, training, and social welfare policies [6,53]. Indeed, these assumptions and social and economic projections emanating from them have been subsequently echoed by many mainstream economic scholars [1,42,65] and policymakers [9].

Two differences between the original ALM task model and the newer FO susceptibility to computerization approach should be highlighted. First, the original task model focused on developing and testing a theory, the validity of which was probed by confronting it with several decades of historical evidence. Distinctly, FO proposed a forecasting methodology adapted from studies that predicted susceptibility to offshoring. This forward-looking methodology is necessarily more speculative, and its implications should be interpreted with greater uncertainty.

Second, the latter model relaxes assumptions on what tasks can be performed by computers, while the former restricts computers to automating only routine tasks. There is, of course, a substantial overlap of presumed automatable occupations between the models (which we illustrate in Fig. D1 in the appendix). A key point, however, is precisely the extent to which they differ: Impacts on occupations that only recently became susceptible to automation, or 'newly-automatable occupations,' may reflect the unique changes attributable to AI. The timing differences across the two models are thus important because, while automation has replaced routine jobs for decades, it is not clear how much of an impact AI has had to-date, and many of these impacts should be expected to manifest further in the future.

Of note, some have cautioned that an excessive emphasis on tasks without consideration of the working environment, task heterogeneity within occupations, and broader economic and contextual factors could lead to unduly high estimates of job displacement [22,66,67].[2] Yet we see no *inherent* contradiction between perspectives centered on tasks and those that emphasize socio-environmental factors. To that end, this paper bridges these perspectives by treating the task as the implicit unit of analysis, while incorporating a broader set of characteristics regarding job context and content variables in the conceptual framework and analysis.

In sum, while both the ALM and FO models and surrounding literature have focused on job displacement, wages, and productivity [61,62,68], our contribution is to extend this literature to the neglected topic of well-being. To do so, we rely on the FO automation risk measure, as it has been updated to reflect the newest technological developments and is therefore more likely to help us measure how automating technologies—particularly AI—may affect worker well-being in the present and coming years.[3]

We use this measure to systematically explore different mechanisms by which automating technologies may impact working environments and worker well-being. Impacts may be realized through multiple channels, including those that are present-oriented (e.g., making work easier or harder) or future-oriented (e.g., through expectations about job security). Such an analysis helps to shed light on multi-faceted changes to work environments, suggest possible heterogeneous effects on worker well-being, and expose measurement challenges. Below, we introduce the idea of well-being in general, and in the context of technological adoption in the workplace.

2.3. Technological impacts on worker well-being

Well-being is a complex and multi-dimensional concept, which has been defined and operationalized in multiple and at times inconsistent ways. A major division in the literature, according to Fisher [69]; is between those who view overall well-being as *hedonic*—temporary pleasant feelings—versus *eudaimonic*—a broader notion of self-actualization involving elements such as inner growth and autonomy. Recently, a third dimension of well-being which addresses collective impacts on social groups and communities, has begun to receive increased attention [70]. Well-being is also considered to have both objective and subjective aspects, where the former are associated with traditionally quantified socio-economic metrics like life expectancy or income [71,72], while the latter are often identified with metrics in psychology such as life satisfaction and perceived flourishing [73,74].

Well-being at work is a subset of overall well-being—and arguably among the most essential [75]. Reflecting the complexity of its overarching concept, worker well-being includes objective measures such as one's paycheck and benefits as well as subjective aspects such as motivation, satisfaction, social belonging, and meaningfulness. These elements of working life affect workers' performance and turnover at the job—as long ago realized by firms and their human resources offices [76,77]. Moreover, worker well-being has clear broader social and policy implications, as mental and physical health consequences spill over to life at home, impacting families, communities, and society [78].

Changes at the workplace, including the introduction of new technologies, have the potential to profoundly affect worker well-being by changing tasks, processes, and structures within workplaces. During moments of technological transition, for instance, scholars have noted heightened levels of occupational stress and a perceived lack of autonomy or control among workers. Workers experience concerns about roles and tasks changing [79], being insufficiently trained, or losing their jobs altogether [80]. Under such circumstances, organizations and governments can play a fundamental role in reducing worker insecurity and stress by, for example, providing a safety net outside of work to reassure workers [81] and involving employees in the technology implementation process [33].

Yet, despite this history and accumulated knowledge, debates surrounding current automating technologies have paid insufficient attention to potential impacts of technological change on worker well-being. In contrast, previous waves of automation were accompanied by more serious expressions of concern in the policy and scholarly realms. (Why discourse on technology and worker well-being differs today is a fascinating question beyond the scope of this paper.) To explain how these research questions were advanced in the past, we borrow from three studies discussing the introduction of the computer into the workplace as well as more recent work examining automation risk and job insecurity. We use this literature to help conceptualize how AI and automation might affect worker well-being going forward.

The first is a study by Baldry [13]; who developed a model that moves beyond an idealized understanding of well-being (e.g., Maslow's [82] hierarchy of needs) to better specify its context and surrounding causal relations. Specifically, Baldry argued that the impact of technology on the working environment is a product of two interrelated factors, the *content* and the *context* of the job. The content includes a set of overlapping factors, ranging from the characteristics of the main work activities (whether cognitive or manual, diverse or repetitive) and required skills, to the degree of autonomy and judgment required from workers. The context, in turn, considers working conditions, the social organization of work, the role of one's job in the organization, and the type and degree of supervision. Here, the broader socio-technical environment and management decisions play a crucial role, as "the way technology is used and what it is used for are the result of a series of decisions made inside and outside the organization." ([13]; p. 64).

Contrary to recent discourse which treats AI and automation in a deterministic fashion [67,83], Baldry's model clarifies that the effect of technology on well-being is not predetermined, and neither necessarily good nor bad. Rather than viewing certain well-being impacts as inevitable or as mere unintended consequences of the technological process, technology's impacts should instead be viewed as part of a contextual social-technical process, one significantly shaped by decision-makers and the broader firm, industry, and socio-economic environment. Indeed, recent studies focusing on technology adoption during the current AI revolution have reiterated that managerial choice and employee agency can foster greater acceptance of new technology along with other positive outcomes [33,81,84].

Second, Cooper [14] studied how the introduction of computers in the workplace and individuals' interactions with their evolving working environment could increase occupational stress. In his framework, six main factors impact workers: factors intrinsic to the job, workers' roles in the organization, career development, relationships at work, organizational culture and climate, and the interface between the job and the home. These six factors may result in harmful individual symptoms (especially negative short- and long-term health outcomes) as well as certain organizational "diseases" (e.g., absenteeism, turnover, apathy, and difficult industrial relations).

[2] Further limitations of the FO measure and strategies to mitigate them are discussed in detail in Section 3.1.

[3] We also match the ALM measure to our dataset and repeat our analyses, which leads to highly similar findings. However, in the ALM case, we are only able to match the data for a shorter period (2002–2010), before many of AI's impacts are likely to be felt, whereas in FO we are able to extend the analysis up to 2018–another reason for preferring the later measure.

The introduction of new technologies can affect well-being through each of the six factors in Cooper's model, though the nature of these impacts need not present identically across different contexts or for different types of workers. A further interesting consequence of the complexities of well-being is that some paradoxes seem to emerge. Some of the factors that increase stress, for instance, also increase job satisfaction. An example is a job that requires a worker to solve puzzles or address challenging situations: while facing these challenges may be stressful, overcoming them is rewarding and satisfying. These idiosyncratic aspects of well-being at work help explain apparently conflicting elements represented in some of our hypotheses.

Third, Gutek and Winter [15] studied the effects of computer use on white-collar workers. They developed a conceptual framework in which two psychological mechanisms mediate the relationship between computer use and job satisfaction. The first mechanism is *symbiotic interaction*, or the degree to which the workers feel that they and the computers work together, and the second is *perceived* [external] *control*, or the degree to which workers perceived they were monitored by the computer. Gutek and Winter expected that smooth and efficient interaction between users and the computers, a positive form of complementarity, would be associated with higher job satisfaction. Conversely, the belief that computers acted as artifacts of surveillance would lead to lower job satisfaction. However, their framework did not account for the possibility that technology could produce increased complementarity and control/surveillance simultaneously, a possibility reflected in our hypotheses.

Finally, while much of the recent scholarship addressing automation and AI has emphasized labor disruption and its implications for wages, unemployment, and training, one exception is a 2018 study by Patel and colleagues [85], who directly measure the effects of automation risk on health. The authors also employ the automation risk measure developed by FO, and find that, at the U.S. county level, a 10% point (pp) increase in automation risk worsens general health by 2.4 pp, physical health by 0.8 pp, and mental health by 0.6 pp. Importantly, these negative well-being effects are argued to be mediated by workers' job insecurity, a variable that is known to impact well-being in the psychological literature [86–88], and one that does predict eventual job loss [89].

Insecurity due to automation risk must also be understood in the context of other contributors to insecurity. In particular, employee characteristics (e.g., age, gender, job prestige, educational level, temporary contract status), economic and labor market conditions (e.g., economic growth, unemployment rates, personal experience with unemployment, employment protections, social safety net), organizational context (e.g., managerial practices, opportunities for participation), and cultural factors (e.g., uncertainty avoidance, attitudes toward technology) may all influence worker insecurity [90]. Further, automating technologies could also induce insecurity about the loss of *valued features* of one's job, such as "opportunities for initiative or task discretion," *even when one's employment itself is not at risk* ([79]; p. 37). A contribution of this last line of research is thus to extend the literature on job insecurity and well-being to automation specifically by attending to automation risk—a channel we scrutinize further in our hypotheses and models.

Lessons from these studies guided the elaboration of our conceptual framework. Foremost, we specify job content and context as mediating variables in the pathway between technological adoption and worker well-being. Incorporating these socio-environmental aspects into our analyses helps provide a more robust treatment of automation's impacts on the workplace, beyond a straightforward assessment of the tasks and occupations at risk of automation. Further, we cope with the complexity of well-being by acknowledging multiple mechanisms through which technology can impact workers. As such, we propose alternative (and potentially conflicting) hypotheses to reflect these multiple channels of impact.

2.4. Conceptual framework

Fig. 1 depicts our conceptual framework. First, we represent new technology, in this case automation and AI, as an 'exogenous' shock to the system. Of interest is the impact of this new technological input on automation risk, which we define as the possibility that a particular job may be impacted by automation, and reflects the possibility of substituting for or otherwise transforming a job.

Next, in avoiding a deterministic assumption, *we assume that automation risk impacts technology adoption, but only as moderated by a set of environmental and socio-technical factors*. Our research does not probe all of these factors in depth, but we discuss some elements briefly here for illustrative and theory-building purposes. First, individual occupation types should be impacted differently, given the status or power of the workers individually or collectively [35,91], and the nature of the work. Second, key managerial decisions in the firm and elements of industry matter here as well. These include levels of competition, concentration, networks, firm size, input factors, labor markets, slack resources, risk-taking, R&D investment, and other factors important in firm and industry innovation behavior [92–94]. Third, elements of the broader socio-economic environment are also important, such as GDP, interest rates, antitrust policy, economic volatility, and unionization [95,96]. Finally, the existence and penetration of complementing technologies and innovations is critical to a firm's capacity and willingness to implement AI and automation [42].

Our conceptual framework does not attend to workers who are substituted for and ultimately displaced by technology, though these workers are represented in the top right. Instead, *we focus on workers who are complemented by technology adoption and remain at work*, represented in the large horizontal box at the bottom. Here we represent aspects of both job content and job context, as per Baldry [13]. Job content may be influenced by (or influence) technology adoption via changes in work tasks (such as the degree of routine/manual work), workload intensity, and the degree of worker autonomy. Relevant features of job context include workplace safety and conditions, socialization, and opportunities for career advancement and other benefits.

Our framework also incorporates the possibility that automation risk may impact worker well-being through expectations, mediated by workers' awareness of this possibility and beliefs about its likelihood [97]. Research by Patel et al. [85] indicates that automation risk may induce negative effects on health, and work by Gallie et al. [79] provides evidence that workplaces employing advanced technology induce more job insecurity, though the effects are only borderline significant. However, these studies do not explicitly model whether workers who report higher insecurity are aware of the specific level of automation risk they face, and worker awareness and fear of automation may depend on worker characteristics [90]. Workers might also be aware of automation risk generally, but not perceive risk in the case of their own job, in which case this channel may be insufficiently influential compared to other causes of insecurity and given the overall job insecurity trend [56].[4] As such it remains unclear to what extent the automation-awareness-insecurity channel is in fact active.

