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# Industry 4.0 and the Job Quality and Well-Being of Manufacturing Workers

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## ABSTRACT

This paper reports an international survey of how Industry 4.0 (I4.0) technologies are affecting job quality and employee well-being in manufacturing. Consistent with the theory that greater capital intensity and technological/operational uncertainty predict greater worker participation in management, the results more strongly support the optimistic rather than the pessimistic view of how I4.0 technologies will affect job quality. Greater use of the most prevalent I4.0 technologies is associated with greater involvement in decision-making, which leads to higher job satisfaction and better psychological health. Greater use of I4.0 technologies is not associated with work intensification. This suggests that I4.0 technologies can help humanize work, although our data suggest that the transformation to a smart factory may imply that employee involvement is associated with more highly qualified workers. The study does not rule out the emergence of digital Taylorism through increased managerial control and work intensification as I4.0 technologies are progressively debugged.

## 1 | Introduction

Digital transformation is a principal feature of the policy agendas of many countries with "national digital strategies" now "close to ubiquitous" (OECD 2024, 17). It has become customary to talk of the "fourth industrial revolution" (Industry 4.0; hereafter, I4.0), a term signifying a major transformation beyond the information and communication technology (ICT) or "third industrial revolution" of the last fifty years, which built upon the mechanization of factory production and the electrification of the power grid that shaped the first two industrial revolutions (Kagermann et al. 2013; Vereycken, Ramioul, Desiere, et al. 2021).

However, little research has focused on how I4.0 affects the quality of work and employee well-being in manufacturing companies (Adeniji and Boxall 2024; Berg et al. 2023). Instead, most research on I4.0 has concentrated on developing and optimizing its enabling technologies (Lu 2017; Oeij et al. 2024). Our goal in this paper is to help address the issue of how I4.0 impacts the job quality and well-being of manufacturing employees. We do not focus on the extent to which I4.0 may impact job numbers but on how the work of employees involved with I4.0 influences their quality of working life: as they implement the technologies it involves, does it enhance or undermine their well-being? Our study is based on a comprehensive international survey of manufacturing workers conducted in 2020 employing structural equation modeling for the analysis.

With numerous nations now seeking to preserve and foster domestic manufacturing to improve their resilience in the face of regular supply-chain disturbances, the study addresses a question of major social consequence (Oeij et al. 2024). A highly skilled, sustainable manufacturing workforce is a strategic asset for economic and societal well-being. This is true across the board and especially so in countries at the far end of fragile, just-in-time supply chains, such as Australia and New Zealand (Skilling 2022; Australian Industry Group 2025). In this context, if we are to enhance manufacturing capabilities and sustainability, we need an understanding of how I4.0 is affecting key work

**Key Points**

- How I4.0 manufacturing technologies are affecting job quality and employee well-being is of strategic importance.
- This study finds that the more prevalent I4.0 technologies are associated with greater employee involvement in decision-making, which leads to higher job satisfaction and more positive psychological health.
- It does not find a link between greater use of I4.0 technologies and work intensification.
- The study is more supportive of an optimistic than a pessimistic view of how I4.0 will affect job quality.
- This, however, does not rule out increasing managerial control, work intensification, and variability in worker experiences over time and across contexts.

characteristics and worker outcomes and, thus, the prospects of recruiting and retaining a competent and motivated manufacturing workforce. While the paper contributes to the debate in the academic literature between optimistic and pessimistic theoretical perspectives of the impacts of I4.0 on worker well-being, the issue is much more than academic: it relates to an important societal problem.

The paper is conventionally organized. It begins with a review of the literature on the nature of I4.0 manufacturing, which leads into a discussion of job quality and employee well-being, in which we set up our hypotheses. We then report our data, methods, and results, leading into our discussion and conclusion.

## 2 | I4.0 Manufacturing

I4.0 manufacturing involves the melding of the digital sphere with manufacturing (Kang et al. 2016). Rüßmann et al. (2015) refer to the "nine pillars" of I4.0: big data and analytics, autonomous robots, simulation, horizontal and vertical system integration, the industrial internet of things, cybersecurity, the Cloud, additive manufacturing, and augmented reality. Although parts of these technologies have been in place for some time, they argue that I4.