We expect that—as a result of automation risk and subsequent technology adoption patterns—job content, context, and future expectations may interact jointly to influence worker well-being, though the nature and direction of these causal relationships begs further examination. Finally, we list the four key well-being measures used in our study as examples, all of which are important and mainstream measures of well-being. These are job satisfaction [15], stress, health [14], and job

[4] "All jobs have become increasingly precarious in the past four decades, though some jobs and persons are more vulnerable than others to both the risk and consequences of job loss. Since both good jobs (for example, well-paid consultants) and bad jobs are generally insecure, it has become increasingly difficult to distinguish good and bad jobs on the basis of their degree of security." [56]; p.10).

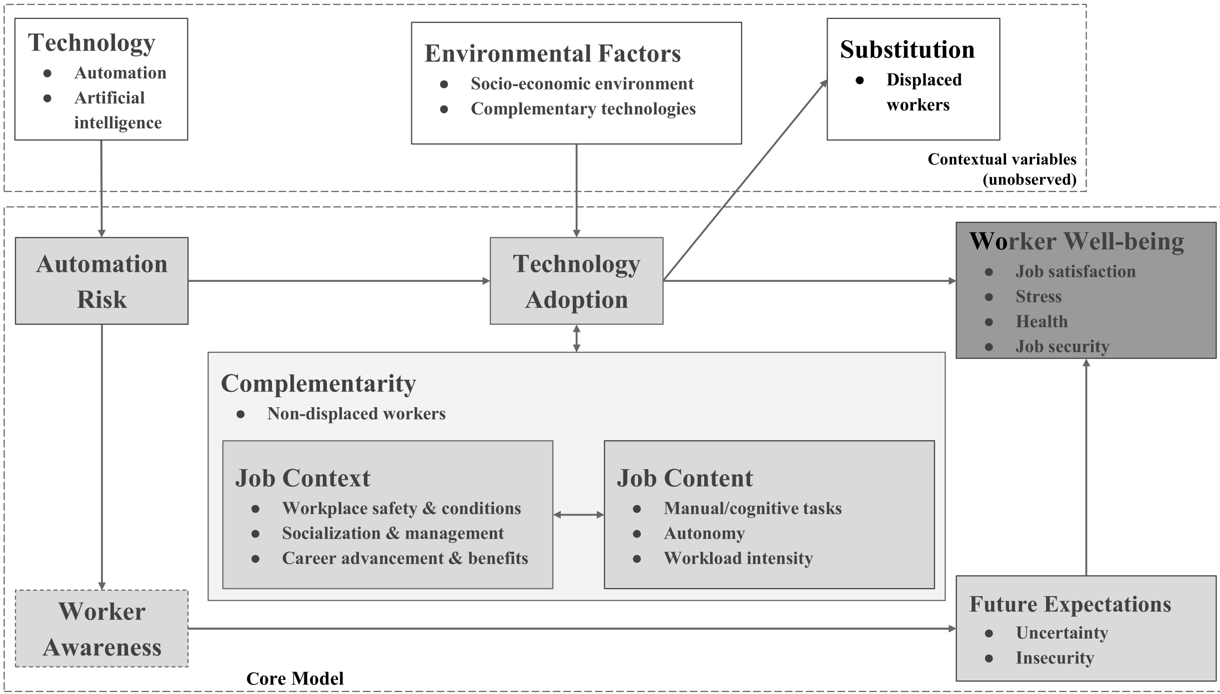


Fig. 1. Conceptual framework of AI and automation's impact on worker well-being.

security [86]. Our conceptual framework does not and cannot fully explicate all the dimensions of technological adoption in the workplace and worker well-being. However, we can begin to address this knowledge gap through model building and hypothesis testing, a process we introduce below.

2.5. Hypotheses

We offer five exploratory hypotheses to consider how automation and AI may affect worker well-being, informed both by general discourse and by the literature in automation/AI, psychology, organizational science, and well-being. These mechanisms are not mutually exhaustive, nor are they mutually exclusive: for example, we might expect that different channels of impact will be activated for different kinds of workers based on their specific characteristics and working environments. Therefore, hypotheses about the relative strength of specific well-being impacts within each mechanism are offered more tentatively. Our five hypotheses are as follows:

- **H1: Creative freedom hypothesis.** Those workers fortunate enough to not be displaced by technology might instead be complemented or augmented [98] through a positive, symbiotic interaction [15]. Workers should experience more autonomy as they are freed from mundane, routine tasks, and are empowered to use their creative skills [99]. As Brynjolfsson and McAfee ([1]; p. 5) argue, "There's never been a better time to be a worker with special skills or the right education." As a result, aspects of well-being like job satisfaction, health, and meaningfulness might increase, while negative aspects like stress might decrease.
- **H2: Cognitive overload hypothesis.** However, a decrease in routine tasks and corresponding increase in cognitively demanding tasks could also make work much more difficult if workers have no respite from cognitively intense tasks which generate mental overload [100,101]. While some increase in work challenge might improve job satisfaction [14], too much additional cognitive load might instead induce stress, decrease job satisfaction, and harm health.
- **H3: Loss of meaning hypothesis.** For some workers, automation may replace aspects of their work considered core to their identity and sense of meaning. For example, teachers might find their roles relegated to facilitation of computerized education [102], with creative aspects of instruction delivered by intelligent tutoring systems [103] while truckers who once found meaning in driving are similarly relegated to supervisory roles in the passenger seat of self-driving trucks [104]. On this view, even if work becomes less stressful and easier, it also becomes less meaningful [53,105], decreasing job satisfaction and potentially health.
- **H4: Surveillance and control hypothesis.** Automation and AI can also be used to exert control over all aspects of work, ranging from scheduling software [106] to constant video surveillance and attention-tracking which aim to optimize performance metrics to the second. For example, a tool used by automotive parts company Denso monitors employees from multiple angles and shows workers a smiley face or frown based on their timeliness and performance metrics [108]. Worker-tracking technologies in Amazon warehouses

similarly prescribe specific employee actions and timelines [107], leading employees to skip socialization and even bathroom breaks. Workers have indeed expressed anxiety over AI systems that monitor or measure their performance, with the additional consequence of potentially violating privacy [32]. A decrease in autonomy and increased levels of surveillance might therefore increase stress and decrease job satisfaction and health [109].

- **H5: Job insecurity hypothesis.** The last hypothesis focuses on anticipatory or forward-looking effects. On this view, workers aware of automation risk may experience fears of rapid job change or especially displacement [90,97], inducing feelings of job insecurity [79], increasing stress, and worsening health [85]. The link between job insecurity and negative well-being outcomes is not novel in the psychological literature: De Witte, Pienaar, and De Cuyper [86] found in a 30-year meta-analysis that job insecurity negatively impacts both worker psychological well-being and somatic health. The evidence surrounding the extent to which this mechanism applies in the context of automation, however, is not yet clearly established, and one of this paper's goals is to help to close that gap.

Disentangling specific forms of technology adoption of AI/automation, changes to job content and context, and well-being impacts is complicated. As noted, we might expect various mechanisms to apply to different workers. For example, we might expect workers with higher incomes, skill levels, and bargaining power to benefit from more creative freedom and symbiotic interaction, while workers with less organizational status and bargaining power are subject to increased surveillance and control. Moreover, the mechanisms affecting a worker, or an occupation may evolve as workplace implementations of technology are tested and change over time through managerial decisions and in response to labor and socio-economic pressures. Finally, defining, operationalizing, and measuring AI and automation is no simple task, as boundaries and perceptions surrounding these technologies are fluid and shift over time [110]. As such, we do not expect to be able to sharply or definitively test all these hypotheses or their relationship with the many possible subgroups of workers, but we do aim to provide some preliminary evidence and especially theoretical directions for future research.

3. Methodology

3.1. Data

The General Social Survey (GSS)[5] is the main data source in this research. GSS is a survey administered since 1972 on a biennial basis to monitor trends in attitudes, behaviors, and demographics across the United States, and is considered a foundational resource in social science research. The GSS has a fixed set of questions, including a standard demographic and work-related core, as well as "topics of special interest" which vary over time. It has been used extensively to study issues of interest for this study, including physical and mental health, job satisfaction, and worker well-being [111]. Of particular importance for this research is the Quality of Worklife (QWL) module, jointly designed by the National Institute for Occupational Safety and Health and the National Science Foundation. The QWL module was administered in the years 2002, 2006, 2010, 2014 and 2018, and provides in-depth information about worker characteristics, experiences, and perceptions of their workplaces.

We adopt three main dependent variables from the GSS: *job satisfaction*,[6] *stress at work*,[7] and *overall health*.[8] As emphasized above, these variables do not capture all the complexities of well-being and they may reflect measurement challenges such as social desirability bias [112]. However, these measures—self-reported job satisfaction, stress, and overall health—capture several prominent dimensions of well-being that are central to work in the context of technological change, as discussed in Section 2. Finally, to test the job insecurity hypothesis, we separately analyze *job security*[9] as a fourth variable of interest.

The key independent variable is *automation risk*, which we operationalize using FO's (2017) susceptibility to computerization measure and consider as a measure of risk resulting from both older automating technologies and newer AI techniques. In short, FO extracted occupation-level task information from the 2010 O*Net database, estimated automation risk per occupation given task distributions, and matched results with the 2010 Standard Occupational Classification (SOC) codes. FO's research resulted in a probabilistic measure of automation risk ranging from 0 to 1 for 702 occupations. The GSS, however, uses the Census Occupations Classification (COC) codes rather than the SOC, making a direct conversion unfeasible.

We therefore carry out a two-step process to match probabilities estimated in the FO study to the occupation codes used in the GSS. First, we use a crosswalk table provided by the US Census Bureau which maps 525 occupations codes from the 2010 SOC to comparable 2010 COC codes. As FO's codes are more finely detailed than the ones listed in the Census crosswalk file, the correspondence is imperfect. With additional matching, we are able to assign probabilities to 477 of the 525 codes (90.8%) in the Census crosswalk table.[10] Second, we merge these probabilities with the occupation codes used by GSS. Overall, we successfully match 402 of 452 2010 COC codes in GSS to the automation risk measure from FO, representing a loss of only 5.7% of the original GSS sample (347 of 6066 observations). We standardize the measure of automation risk to enhance interpretability, as presented in Table 1.

The FO measure has been subject to criticism, in part due to the subjectivity behind the task classification, the use of expert predictions, and the omission of other contextual factors [66,114]. Indeed, any forecasting methodology which tries to offer predictions about topics characterized by as much uncertainty as AI will necessarily incur some limitations. However, somewhat reassuringly, a study by the Federal Reserve Bank of Philadelphia [115] carried out an empirical analysis using two alternative

[5] "The General Social Survey (GSS) is a project of the independent research organization NORC at the University of Chicago, with principal funding from the National Science Foundation." [113].

[6] Job satisfaction is measured with a 1–4 Likert scale in which: 1 = not at all satisfied, 2 = not too satisfied, 3 = somewhat satisfied, and 4 = very satisfied. The original question is "All in all, how satisfied would you say you are with your job?"

[7] Work stress is measured with a 1–5 Likert scale in which: 1 = never, 2 = hardly ever, 3 = sometimes, 4 = often, and 5 = always. The original question is "How often do you find your work stressful?"

[8] Overall health is measured with a 1–5 Likert scale in which: 1 = poor, 2 = fair, 3 = good, 4 = very good, and 5 = excellent. The original question is "Would you say that in general your health is Excellent, Very Good, Good, Fair, or Poor?"

[9] Job security is measured with a 1–4 Likert scale in which: 1 = not at all true, 2 = not too true, 3 = somewhat true, and 4 = very true. The original question asks the respondent to give her opinion about the following statement: "The job security is good."

[10] Even though the Census crosswalk table and FO both list 2010 SOC codes, the FO codes are more detailed than those provided by the Census: originally, there were 702 codes in the former and 525 in the latter. After merging, we found a direct correspondence for 372 codes, while 330 codes are only present in FO and 153 only in the Census table. Most of the codes that do not directly correspond fail to match because of the higher detail of the FO table. Thus, we manually matched 115 additional codes by averaging probabilities across subcodes under the same original code: for instance, to estimate the probability of computerization for occupation code 11–2020 (in the Census table), we averaged the probabilities for 11–2021 and 11–2022 (in the FO table). Therefore, we ended up with probabilities for a total of 477 (372 + 115) out of the 525 occupations in the Census crosswalk.

Table 1
Summary statistics.

Variable	Mean (Std. Dev)	Range
Dependent Variables		
Job Satisfaction	3.35 (0.73)	[1–4]
Job Stress	3.09 (1.02)	[1–5]
Overall Health	3.66 (1.01)	[1–5]
Job Security	3.38 (0.82)	[1–4]
Independent Variables		
Automation Risk	0.50 (0.37)	[.003–0.99]
Standardized Risk	0.00 (1.00)	[-1.35-1.31]
Factors		
Work Conditions	0.01 (0.99)	[-4.68-2.17]
Social Context/Management	0.01 (0.99)	[-4.40-1.97]
Benefits	0.00 (1.00)	[-3.86-3.08]
Manual Work	0.00 (1.00)	[-2.15-2.58]
Workload	0.00 (1.00)	[-2.86-4.07]
Autonomy	0.01 (1.00)	[-5.33-2.37]
Control Variables		
Year		
2002	0.25 (0.43)	[0,1]
2006	0.23 (0.42)	[0,1]
2010	0.15 (0.36)	[0,1]
2014	0.17 (0.38)	[0,1]
2018	0.20 (0.40)	[0,1]
Age	42.27 (13.22)	[18–88]
Gender		
Male	0.48 (0.50)	[0,1]
Female	0.52 (0.50)	[0,1]
Race/Ethnicity		
White	0.69 (0.46)	[0,1]
Black	0.15 (0.36)	[0,1]
Latino	0.12 (0.33)	[0,1]
Other	0.04 (0.20)	[0,1]
Married	0.47 (0.50)	[0,1]
Part-Time Job	0.16 (0.37)	[0,1]
Educational Attainment		
Less than High School	0.08 (0.28)	[0,1]
High School	0.51 (0.50)	[0,1]
Junior College	0.10 (0.29)	[0,1]
Bachelor's Degree	0.20 (0.40)	[0,1]
Graduate Degree	0.11 (0.31)	[0,1]
Industry		
Agriculture, Forestry, Fishing, & Hunting, and Mining	0.01 (0.12)	[0,1]
Construction	0.07 (0.25)	[0,1]
Manufacturing	0.11 (0.31)	[0,1]
Wholesale and Retail Trade	0.14 (0.34)	[0,1]
Transportation & Warehousing and Utilities	0.06 (0.24)	[0,1]
Information	0.03 (0.16)	[0,1]
Finance and Insurance, & Real Estate, & Rental and Leasing	0.07 (0.26)	[0,1]
Professional, Scientific, and Management, & Administrative, and Waste Management Services	0.09 (0.28)	[0,1]
Educational Services, & Health Care and Social Assistance	0.23 (0.42)	[0,1]
Arts, Entertainment, and Recreation, & Accommodation and Food Services	0.09 (0.28)	[0,1]
Other Services, Except Public Administration	0.05 (0.22)	[0,1]
Public Administration	0.05 (0.22)	[0,1]

automation risk measures [116,117], and found consistent results whether the FO or another measure was used. Nevertheless, in light of the uncertainty inherent in the FO measure and the possibility that their predictions of automation risk are (perhaps upwardly) biased, we carry out alternative specifications in which only occupations in the bottom and top tails of the probability distribution are considered—occupations where it is reasonable to assume there is less uncertainty about what can and cannot be automated. We also replicate our main findings using the backwards-looking ALM measure and find highly consistent results, providing greater confidence in the reliability of the FO measure.[11] For these reasons, we employ the FO measure of automation risk as the primary independent variable in our analyses.

We use the following covariates as controls in most of our models: year, age, gender, race/ethnicity, marital status, education level, part-time work status, and industry. We also develop and include six factor variables in our models to control for content and context of job characteristics, as informed by the literature and our conceptual framework. These additional factor variables help to address possible concerns about omitted variable bias and robustness of model specification.

We obtain the following six factors from a principal components factor analysis based on 31 underlying variables from the QWL module deemed relevant to our conceptual framework[12]: i) *social context and management,* ii) *workplace safety and conditions*, iii) *autonomy*, iv) *workload*, v) *career advancement opportunities and benefits*, and vi) *manual work*. Table A1 in the appendix presents the rotated factor loadings for each of the six factor variables.[13] The Cronbach's alphas reflect an adequate to high level of internal consistency/reliability (alpha at or above 0.7) for the group of variables that constitute each factor.

Our final sample comprises 5718 workers who were working either full- or part-time, aged 18 and over, for whom there was available information for the variables of interest. Table 1 provides some descriptive statistics of the variables used in the models.

3.2. Empirical strategy

3.2.1. Impacts of automation and AI on worker well-being

Our empirical investigation[14] begins with a series of OLS models in Section 4.1. We first regress each well-being variable separately on the standardized measure of automation risk. This model allows us to assess the bivariate association (or correlation) between a one standard deviation increase in automation risk and the well-being outcomes of interest. Next, we add sets of covariates gradually and observe how the impacts of automation risk on well-being respond. These covariates

[11] Results based on the alternative ALM specification are available upon request.

[12] We opted for factors over individual variables as their interpretation was more intuitive and in line with our conceptual framework, balancing comprehensiveness with parsimony. As robustness checks, we evaluated our models using individual variables instead of factors and did not find significant differences in the coefficients of interest or general statistics of model fit.

[13] Based on theory, we expected to see some correlation between the factors and therefore did not want to impose an orthogonality constraint unnecessarily. We followed the advice of Tabachnick and Fiddell [118] who suggest using oblique rotations if the correlation between rotated factors is above 0.32. Therefore, we performed three separate oblique rotations (promax powers 2, 3 and 4), and examined the loadings and correlations between the factors in each case [119]. Across the three rotations, we found no major difference between the variables loaded in each factor. Regression analyses using factors as independent variables produced substantially similar results for all three rotations as well. Our preferred rotation was promax 2, as it reduced factor correlations substantially and therefore multicollinearity. Promax 2 rotations and the corresponding correlation matrix are presented as Tables A1 and A2 in the appendix.

[14] Replication code and data to allow for reproduction of our main results are available at: https://doi.org/10.7910/DVN/6TDHPF.

increase our confidence (but by no means guarantee) that identified associations can be interpreted in a causal manner.

First, we add the initial set of worker covariates described above, including part-time work status and industry, as the omission of these covariates may lead to spurious effects. Then, we control for characteristics of job content and context by incorporating the six researcher-created factor variables. In addition to allowing us to determine the effects of interest after we control for worker and job characteristics, this strategy helps us to understand the causal pathways through which automation risk may affect well-being. To study the individual effect of each factor variable, we perform progressive and one-factor-at-a-time analyses, which are reported in Table B2 in the appendix. In the main body of the paper, we report a subset of these analyses. The full model, which includes both worker covariates and job content and context factor variables is the following:

$$y_{it} = \alpha_i + \vartheta year_t + \beta risk_i + \gamma X_{it} + \delta L_i + \varepsilon_{it} \tag{1}$$

where the dependent variable y_{it} is one of the well-being variables (i.e., job satisfaction, stress, health, or job security) for individual i in year t. $Risk_i$ is the standardized automation risk of the individual's occupation and β is the primary coefficient of interest. To account for over-time variation that may be related to business cycles and other socio-economic or environmental factors, we also include a full set of year fixed effects, $year_t$. Finally, $\boldsymbol{X}_{it}$ is a vector of individual worker covariates and $\boldsymbol{L}_i$ is a vector of the six factors used to control for job content and context.

This first set of analyses allows us to evaluate the general relationships between automation risk and worker well-being outcomes, to assess possible differences across dimensions of well-being, to see whether effects persist after including a wide variety of controls, and to consider possible causal mechanisms through which automation affects well-being. Based on the identified effects (or lack thereof) on well-being, and possible causal channels, we discuss how this evidence supports or contradicts the hypotheses in Section 2.5, which again are the creative freedom hypothesis (H1), cognitive overload hypothesis (H2), loss of meaning hypothesis (H3), and surveillance and control hypothesis (H4). We discuss the job insecurity hypothesis (H5) in a separate analysis.

3.2.2. Sensitivity analysis

While we incorporate a significant number of covariates based on theory and our conceptual framework, it is difficult to fully establish causation in observational research. Therefore, we perform a simple sensitivity analysis using the E-value measure developed by VanderWeele and Ding [120]. The E-value is defined as “the minimum strength of association on the risk ratio scale that an unmeasured confounder would need to have with both the treatment and the outcome to fully explain away a specific treatment-outcome association, conditional on the measured covariates” (p. 2). The E-value helps provide context on how likely it is that there exists an omitted variable that would significantly change the study findings.[15]

3.2.3. Alternative specifications

To assess the reliability of any findings, we also run the full set of models above using two alternative specifications of automation risk, reflected below in model 2. We convert the continuous automation risk variable into a dummy variable (***highrisk**$_i$*) in which low risk equals 0 and high risk equals 1. We create a corresponding dummy variable reflecting the 75/25 thresholds, and separately create one reflecting more extreme 95/5 thresholds.[16] For instance, in the first alternative specification, jobs facing 25% or less risk of automation are considered *low risk* (127 occupations, N = 2111), while jobs facing 75% or more risk of automation are considered *high risk* (171 occupations, N = 2189).

$$y_{it} = \alpha_i + \vartheta year_t + \beta highrisk_i + \gamma X_{it} + \delta L_i + \varepsilon_{it} \tag{2}$$

These alternate specifications allow us to determine the effects of automation risk when one works in high-risk (and very high-risk) jobs as compared to low-risk jobs, a perhaps more intuitive measure and one for which we anticipate more extreme impacts on well-being. Our sample sizes are reduced in these analyses to 4300 and 1622 from the full sample in model 1, where N equals 5718. As discussed, this strategy of focusing on very high-risk and very low-risk workers, jobs for which there should be less debate about automation risk, helps respond to concerns that FO's methodology may not accurately predict automation risk.

3.2.4. Differences over time

Our next set of analyses, in Section 4.2, relaxes the assumption in (1) that automation risk is time-invariant by including a set of interaction terms with the year variables. This difference-in-differences specification makes sense intuitively if the prevalence or intensity of automation have changed over the period covered by our data, especially if the range of what can possibly be automated has expanded, as per FO's arguments. Our differences-in-differences analyses use the following model specification:

$$y_{it} = \alpha_i + \vartheta year_t + \beta risk_i + \phi risk_i {*} year_t + \gamma X_{it} + \delta L_i + \varepsilon_{it} \tag{3}$$

In (3), the coefficient represents the effect of automation risk on the respective well-being outcome variable in the year 2002, and ϕ represents the additional effect of automation risk associated with each $year_t$ covered in the dataset as compared to the effect of automation risk in the base year. As before, we repeat the same logic of adding sets of variables (first worker covariates, then job content and context factors) progressively to have a better grasp of possible causal mechanisms.

This analysis allows us to consider whether the effects of automation on well-being are changing over time, for example by decreasing stress or job satisfaction as compared to earlier years. This is important for analyzing the plausibility of our hypotheses, as changes over time may suggest the ways in which workplace adoption of automation and AI is evolving.

3.2.5. Insecurity hypothesis

Our last analyses in Section 4.3 explore the extent to which we can explain effects of automation risk on well-being through the *insecurity* channel—namely, we test the job insecurity hypothesis (H5) that people experience less well-being *because* the threat of automation makes them feel less secure about their jobs. As noted, Patel and colleagues [85] do find evidence consistent with this mechanism, though their analysis relies on relatively coarse county-level data and does not explicitly account for worker awareness, which is arguably the key mediator of this mechanism.

We first regress our measure of job security on automation risk to verify whether increased automation risk induces insecurity. We do so in a bivariate regression and when controlling for worker and job covariates. Then, we repeat the base models in (1) for satisfaction, stress, and health with job security included as an additional *independent* variable. If worker insecurity is a significant channel influencing worker well-being, we should expect to see substantive changes to coefficients on risk when insecurity is included, compared to the base models in 4.1 when

[15] To compute E-values, we adjust our models to obtain odds-ratios rather than predicted effects by unit increases, which are then used to calculate risk ratios. We adjust the core model by replacing the dependent variables and the automation risk variable by dummies and run logistic regressions. For example, we convert the ordinal job satisfaction variable into a dummy equal to 1 for ‘satisfied’ and 0 otherwise. For automation risk, we replace the continuous variable by two different binary specifications: above the 50th risk percentile or below it, and above the 75th percentile or below it. Note that these specifications do not change the conclusions as compared to our main models.

[16] When employing the 95/5 thresholds, we have 70 occupations and 1105 observations at or below the 5% risk level, and 40 occupations and 517 observations above at or above the 95% risk level.

Table 2
Impacts of automation/AI on worker well-being: OLS regressions.

Variables	Job Satisfaction			Job Stress			Overall Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk	−0.09***	−0.06***	−0.01	−0.12***	−0.08***	−0.05***	−0.14***	−0.08***	−0.06***
	(−0.13)	(−0.09)	(−0.01)	(−0.12)	(−0.07)	(−0.05)	(−0.14)	(−0.08)	(−0.06)
Factor Variables:									
Work Conditions			0.26***			−0.17***			0.09***
			(0.35)			(−0.16)			(0.08)
Social Context			0.07***			−0.06***			0.04***
			(0.10)			(−0.06)			(0.04)
Benefits			0.11***			0.00			0.06***
			(0.15)			(−0.00)			(0.06)
Manual Work			0.02*			−0.09***			0.02
			(0.02)			(−0.09)			(0.02)
Workload			−0.11***			0.36***			−0.07***
			(−0.16)			(0.35)			(−0.06)
Autonomy			0.14***			0.12***			0.06***
			(0.20)			(0.12)			(0.06)
Control Variables		✓	✓		✓	✓		✓	✓
Constant	3.35***	3.28***	3.11***	3.09***	2.62***	2.97***	3.66***	3.86***	3.80***
R-squared	0.02	0.07	0.42	0.01	0.07	0.27	0.02	0.06	0.09

Notes: 1. N = 5718. 2. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. 3. Control variables include gender, race/ethnicity, age, age-squared, marital status, education status, part-time job, industry, and year. 4. Normalized beta coefficients in parentheses. Beta coefficients should be interpreted in terms of standard deviation effects. For instance, a one standard deviation increase in autonomy is associated with an increase in job satisfaction of 0.20 standard deviations, holding the other variables constant (column 3). 5. Full results available in Table B1 in the appendix.

insecurity is not included.

4. Results

4.1. Impacts of automation and AI on worker well-being

Our primary models which depict the impacts of automation risk on worker well-being are shown in Table 2.[17] We first estimate bivariate associations between automation risk and well-being without controlling for any covariates. Columns 1, 4, and 7 show these initial models, with unstandardized coefficients (as well as standardized coefficients in parentheses). The results are as follows: a one standard deviation increase in (the standardized measure of) automation risk is associated with a decrease in job satisfaction of −0.09, stress of −0.12, and overall health of −0.14 units in their respective scales (corresponding to standardized reductions of −0.13, −0.12 and −0.14 standard deviations of each dependent variable).

However, as these simple bivariate associations do not reflect fully specified models, we add in demographics (i.e., age, gender, race/ethnicity, marital status, education level), industry, year fixed effects, and part-time work control variables in columns 2, 5, and 8. Controlling for these variables helps to minimize the possibility of spurious effects; this translates into reduced coefficients on automation risk. The coefficients on job satisfaction, stress, and health decrease by 33%, 33%, and 43%, respectively. However, they remain highly statistically significant and in the same direction.

In columns 3, 6 and 9, we add the six researcher-created factors to control for job content and context, causing a further reduction in coefficient magnitudes. The coefficients on the factor variables have the expected signs. Better working conditions and social context are associated with more satisfaction and health and less stress. Conversely, increased workload reduces satisfaction and health, but increases stress. More benefits are associated with more satisfaction and health but do not significantly affect stress. Manual work reduces stress, probably by reducing cognitive load. Interestingly, higher autonomy brings more satisfaction and health but also more stress.

As some of the effects of automation risk may be transmitted through one or more of these factors, the coefficients on automation risk resulting from these specifications may underestimate the true total effect of automation and AI in worker well-being. Nevertheless, using this conservative specification, we still find a negative effect of automation risk on job stress and overall health on the order of −0.05 and −0.06 standard deviations, respectively. However, we have no convincing evidence of effects on satisfaction once controlling for this wide range of job characteristics.

Across the specifications, the conclusions remain similar: for individuals with similar demographic characteristics, working in the same industries and for a similar number of hours, automation risk is meaningfully associated with decreases in stress and health. This finding sheds light on our set of hypotheses. The most optimistic hypothesis, the creative freedom hypothesis (H1), posits that workers fortunate enough to not be displaced by technology will be complemented through a positive, symbiotic interaction. Our findings cast doubt on this popular hypothesis often used to describe the ostensible benefits of automation-worker complementarity. Our results show that job satisfaction does not increase; it may decrease or remain neutral at best. Moreover, health outcomes appear to decrease, a clearly negative finding for worker well-being.

The finding that stress decreases may seem counterintuitive at first glance, as a reduction in stress is presumably a good outcome for worker well-being. However, as discussed in Section 2, human well-being admits of seemingly paradoxical patterns. The loss of meaning hypothesis (H3) makes the most sense of this pattern. It suggests that, *while work may be getting easier, it is not becoming better*. Instead, high levels of automation may reduce the difficulty of one's work, but at the cost of inducing a relative increase in repetitive, boring, or insufficiently challenging tasks. Despite the one potentially positive effect on well-being

[17] A brief discussion of correlations is helpful for assessing general relationships depicted in the conceptual framework in light of expectations, as well as for interpreting results (a correlations table is available in Table A2 in the appendix). Automation risk is negatively correlated with job satisfaction, stress, and health, and with all six factors. Overall, the correlations are modest but meaningful, with the highest values in the case of autonomy (−0.27) and manual work (−0.25). Further, all the factors except for workload are positively correlated to job satisfaction and health. Correlations are stronger with job satisfaction, which is expected as this variable is a direct product of workplace experiences, whereas overall health depends on several other aspects of life. Differently, stress is positively correlated with autonomy, benefits, and workload, but negatively correlated to work conditions, social environment/management, and manual work.

then—a reduction in stress—automation does not appear to lead to the kind of creative freedom that some optimists about technological complementarity imagine.

Despite the significant number of covariates included, it is difficult to fully establish causation in this kind of study. Therefore, we employ a sensitivity analysis to assess the plausibility that an omitted variable would explain away observed statistically significant results for stress and health, using the E-value measure developed by VanderWeele and Ding [120]. After converting our models into logistic regressions based on binary specifications of automation risk (above versus below 50% risk) and the dependent variables, we conclude that we would need an unmeasured confounder associated with both the respective dependent variable and automation risk by risk ratios of 1.43-fold in the stress model and 1.60-fold in the health model, conditional on the measured covariates, in order to explain away observed effects. While we cannot be certain, the sensitivity analysis suggests that there would need to be an omitted variable significantly stronger than automation risk, and it is somewhat less likely that there is an omitted variable of this strength, given the number of covariates already included.[18]

To better understand the causal mechanisms at play, we also estimate one-factor-at-a-time models for each well-being outcome (see Table B2 in the appendix). For stress and health, the inclusion of any single factor does not affect the coefficient on automation risk dramatically, nor change the main conclusions above. For job satisfaction, however, controlling for the *autonomy* factor alone causes the coefficient on automation risk to drop to nearly zero and lose its statistical significance. Autonomy, perhaps unsurprisingly given how automation impacts worker agency and discretion, appears especially important. Indeed, automation risk has a large, negative bivariate association with autonomy (−0.27), the largest of any of our six factor variables. Autonomy is associated with increases in stress as well as job satisfaction and health, which aligns with the idea that more challenging work can create better work.

Unfortunately for proponents of H1, automation risk is associated with *decreased* autonomy, which likely contributes to the corresponding decrease in stress and health and neutral or negative effects on job satisfaction. However, there is one optimistic note here: if adopters of automating technologies in the workplace take note of these findings and adopt automation in ways which increase rather than decrease autonomy, positive effects on worker well-being may follow.

Fig. 2 depicts our primary results, using the full specifications for each well-being outcome from columns 3, 6, and 9, as well as two additional specifications of our primary measure of automation risk. The first alternative specification introduces a dummy variable contrasting high-risk against low-risk workers, measured as workers and occupations with 75% or higher risk compared to workers with 25% or lower risk using the FO measure. The second alternative specification uses 95% and 5% thresholds, representing even more extreme ends of the distribution of worker risk. The rationale for comparing these extremes lies in the expectation that these should surface the most dramatic impacts—an analysis that should be clear as we move into the next section.

The results across these three specifications suggest few effects of automation risk on job satisfaction, if any. On the other hand, stress and health manifest statistically significant negative effects. We expect the 75/25 (dotted pink lines) and especially the 95/5 specification (dashed green lines) to exhibit more extreme effects compared to the primary models (continuous grey lines). Notably, the effect of automation risk on overall health does appear to have a substantially larger negative magnitude as these specifications become more extreme. Interestingly, in the 95/5 specification, high-risk workers appear to experience more stress compared to their counterparts than in the 75/25 specification, though the difference is not significant, likely due to the sample size reduction. We suggest here that any benefits of decreased stress appear to be *less concentrated on the highest-risk workers*. This is important as the highest-risk workers are those most likely to have faced automation in the workplace over time, a discussion we turn to below.[19]

4.2. Over-time differences

The models in 4.1 assume by construction that the effects of automation and AI have remained constant over the period of analysis. However, there are good reasons to think that the prevalence and intensity of workplace adoption of automation, including new forms of automation due to AI, have changed significantly between 2002 and 2018. Paying attention to these over-time changes is important, as how automation evolves may signify different over-time effects on well-being worth monitoring and responding to.

The difference-in-differences models in Table 3 allow us to examine possible time-variant effects in the past two decades (see Table B3 in the appendix for the full results). For each well-being outcome, the primary coefficients on automation risk correspond to the effects in the year 2002. The *risk*year* interaction terms then correspond to the differences between the indicated year and the beginning of the study period. The first observation worth highlighting is that the primary coefficients on automation risk as well as coefficients on the covariates and factor variables are largely similar to those reported in Table 2. This aligns with our expectations.

There are, however, a few new findings worth noting, especially the pattern of over-time changes in job stress. In Table 3, in the year 2002, automation risk is most strongly associated with stress rather than satisfaction or health, and this effect is highly robust to the inclusion of covariates and factors. Yet, this strong effect appears to weaken over time as represented by positive interaction terms in 2006, 2010, 2014, and 2018. For example, in 2018 as compared to 2002, the reduction in stress associated with automation has *lessened* in magnitude from −0.12 to −0.05 (a relative *increase* in stress of 0.07). The finding that the stress-reduction effect of automation is weakening is of potential concern, as this is arguably the sole 'good' impact of automation on worker well-being.

Distinctly, there is no evidence of over-time changes in the effects of automation risk on satisfaction once we control for job content and context, reflected by the small coefficients and lack of significance for the interaction terms. This is not surprising as we have already identified that the autonomy factor, also included in Table 3, can substantially explain the effects of automation risk on job satisfaction by itself. Finally, there is no evidence that automation risk affected health in 2002 once covariates and especially factor variables are included. This remains true for every year, except in the *risk*2018* interaction. However, we interpret the negative interaction effect for 2018 with caution, as these effects do not present in any consistent fashion over time.

Why might worker stress associated with automation be rising (or decreases in stress disappearing) over time as compared to 2002? A possible explanation is that another of the hypotheses such as the surveillance and control hypothesis (H4) is becoming increasingly relevant. While automation may have initially substituted for certain difficult worker tasks in a manner that *reduced* stress, as the adoption of

[18] If we were to split automation in dummies at the 50th percentile instead, the E-values would be even larger: 1.77 for stress and 1.63 for health.

[19] As discussed in Section 2.2, the automation risk measure developed by FO is a forward-looking one, as some of the technologies conceptualized in FO's method have not been fully developed or scaled to the market yet (and are only expected to do so in the next 10–20 years). However, the FO scale also incorporates routine/repetitive tasks among those that lead occupations to be at risk of computerization, and for those, the effects of automation have already been felt by the workforce for a few decades, as shown extensively in ALM's and others' work. As a result, despite the forecasting element in FO, there is substantial overlap with ALM's older measure, as shown in Fig. D1 in the appendix, which supports the use of FO's measure to investigate past impacts as well to consider future ones.

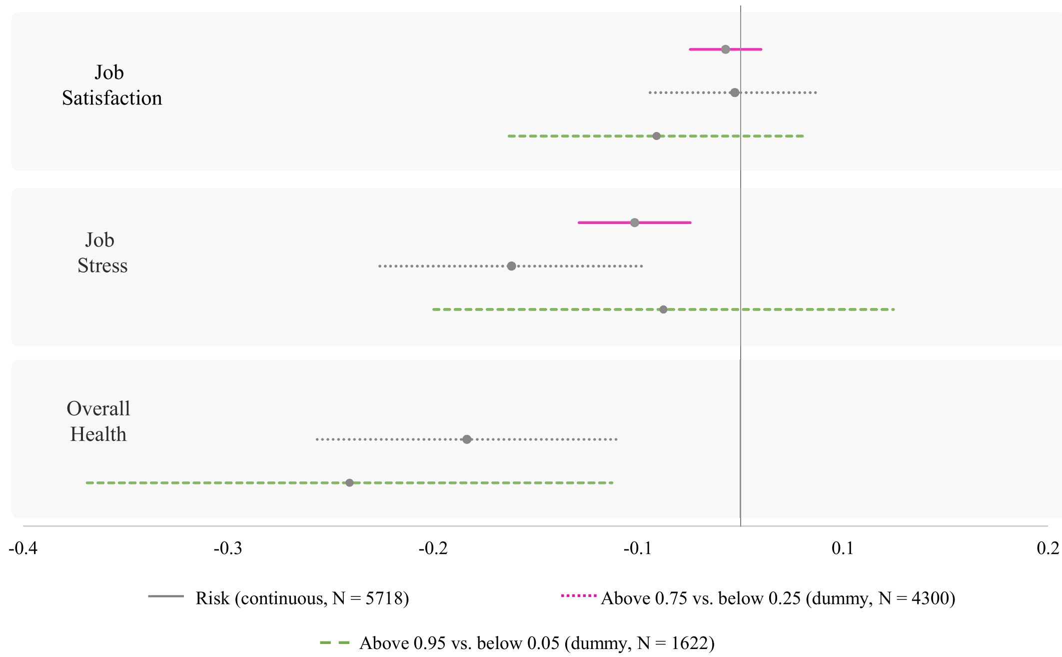


Fig. 2. Impacts of automation/AI on worker well-being: Alternative specifications.
Notes: 1. Coefficients and 95% confidence intervals of different specifications of automation risk on worker well-being, obtained from OLS regressions. 2. Models include standard controls and factor variables (see text for details). 3. Coefficients should be read as: for the standardized variable, the effect of a one standard deviation increase in automation risk; for the dummy variables, the difference in expected outcomes between high- and low-risk jobs.

Table 3
Over-time impacts of automation/AI on worker well-being: Difference-in-Difference regressions.

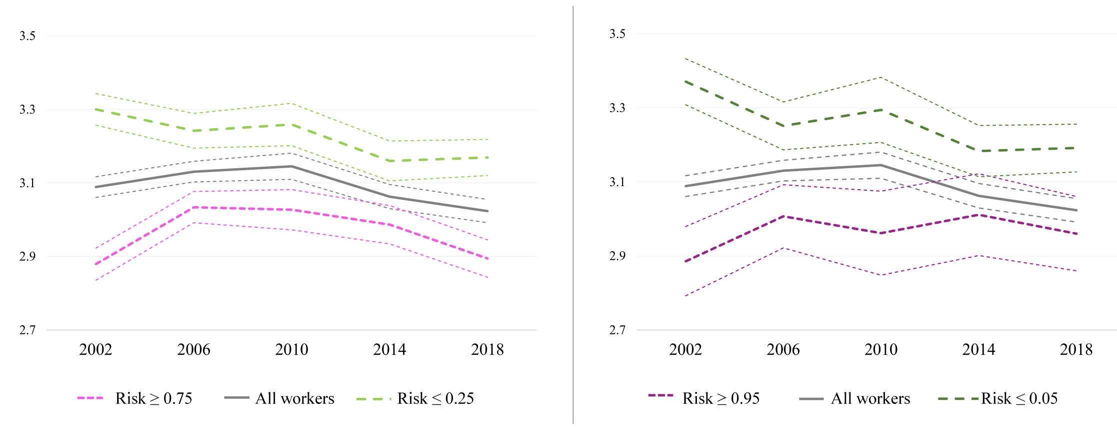
Variables	Job Satisfaction			Job Stress			Overall Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk	−0.09***	−0.06***	−0.01	−0.12***	−0.14***	−0.12***	−0.14***	−0.05*	−0.02
Year 2006		−0.06**	−0.02		0.04	0.01		−0.12***	−0.10***
Year 2010		−0.09***	−0.08***		0.09**	0.06		−0.12***	−0.11***
Year 2014		−0.03	−0.02		0.02	−0.01		−0.08**	−0.08*
Year 2018		0.00	0.01		−0.02	−0.06		−0.21***	−0.20***
Risk*2006		−0.01	−0.02		0.09**	0.13***		−0.03	−0.04
Risk*2010		−0.03	−0.01		0.09**	0.06*		−0.04	−0.03
Risk*2014		0.01	0.01		0.11***	0.10***		−0.01	−0.01
Risk*2018		0.02	0.01		0.08**	0.07*		−0.09**	−0.09**
Control Variables		✓	✓		✓	✓		✓	✓
Factor Variables			✓			✓			✓
R-squared	0.02	0.07	0.42	0.01	0.08	0.27	0.02	0.06	0.09

Notes: 1. N = 5718. 2. ***p < 0.01, **p < 0.05, *p < 0.1. 3. Control variables include gender, race/ethnicity, age, age-squared, marital status, education status, part-time job, and industry. Constant omitted in table. Factor variables' coefficients remain similar to the ones shown in Table 2. 4. Full results available in Table B3 in the appendix.

Table 4
Evaluating the insecurity hypothesis.

Variables	Job Security			Satisfaction	Stress	Health
	(1)	(2)	(3)	(4)	(5)	(6)
Risk	−0.05***	−0.03**	0.01	−0.01	−0.05***	−0.06***
Job Security				0.09***	−0.05***	0.04**
Control Variables		✓	✓	✓	✓	✓
Factor Variables			✓	✓	✓	✓
R-squared	0.00	0.03	0.25	0.42	0.27	0.09

Notes: 1. N = 5710. 2. ***p < 0.01, **p < 0.05, *p < 0.1. 3. Control variables include gender, race/ethnicity, age, age-squared, marital status, education status, part-time job, industry and year. Constant omitted in table. 4. Full models available at Table C1 in the appendix.



A1. Above 75% and below 25% risk.

A2. Above 95% and below 5% risk.

Fig. 3. Predicted stress levels by year and risk level.
Notes: 1. Predicted values and confidence intervals from Diff-in-Diff model reported in Table 3, column 6. 2. All models control for the standard covariates and factor variables. 3. Results for job satisfaction and health are available in Fig. B1 in the appendix.

automation and AI matures and evolves, there may be new forms of automated surveillance and control technology in place which monitor or prescribe worker behavior in a manner that *increases* stress. If H4 is indeed coming to bear, we might expect results to be concentrated on the highest-risk workers, as many of these workers have been at high risk for a longer period of time. These workers may also face the most scrutiny and highly prescriptive forms of management, exacerbated by how managers are adopting workplace automation. Here, the results in Fig. 2 may be relevant, as they suggest that the highest-risk workers (95% risk and above) experience less stress reduction (or relatively higher stress) when compared to their low-risk counterparts than do 75% risk workers.

To more thoroughly evaluate the possibility that different risks may translate into distinct dynamics over time, we plot mean predicted stress for workers experiencing different levels of automation risk by year. As shown in Fig. 3, there are visible differences in the levels and trends of worker stress (we plot similar figures for job satisfaction and overall health in Fig. B1 in the appendix). First, workers in the bottom 25% and 5% of the risk distribution (in light and dark green) exhibit substantial decreases in stress over time. In contrast, their counterparts (in light and dark purple) facing a 75% risk of automation exhibit little change or even a slight increase in stress, while those facing a 95% risk of automation appear to exhibit notable increases in stress over time. While we cannot statistically distinguish the above 95% and 75% trends or the below 5% and 25% trends, these results provide some preliminary evidence in support of the idea that groups at different risk levels may reflect different hypotheses or mechanisms related to automation.

The results in this section should be interpreted with caution. The labor force composition has changed as younger generations have entered and older ones retired. Some newer workers may have entered a workforce in which automation was always in place, resulting in minimal changes to their experience of automation or their well-being outcomes. Other workers may have left the workforce due to automation or other reasons, limiting our ability to observe differences in well-being over time. The specific forms of automation and AI in place also vary by occupation and over time in ways that are hard to model. We cannot disentangle all these elements here, an unavoidable limitation of our analysis. For this reason, we suggest caution in generalizing results when our findings are not strong and consistent. More research will be needed to evaluate our results.

4.3. *Insecurity hypothesis*

In the final section of our analysis, we turn to the insecurity hypothesis (H5), according to which insecurity is an important variable mediating automation risk's impact on worker well-being. Under this mechanism, automation risk might lead to worse well-being if workers anticipate negative future impacts on their employment status (substitution) or working conditions (complementarity), and develop anxiety, stress, or fear in response. This hypothesis, building on literature on work insecurity, had been extended to the case of automation and tested by Patel and colleagues [85]. They find evidence that higher automation risk is associated with worse health outcomes at the county level.

Our analysis is similar, but we focus on the individual (not county) level and on broader measures of well-being (not limited to health). We divide our analysis into two stages[20] to better understand the causal mechanism. First, we test whether automation risk affects job security, when controlling for covariates. Then, we test whether insecurity *induced by automation risk* affects well-being by adding the job security variable as a covariate to the core well-being regressions in Section 4.1.

In columns 1–3 of Table 4, we therefore repeat the basic well-being model specifications from 4.1, but with job security as the dependent variable. The results in column 1 suggest a substantively small negative association between automation risk and job security. The coefficient shrinks further as we add demographic, industry, and part-time work covariates (column 2), and becomes insignificant once job content and context factors are included (column 3).[21]

While automation and job security are perhaps surprisingly not strongly related, insecurity does appear to significantly influence all well-being outcomes, in line with prior literature. However, these effects *do not* appear to be transmitted because of insecurity *induced specifically by automation risk*. Columns 4–6 in Table 4 show the results from these analyses, which repeat the models from columns 3, 6, and 9 in Table 2

[20] It should be noted that this does not constitute a two-stage least squares strategy, as job insecurity does not qualify as an ideal instrument for a few reasons. First, the correlation between insecurity and automation risk is very low (−0.06), making its relevance questionable. Second, insecurity directly affects the well-being variables, as identified in prior literature and in Table 4, violating the exclusion restriction assumption.

[21] The association between automation risk and insecurity is smaller than for most factors.

but add job security as a control variable. The coefficients on automation risk and on the other covariates remain virtually unchanged as compared to Table 2 when job security is added, suggesting that insecurity is not a major channel through which automation and AI affect well-being.

These results are robust to specifications reported in Table C2 in the appendix. In particular, we expect the insecurity channel to show up—if nowhere else—amongst workers facing the highest levels of automation risk. To test this possibility, we repeat model (3) from Table 4, replacing the continuous specification of automation risk with dummy variable representations of high vs. low risk as introduced in 4.1. We also employ a novel identification strategy using measures of automation risk from both FO and ALM, which exploits the over-time difference in the two models' conceptualizations of automation risk and the evolution of automating technologies. Here, we define a group of *newly risky* workers, defined as those who face risk above 75% (alternatively 95%) in FO, but who face risk below 25% in the original ALM conceptualization. We expect that these newly risky workers should not have experienced changes to their work environment as a result of automation but may be subject to future risks. Thus, if insecurity is a channel affecting well-being, it should be visible in these workers, while the other channels (or hypotheses) should not be in play. We compare these newly risky workers with workers who remained at low risk (below 25%) in both categorizations, which we refer to as *never risky* workers. The results in all specifications fail to provide evidence of H5, and in sum cast significant doubt on the validity of the insecurity hypothesis.

These results suggest, contrary to the findings of Patel and colleagues [85], that the evidence in support of the insecurity channel hypotheses (H5) is not compelling. It does not seem to be the case that high-risk workers are anticipating future effects of automation and suffering harm to their well-being as a result.

How is it possible that workers at high risk are not experiencing well-being harms resulting from the risk of automation? One possibility is that workers are not aware of these risks. Awareness might require workers to be well informed about research like that of FO, or media coverage discussing automation risk in professions like theirs directly. Thus, if workers are not aware of automation risks, they should not feel any automation-induced insecurity. Unfortunately, however, we are not able to account for awareness of risk in our models, an omission also present in the work by Patel and colleagues.[22] We acknowledge this as a potential limitation and suggest that testing this relationship will be important for those exploring this issue.

Alternatively, it is also possible that *even when aware of automation risk*, people do not relate it to their own work, but only to others' work. This may reflect a cognitive bias like the fundamental attribution error, in the sense that individuals deem their own work irreplaceable even if they acknowledge their occupation faces risks generally. This explanation is backed up by results from a Pew Research Center [121] survey, which found that, while 53% believe that software engineers and 77% believe fast food workers face high levels of automation risk, only 30% of respondents saw their *own* jobs as at risk of automation. Research by Coupe [122] on automation risk also suggests that a small share of individuals experience job insecurity due to automation specifically as compared to insecurity resulting from other factors, and findings by Gallie et al. [79] also suggest factors like employee influence over decisions are more important. Consequently, the insecurity channel may be a weak mechanism, not due to lack of awareness but because people (somewhat inconsistently) do not self-identify as being at risk, and because other factors more strongly shape feelings of insecurity.

In conclusion, our results here suggest that even though job security is an important channel affecting worker well-being generally, it does not at present seem to be a influential factor in explaining the effects of automation risk on worker well-being. The mechanisms reflected by our other hypotheses may be ultimately more salient at this time.

5. Discussion

This study sheds light on the critical topic of worker well-being in the context of ongoing and impending technological change. This dimension has been largely overlooked in surrounding discourse and scholarship, which often focuses on labor displacement that may result from automation and AI. This seeming lack of concern over well-being may be partially explained by the common assumption that workers who are not substituted by technology are complemented by it, and better off as a result. This optimistic perspective is, unfortunately, borderline naïve and relies on an overly simplistic understanding of the relationship between technology adoption and worker well-being, one that fails to fully consider socio-technical systems. Most fundamentally then, our contribution is to facilitate conceptual and empirical exploration of automation and AI's impacts on work in a way that recognizes the complexities of well-being.

This exploratory work is certainly subject to several limitations, some of which have been discussed previously. Nevertheless, our study and conceptual framework can help to raise some key conceptual and measurement issues worthy of consideration by scholars. Foremost, our data and analytical methods are observational, rendering the identification of causation difficult. As such, we cannot be certain other factors are not in play, though we do perform a variety of specifications and a sensitivity analysis which help to bolster our confidence. Further, despite our efforts to better conceptualize well-being in the context of technology adoption, we focus on only a few dimensions of well-being. A much larger body of research will be needed to probe the depths of this topic. Our measure of automation and AI in the workplace is also a forward-looking proxy, rather than a definitive measure of automating technology itself. Clearly defining and measuring automation and AI is likely to remain a challenge in this field, especially as the forms of technology adopted in the workplace evolve in tandem with a changing workforce and broader socio-economic environment.

These limitations aside, our findings suggest some clear and important conclusions. Most immediately, *the adoption of automating technologies at work does appear to consistently affect worker well-being across two very important dimensions: job stress and overall health*. These findings are robust to a series of alternative specifications and a wide variety of control variables. Moreover, these effects intensify for workers in jobs facing higher levels of automation risk. On the other hand, we do not observe consistent positive (or negative) changes to job satisfaction.

Evaluating these results in light of our proposed hypotheses tells a dynamic and surprising story. There are indeed effects of automation and AI on well-being, but they are not in line with the most optimistic hypothesis (the creative freedom hypothesis, H1), that is so prevalent in public, policy, and scholarly discourse. Complementarity of human and machine does not appear to be a straightforward case of positive symbiotic interaction. Workers who are complemented by automating technologies do not appear to be more satisfied with their work, and may experience worse health outcomes. Our most important contribution to scholarly and public discourse may be the finding that *complementarity is not a uniform good*, just as substitution of workers perhaps should not be considered a uniform bad.

Instead, the hypothesis which appears to best fit the evidence is the loss of meaningfulness hypothesis (H3), in which more automation makes work easier, but at a cost. Though we do not establish statistically significant negative effects on job satisfaction in our most conservative models, the general trend is negative or neutral at best. Thus, while a decrease in worker stress *might* be considered a good outcome initially, it may be at the cost of making work less interesting, challenging, meaningful, and satisfying. This is a far departure from the creative freedom

[22] At this time, the only variable that we identified as a potential proxy for awareness of automation risk was available in 2008, a year for which we do not have job security or well-being variables.

that optimists imagine results from increased automation and AI at work.

Our over-time findings add further complexity to the story. While automation risk is consistently associated with a decrease in stress, this decrease has been tempered considerably since 2002. The trends we detect suggest that automation and AI may be gradually 'adding the stress back into work,' especially in the highest-risk jobs. If this trend continues, automation could even contribute to increased stress in the coming years.

Though more work is needed to evaluate these patterns, we posit that other hypotheses, such as the cognitive overload (H2) or the control and surveillance hypotheses (H4), may be coming into play. The former hypothesis considers that the automation of easy, routine work may lead to a surplus of more difficult, cognitive work, likely to make work more stressful. The latter hypothesis considers that automation and AI may be increasingly used to monitor, measure, and manage workers in potentially disturbing ways. While there is anecdotal evidence that both hypotheses are relevant, their prevalence and future remain to be seen. Yet, they strongly urge attention by scholars, business managers, and public decision-makers to minimize detrimental usages of automation and consider how to augment working environments in positive ways [98].

Finally, our work casts doubt on the job insecurity hypothesis (H5), contradicting the limited work we are aware of on the topic. We find no evidence that automation is exacerbating feelings of insecurity, or that insecurity induced by automation is affecting well-being. Workers may be unaware of automation risk altogether or may simply believe their colleagues' jobs are more vulnerable than their own. This finding raises questions: if predictions of high levels of automation risk are correct, should workers be more worried? Should there be more efforts to inform them, to help empower or prepare them? The issue of worker insecurity is far from settled; more work is needed, and with some urgency.

Across all models, aspects of job content and context—represented in this study as factor variables—are mediators of well-being indispensable to understanding causal pathways. The implication is clear: if managers adopt automating technologies in ways which more fully consider these interrelated social and technical factors, positive rather than negative effects may follow. This finding reminds us that technology is not neutral, and that the adoption of technologies following technological revolutions should be accompanied by a contextual discussion in society and in the workplace, as recommended by the International Labour Office - ILO [80] in the past.

In addition to the findings highlighted above, there are several opportunities surfaced by our study worth addressing in future scholarship. First, analytical and measurement challenges surround our conceptual framework, especially the causal relationships between automation and job context and content factors. These variables and others may directly affect well-being but also mediate the risk of automation in the first place. These relationships need to be disentangled. Second, the kinds and effects of automation and AI will vary across occupations, worker types, industry, education and skill levels, race/ethnicity and gender. Different socio-technical mechanisms are likely to be in play, especially as conditions on the ground and in the nature of the technologies themselves change over time. Third, defining and measuring the use of automation and AI in the workplace remains a significant challenge. To improve our understanding of these and other issues, we encourage other scholars to explore and model specific elements of our conceptual framework, and to extend and revise it. We recommend that careful studies involving a wide variety of qualitative and quantitative methods should be performed, including ethnographic, survey, observational, forecasting, and experimental approaches, among others.

6. Conclusions

The well-being of workers is an issue of tremendous social importance, yet one that is often overlooked in discussions of automation, AI, and the future of work. Too often, scholarly and policy discourse has simplistically emphasized the goods of technological complementarity contrasted against the harms of technological substitution. Distinctly, our research examines the skill-biased technological change literature and well-being literature to explicitly conceptualize automation and AI's possible mixed effects on worker well-being. We consider five such hypotheses through empirical analysis, using three dimensions of well-being, longitudinal data from 16 years of the GSS QWL module, and a measure of automation risk.

Despite findings that automation and AI may be associated with lower stress, negative results regarding worker health, and mixed effects regarding job satisfaction do not support the most optimistic view of technological complementarity. That the decrease in stress appears to be shrinking in recent years, and that effects are concentrated on the highest-risk workers demands special attention. Our conceptual framework, results, and the history of technological adoption indicate that *technological complementarity should not be viewed as a uniform good.* Moreover, they emphasize that the impacts of automation and AI are not deterministic nor independent of the work environment in which they are adopted; rather these technologies influence and are influenced by job content and context, as well as by broader socio-technical and economic factors.

As such, it may be insufficient to educate and train workers in the hopes that workers with skills that complement technology will ultimately fare well in the workplace. A more robust course of research and action is prudent. Scholars will have a key role in increasing decision-makers' awareness and understanding of the complexities of worker well-being. In turn, managers, firms, and policymakers can avoid assumptions of technological determinism and exercise their agency meaningfully by shaping work conditions, technological adoption, and regulation of automation and AI in the interest of worker well-being.

In sum, during this key moment in the adoption of automation and AI in our society and workplace, it is worthwhile to remember Kranzberg's [123] adage that "technology is neither good nor bad; nor is it neutral."

Author statement

Luísa Nazareno: conceptualization, formal analysis, writing, investigation, methodology, visualization. **Daniel S. Schiff**: conceptualization, writing, formal analysis, investigation, methodology, visualization.

Declaration of competing interest

None.

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Appendix A. Descriptive tables

Table A1
Factor loadings.

Variable Description and Factor	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Unique-ness
Social Context & Management	**α: 0.85**						
Relations between management and employees (*)	0.72	0.17	−0.08	−0.04	0.00	−0.03	0.39
Coworkers take a personal interest in respondent (R)	0.64	−0.05	0.11	0.05	0.15	0.03	0.52
R is likely to be praised by supervisor	0.63	0.01	−0.02	0.08	0.12	0.03	0.59
Supervisor is concerned about welfare	0.58	0.14	−0.09	0.03	0.25	0.04	0.51
R trusts management at work	0.57	0.39	0.06	0.00	−0.12	0.02	0.33
Promotions are handled fairly	0.53	0.13	−0.09	−0.03	0.45	−0.04	0.41
Coworkers can be relied on when R needs help	0.47	−0.04	0.06	−0.20	0.14	0.03	0.63
Workplace runs in smooth manner	0.45	0.37	0.08	−0.16	−0.11	−0.02	0.41
R is treated with respect at work	0.39	0.34	0.27	−0.01	−0.11	0.08	0.44
Workplace Safety & Conditions		**α: 0.87**					
There are no shortcuts on worker safety	−0.03	0.84	0.00	−0.01	0.09	0.02	0.29
Worker safety is a priority at work	0.03	0.84	−0.01	0.02	0.12	−0.01	0.27
Management & employees work together for safety	0.11	0.84	−0.01	0.02	0.07	0.01	0.22
Safety and health condition are good at work	0.07	0.78	0.03	0.00	0.04	0.07	0.31
Work conditions allow productivity	0.17	0.39	0.28	−0.21	−0.07	−0.06	0.49
Autonomy			**α: 0.70**				
R does numerous things on job	−0.04	0.01	0.72	0.15	0.06	0.02	0.47
Job allows R's use of skills	0.01	0.16	0.71	−0.07	−0.09	0.02	0.38
Job requires R to learn new things	−0.07	0.00	0.67	0.18	0.22	0.10	0.46
There are opportunities to develop abilities	0.22	−0.03	0.49	−0.10	0.37	0.04	0.44
R knows what is expected on job	0.00	0.25	0.38	−0.20	−0.31	−0.19	0.54
How often R take part in decisions	0.02	0.01	0.37	0.08	0.32	0.01	0.71
R has a lot of freedom to decide how to do job	0.27	−0.09	0.36	−0.23	0.09	0.13	0.64
Workload				**α: 0.69**			
R has too much work to do well	0.23	−0.04	0.02	0.75	−0.08	−0.02	0.49
R has enough time to get the job done	−0.16	0.00	0.07	0.69	−0.07	0.04	0.43
How often there are not enough staff	−0.21	0.03	0.11	0.53	0.13	−0.10	0.59
There is enough help and equip. to do the job	−0.27	−0.09	−0.06	0.51	−0.16	0.05	0.48
Job requires R to work fast	0.07	0.02	0.26	0.47	−0.01	−0.34	0.61
There is enough info to get the job done	−0.28	−0.03	−0.14	0.45	−0.02	0.13	0.57
Career Advancement & Benefits					**α: 0.45**		
R's chances for promotion are good	0.13	0.04	0.09	−0.08	0.68	−0.15	0.47
Fringe benefits are good	−0.01	0.14	0.07	−0.08	0.62	0.07	0.54
Manual Work						**α: 0.62**	
R does repeated lifting (**)	−0.02	0.03	0.08	0.03	−0.03	0.82	0.32
R performs forceful hand movements (**)	0.08	0.03	0.04	−0.02	−0.05	0.80	0.35

Notes: 1. Rotation using promax 2. 2. Variables from Quality of Worklife (QWL) module of GSS. All variables are Likert variables ranging from 1 to 4, except if: * (1–5) and ** (0,1). 3. "R" stands for respondent.

Table A2
Correlations table.

		1	2	3	4	5	6	7	8	9	10	11
1	Automation Risk	1.00										
2	Job Satisfaction	−0.13	1.00									
3	Job Stress	−0.12	−0.26	1.00								
4	Overall Health	−0.14	0.18	−0.10	1.00							
5	Job Security	−0.06	0.37	−0.15	0.12	1.00						
6	Safety & Conditions	−0.07	0.53	−0.27	0.15	0.41	1.00					
7	Social & Management	−0.05	0.34	−0.16	0.11	0.23	0.36	1.00				
8	Benefits	−0.15	0.22	0.01	0.12	0.25	0.14	0.05	1.00			
9	Manual Work	−0.25	0.10	−0.07	0.11	0.02	0.07	0.02	0.13	1.00		
10	Workload	−0.11	−0.30	0.45	−0.07	−0.20	−0.32	−0.23	0.05	−0.02	1.00	
11	Autonomy	−0.27	0.37	0.07	0.15	0.20	0.31	0.32	0.09	−0.01	−0.05	1.00

Appendix B. Regression results: satisfaction, stress, and health

Table B1
OLS regressions (full results).

Variables	Job Satisfaction			Job Stress			Overall Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk	−0.09***	−0.06***	−0.01	−0.12***	−0.08***	−0.05***	−0.14***	−0.08***	−0.06***
Work Conditions			0.26***			−0.17***			0.09***
Social Context			0.07***			−0.06***			0.04***
Benefits			0.11***			−0.00			0.06***
Manual Work			0.02*			−0.09***			0.02
Workload			−0.11***			0.36***			−0.07***
Autonomy			0.14***			0.12***			0.06***
Year 2006		−0.06**	−0.02		0.04	0.01		−0.12***	−0.10***
Year 2010		−0.09***	−0.08***		0.09**	0.06		−0.12***	−0.11***
Year 2014		−0.03	−0.02		0.03	−0.01		−0.08**	−0.08*
Year 2018		−0.00	0.01		−0.02	−0.05		−0.21***	−0.20***
Age		−0.01	0.00		0.03***	0.01**		−0.03***	−0.02***
Age squared		0.00***	0.00		−0.00***	−0.00***		0.00***	0.00***
Female		0.03	0.03*		0.09***	0.07***		−0.04	−0.04
Black		−0.08***	−0.07***		−0.31***	−0.26***		−0.02	−0.02
Latino		0.04	0.01		−0.27***	−0.23***		−0.05	−0.06
Other race/Ethnicity		−0.11**	−0.05		−0.14**	−0.13**		−0.12*	−0.10
Married		0.11***	0.05***		−0.07**	−0.04		0.11***	0.08***
High School		0.04	0.01		0.06	0.05		0.24***	0.23***
Junior College		0.02	−0.05		0.07	0.06		0.35***	0.31***
Bachelor's		0.05	−0.01		0.09	0.06		0.54***	0.50***
Graduate		0.06	−0.01		0.17**	0.10*		0.57***	0.53***
Part-time Job		−0.07***	−0.07***		−0.35***	−0.19***		−0.07*	−0.06*
Industry 1		0.07	0.03		−0.04	−0.04		0.21*	0.18
Industry 2		−0.08	0.04		−0.13	−0.21**		0.19	0.22**
Industry 3		−0.11	−0.02		0.02	−0.07		0.19*	0.22**
Industry 4		0.01	0.13*		0.05	0.02		0.24**	0.28**
Industry 5		−0.09	0.02		0.06	−0.04		0.17	0.20
Industry 6		0.00	−0.03		−0.06	−0.02		0.41***	0.37***
Industry 7		−0.04	−0.03		0.05	0.07		0.26**	0.25**
Industry 8		0.02	0.08		0.02	−0.00		0.17	0.19*
Industry 9		−0.14*	−0.07		0.09	0.01		0.25**	0.27**
Industry 10		0.02	0.01		−0.24*	−0.11		0.22*	0.20*
Industry 11		0.03	0.11		−0.02	−0.06		0.28**	0.30**
Constant	3.35***	3.28***	3.11***	3.09***	2.62***	2.97***	3.66***	3.86***	3.80***
R-squared	0.02	0.07	0.42	0.01	0.07	0.27	0.02	0.06	0.09

Notes: 1. N = 5718. 2. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. 3. Industry codes: 1: Construction. 2: Manufacturing. 3: Wholesale and Retail Trade. 4: Transportation and Warehousing and Utilities. 5: Information. 6: Finance and Insurance, and Real Estate, and Rental and Leasing. Industry 7: Professional, Scientific, and Management, and Administrative, and Waste Management Services. 8: Educational Services, and Health Care and Social Assistance. 9: Arts, Entertainment, and Recreation, and Accommodation and Food Services. 10 Other Services, Except Public Administration. 11: Public Administration.

The table below shows the coefficient on automation risk and on individual factors resulting from the inclusion of one factor at a time across a set of regressions.

Table B2
OLS regressions (one-factor-at-a-time).

	Job Satisfaction		Job Stress		Overall Health		Job Security	
	Coef. on Risk	Coef. on Factor	Coef. on Risk	Coef. on Factor	Coef. on Risk	Coef. on Factor	Coef. on Risk	Coef. on Factor
Work Conditions	−0.04***	0.38***	−0.09***	−0.27***	−0.07***	0.15***	−0.01	0.34***
	(−0.06)	(0.52)	(−0.09)	(−0.27)	(−0.07)	(0.15)	(−0.01)	(0.42)
Social Context	−0.05***	0.23***	−0.09***	−0.17***	−0.07***	0.11***	−0.02	0.19***
	(−0.07)	(0.32)	(−0.08)	(−0.16)	(−0.07)	(0.11)	(−0.02)	(0.23)
Benefits	−0.04***	0.17***	−0.08***	−0.04***	−0.07***	0.08***	0.00	0.21***
	(−0.06)	(0.23)	(−0.08)	(−0.04)	(−0.07)	(0.08)	(−0.00)	(0.25)

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Table B2 (*continued*)

	Job Satisfaction		Job Stress		Overall Health		Job Security	
	Coef. on Risk	Coef. on Factor	Coef. on Risk	Coef. on Factor	Coef. on Risk	Coef. on Factor	Coef. on Risk	Coef. on Factor
Manual Work	−0.06***	0.03***	−0.09***	−0.14***	−0.08***	0.03*	−0.03**	−0.01
	(−0.08)	(0.04)	(−0.09)	(−0.14)	(−0.08)	(0.03)	(−0.03)	(−0.02)
Workload	−0.08***	−0.23***	−0.05***	0.42***	−0.09***	−0.11***	−0.04***	−0.18***
	(−0.11)	(−0.32)	(−0.05)	(0.42)	(−0.09)	(−0.11)	(−0.05)	(−0.22)
Autonomy	−0.01	0.26***	−0.07***	0.02	−0.06***	0.11***	0.01	0.16***
	(−0.01)	(0.36)	(−0.07)	(0.02)	(−0.06)	(0.11)	(0.01)	(0.19)
No Factor	−0.06***		−0.08***		−0.08***		−0.03**	
	(−0.09)		(−0.07)		(−0.08)		(−0.03)	
All Factors	−0.01		−0.05***		−0.06***		−0.01	
	(−0.01)		(−0.05)		(−0.06)		(−0.02)	

Notes: 1. N = 5718 for satisfaction, stress, and health. N = 5710 for job security. 2. ***p < 0.01, **p < 0.05, *p < 0.1. 3. All models include demographics, industry, and part-time status. 4. Normalized beta coefficients in parentheses.

Table B3
DID regressions (full results).

Variables	Job Satisfaction			Job Stress			Overall Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk	−0.09***	−0.06***	−0.01	−0.12***	−0.14***	−0.12***	−0.14***	−0.05*	−0.02
Year 2006		−0.06**	−0.02		0.04	0.01		−0.12***	−0.10***
Year 2010		−0.09***	−0.08***		0.09**	0.06		−0.12***	−0.11***
Year 2014		−0.03	−0.02		0.03	−0.01		−0.08**	−0.08*
Year 2018		−0.00	0.01		−0.02	−0.06		−0.21***	−0.20***
Risk*2006		−0.01	−0.02		0.09**	0.13***		−0.03	−0.04
Risk*2010		−0.03	−0.01		0.09**	0.06*		−0.04	−0.03
Risk*2014		0.01	0.01		0.11***	0.10***		−0.01	−0.01
Risk*2018		0.02	0.01		0.08**	0.07*		−0.09**	−0.09**
Work Conditions			0.26***			−0.17***			0.09***
Social Context			0.07***			−0.06***			0.04***
Benefits			0.11***			−0.00			0.06***
Manual Work			0.02*			−0.09***			0.02
Workload			−0.11***			0.36***			−0.07***
Autonomy			0.14***			0.12***			0.06***
Age		−0.01	0.00		0.03***	0.01**		−0.03***	−0.02***
Age squared		0.00***	0.00		−0.00***	−0.00***		0.00***	0.00***
Female		0.03	0.03*		0.09***	0.07***		−0.04	−0.04
Black		−0.08***	−0.07***		−0.31***	−0.26***		−0.02	−0.02
Latino		0.04	0.01		−0.27***	−0.23***		−0.04	−0.05
Other Race/Ethnicity		−0.11**	−0.05		−0.14**	−0.13**		−0.12*	−0.10
Married		0.11***	0.05***		−0.07**	−0.03		0.11***	0.08***
High School		0.04	0.01		0.06	0.05		0.25***	0.23***
Junior College		0.02	−0.05		0.08	0.07		0.35***	0.31***
Bachelor's Degree		0.05	−0.01		0.09	0.06		0.54***	0.50***
Graduate Degree		0.05	−0.02		0.17***	0.11*		0.57***	0.53***
Part-time		−0.07***	−0.07***		−0.34***	−0.19***		−0.07*	−0.06*
Industry 1		0.07	0.03		−0.04	−0.05		0.21*	0.18
Industry 2		−0.09	0.04		−0.13	−0.21**		0.19	0.22**
Industry 3		−0.12	−0.02		0.02	−0.08		0.19*	0.22**
Industry 4		0.01	0.13*		0.05	0.01		0.24**	0.28**
Industry 5		−0.09	0.02		0.05	−0.05		0.18	0.21
Industry 6		0.00	−0.03		−0.06	−0.03		0.41***	0.37***
Industry 7		−0.05	−0.03		0.05	0.06		0.26**	0.24**
Industry 8		0.02	0.08		0.02	−0.00		0.17	0.19*
Industry 9		−0.14*	−0.07		0.08	0.01		0.25**	0.28**
Industry 10		0.02	0.01		−0.24**	−0.12		0.22*	0.21*
Industry 11		0.03	0.11		−0.02	−0.07		0.28**	0.30**
Constant	3.35***	3.28***	3.11***	3.09***	2.63***	2.98***	3.66***	3.85***	3.80***
R-squared	0.02	0.07	0.42	0.01	0.08	0.27	0.02	0.06	0.09

Notes: 1. N = 5718. 2. ***p < 0.01, **p < 0.05, *p < 0.1. 3. For industry codes, see notes in Table B1.

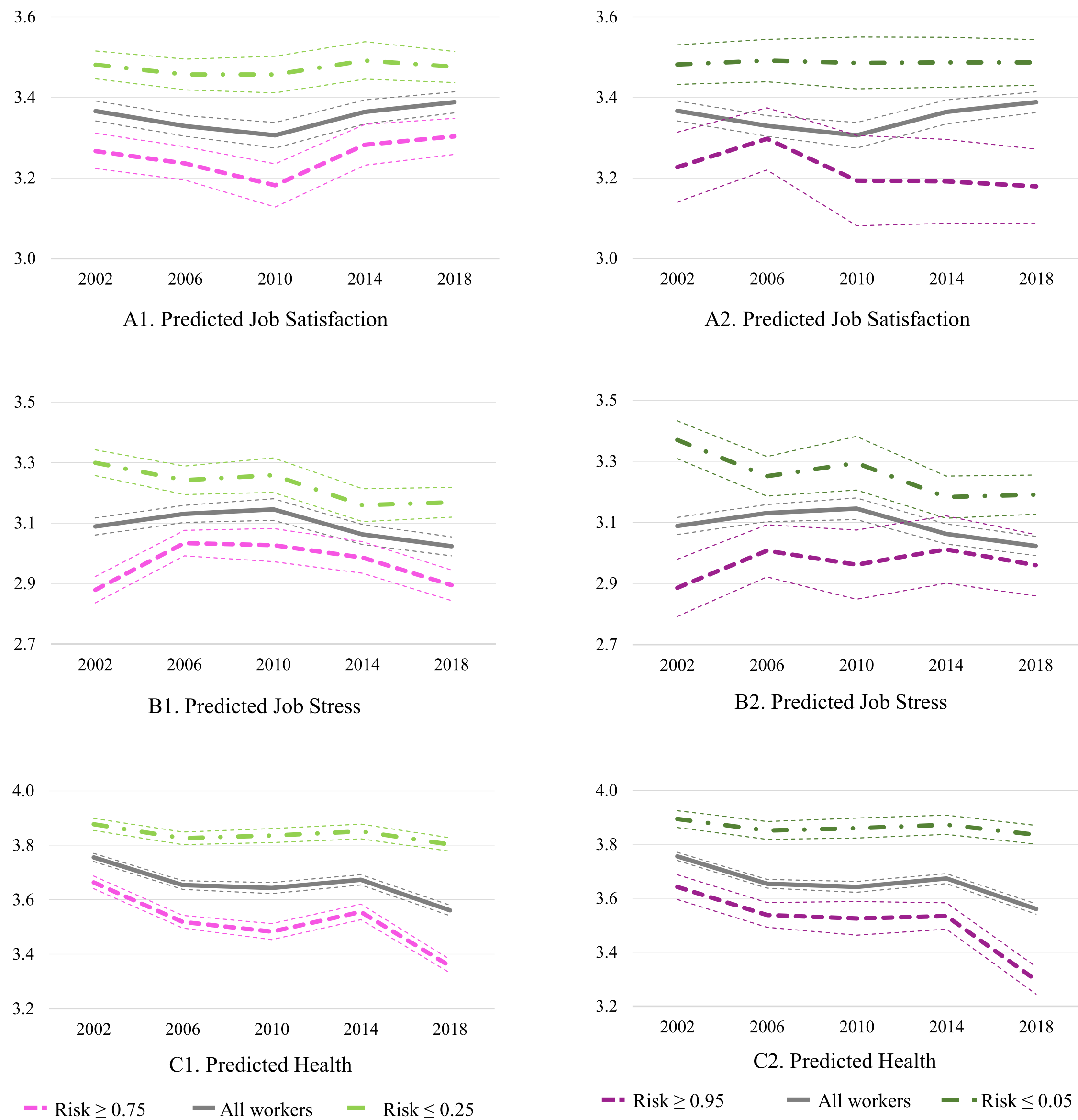

Fig. B1. Predicted well-being by year and automation risk threshold.
Note: 1. Predicted values and confidence intervals from Diff-in-Diff models reported in Table 3. 2. All models control for the standard covariates and factor variables.

Appendix C. Insecurity models

Table C1
Job security regressions (full models).

Variables	Job Security			Satisfaction	Stress	Health
	(1)	(2)	(3)	(4)	(5)	(6)
Risk	−0.05***	−0.03**	0.01	−0.01	−0.05***	−0.06***
Job Security				0.09***	−0.05***	0.04**
Work Conditions			0.26***	0.23***	−0.15***	0.08***
Social Context			0.06***	0.07***	−0.06***	0.04***
Benefits			0.16***	0.09***	0.01	0.05***
Manual Work			−0.04***	0.02**	−0.09***	0.02
Workload			−0.08***	−0.11***	0.36***	−0.06***
Autonomy			0.04***	0.14***	0.12***	0.06***
Year 2006		−0.03	−0.01	−0.02	0.01	−0.10***
Year 2010		−0.08**	−0.06**	−0.07***	0.05	−0.10**
Year 2014		0.04	0.04	−0.02	−0.01	−0.08*
Year 2018		0.14***	0.12***	−0.00	−0.05	−0.20***
Age		−0.02***	−0.01***	0.00	0.01**	−0.02***
Age squared		0.00***	0.00***	0.00	−0.00***	0.00***

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Table C1 (*continued*)

Variables	Job Security			Satisfaction	Stress	Health
	(1)	(2)	(3)	(4)	(5)	(6)
Female		0.01	0.03	0.03*	0.07***	−0.04
Black		−0.12***	−0.11***	−0.06***	−0.26***	−0.01
Latino		0.00	−0.02	0.02	−0.24***	−0.05
Other Race/Ethnicity		−0.12**	−0.08*	−0.04	−0.14**	−0.09
Married		0.08***	0.03*	0.05***	−0.04	0.08***
High School		0.06	0.04	0.01	0.05	0.22***
Junior College		0.06	0.03	−0.05	0.07	0.30***
Bachelor's Degree		0.05	0.02	−0.01	0.06	0.50***
Graduate Degree		0.02	0.00	−0.01	0.10*	0.53***
Part-time		−0.15***	−0.15***	−0.06***	−0.20***	−0.06
Industry 1		−0.14	−0.18**	0.04	−0.05	0.19
Industry 2		−0.21**	−0.12	0.05	−0.21**	0.23**
Industry 3		−0.08	−0.02	−0.02	−0.07	0.22**
Industry 4		−0.05	0.03	0.13*	0.02	0.27**
Industry 5		−0.28**	−0.18*	0.03	−0.05	0.21
Industry 6		−0.07	−0.08	−0.02	−0.03	0.38***
Industry 7		−0.14	−0.11	−0.02	0.06	0.25**
Industry 8		−0.02	0.04	0.08	−0.00	0.18
Industry 9		−0.18*	−0.13	−0.06	0.00	0.28**
Industry 10		0.02	0.01	0.00	−0.12	0.20*
Industry 11		0.06	0.15*	0.10	−0.06	0.29**
Constant	3.38***	3.85***	3.67***	2.78***	3.16***	3.64***
R-squared	0.00	0.03	0.25	0.42	0.27	0.09

Notes: 1. N = 5710. 2. ***p < 0.01, **p < 0.05, *p < 0.1. 3. For industry codes, see notes in Table B1.

Table C2
Job security (alternative specifications)

	Risk specification			
	Standard (continuous)	≥0.75 vs ≤ 0.25 (dummy)	≥0.95 vs ≤ 0.05 (dummy)	Newly vs Never risky (dummy)
	(1)	(2)	(3)	(4)
Coefficient	0.01	0.05*	0.00	0.02
	(0.01)	(0.03)	(0.00)	(0.01)
N	5710	4293	1619	763
R-squared	0.25	0.25	0.24	0.27

Notes: 1. ***p < 0.01, **p < 0.05, *p < 0.1. 2. All models control for the standard covariates and factor variables. 3. Beta coefficients in parenthesis. 4. Newly vs. never risky specification is restricted to years 2002–2010. See text for details.

Appendix D. Automation risk measures

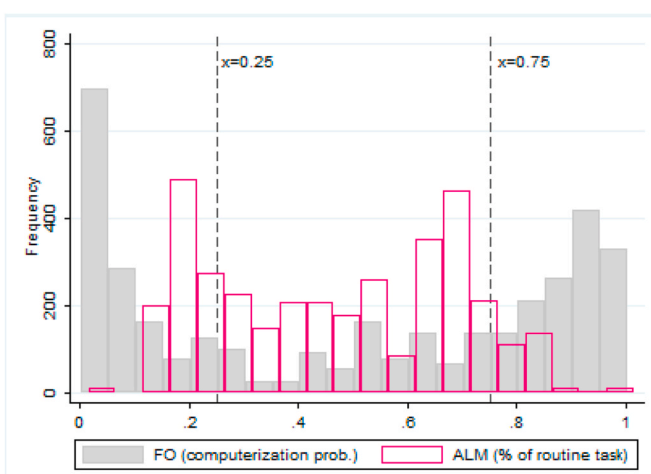

Fig. D1. FO versus ALM distribution of probabilities.
Note: 1. Distribution of probabilities for years 2002–2010 in GSS. 2. FO is based on Frey and Osborne [64]; and ALM is based on Autor, Levy, and Murnane [57]. See methods section for details. 3. In the alternative specification used to test the insecurity channel, newly risky occupations were defined as higher than 0.75 in FO and below 0.25 in ALM, whereas never risky were defined as below 0.25 in both.

Table D1
Occupations and probabilities[a].

Occupation (2010 COC)		Automation risk (FO)	N	Occupation (2010 COC)		Automation risk (FO)	N
Code	Name			Code	Name		
860	Insurance underwriters	0.99	8	8020	Milling and planning machine setters, operators, and tenders, metal and plastic	0.98	1
940	Tax preparers	0.99	4	8740	Inspectors, testers, sorters, samplers, and weighers	0.98	27
2440	Library technicians	0.99	4	8800	Packaging and filling machine operators and tenders	0.98	15
4940	Telemarketers	0.99	8	1900	Agricultural and food science technicians	0.97	2
5340	New accounts clerks	0.99	1	4150	Hosts and hostesses, restaurant, lounge, and coffee shop	0.97	7
5500	Cargo and freight agents	0.99	2	4410	Motion picture projectionists	0.97	2
5810	Data entry keyers	0.99	11	4720	Cashiers	0.97	89
8830	Photographic process workers and processing machine operators	0.99	2	4740	Counter and rental clerks	0.97	7
540	Claims adjusters, appraisers, examiners, and investigators	0.98	18	5140	Payroll and timekeeping clerks	0.97	10
830	Credit analysts	0.98	2	5260	File clerks	0.97	3
4750	Parts salespersons	0.98	10	8250	Prepress technicians and workers	0.97	2
5120	Bookkeeping, accounting, and auditing clerks	0.98	54	8360	Textile bleaching and dyeing machine operators and tenders	0.97	1
5150	Procurement clerks	0.98	1	8540	Woodworking machine setters, operators, and tenders, except sawing	0.97	6
5160	Tellers	0.98	15	135	Compensation and benefits managers	0.96	4
5350	Order clerks	0.98	1	1560	Surveying and mapping technicians	0.96	3
5610	Shipping, receiving, and traffic clerks	0.98	30	4060	Counter attendants, cafeteria, food concession, and coffee shop	0.96	6
5840	Insurance claims and policy processing clerks	0.98	15	4420	Ushers, lobby attendants, and ticket takers	0.96	1
5010	Switchboard operators, including answering service	0.96	4	2850	Writers and authors	0.04	11
5110	Billing and posting clerks	0.96	20	3250	Veterinarians	0.04	1
5400	Receptionists and information clerks	0.96	32	725	Meeting, convention, and event planners	0.04	7
5860	Office clerks, general	0.96	48	110	Computer and information systems managers	0.04	16
7750	Miscellaneous assemblers and fabricators	0.96	39	1220	Operations research analysts	0.04	8
8420	Textile winding, twisting, and drawing out machine setters, operators, and tenders	0.96	2	2100	Lawyers	0.04	32
5100	Bill and account collectors	0.95	10	2200	Postsecondary teachers	0.03	70
5320	Library assistants, clerical	0.95	5	1300	Architects, except naval	0.03	12
5540	Postal service clerks	0.95	11	140	Industrial production managers	0.03	10
5630	Weighers, measurers, checkers, and samplers, recordkeeping	0.95	4	150	Purchasing managers	0.03	5
6320	Operating engineers and other construction equipment operators	0.95	13	1060	Database administrators	0.03	3
8000	Grinding, lapping, polishing, and buffing machine tool setters, operators, and tenders, metal and plastic	0.95	4	1105	Network and computer systems administrators	0.03	17
8256	Print binding and finishing workers	0.95	2	1430	Industrial engineers, including health and safety	0.03	9
8750	Jewelers and precious stone and metal workers	0.95	2	2600	Artists and related workers	0.03	13
8850	Adhesive bonding machine operators and tenders	0.95	1	3000	Chiropractors	0.03	4
(…)				2050	Directors, religious activities and education	0.03	2
				3700	First-line supervisors of correctional officers	0.03	4
3400	Emergency medical technicians and paramedics	0.05	7	2710	Producers and directors	0.02	12
205	Farmers, ranchers, and other agricultural managers	0.05	16	3010	Dentists	0.02	4
1210	Mathematicians	0.05	1	1450	Materials engineers	0.02	1
4620	Recreation and fitness workers	0.05	24	2910	Photographers	0.02	6
2750	Musicians, singers, and related workers	0.04	6	3160	Physical therapists	0.02	9
3260	Health diagnosing and treating practitioners, all other	0.02	2	1460	Mechanical engineers	0.01	16
1360	Civil engineers	0.02	15	3730	First-line supervisors of protective service workers, all other	0.01	8
360	Natural sciences managers	0.02	1	230	Education administrators	0.01	34
1420	Environmental engineers	0.02	4	3255	Registered nurses	0.01	94
300	Architectural and engineering managers	0.02	4	2320	Secondary school teachers	0.01	63
1320	Aerospace engineers	0.02	5	2040	Clergy	0.01	12
1350	Chemical engineers	0.02	1	350	Medical and health services managers	0.01	27
2060	Religious workers, all other	0.02	5	1820	Psychologists	0.01	9
4820	Securities, commodities, and financial services sales agents	0.02	14	420	Social and community service managers	0.01	18
7700	First-line supervisors of production and operating workers	0.02	43	1006	Computer systems analysts	0.01	21
10	Chief executives	0.02	37	3230	Speech-language pathologists	0.01	7
60	Public relations and fundraising managers	0.02	5	137	Training and development managers	0.01	2
726	Fundraisers	0.02	2	136	Human resources managers	0.01	13
650	Training and development specialists	0.01	7	3710	First-line supervisors of police and detectives	0.00	5
1530	Engineers, all other	0.01	5	3060	Physicians and surgeons	0.00	19
5000	First-line supervisors of office and administrative support workers	0.01	95	340	Lodging managers	0.00	4
2000	Counselors	0.01	35	3030	Dietitians and nutritionists	0.00	5
50	Marketing and sales managers	0.01	50	3720		0.00	3

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Table D1 (*continued*)

Occupation (2010 COC)		Automation risk (FO)	N	Occupation (2010 COC)		Automation risk (FO)	N
Code	Name			Code	Name		
					First-line supervisors of firefighting and prevention workers		
700	Logisticians	0.01	4	3150	Occupational therapists	0.00	6
3050	Pharmacists	0.01	8	425	Emergency management directors	0.00	1
2330	Special education teachers	0.01	21	7000	First-line supervisors of mechanics, installers, and repairers	0.00	23
2010	Social workers	0.01	42				

[a] Table D1 illustrates occupations with probabilities below 5 % and above 95 %. Full tabulations can be obtained from the authors by request.

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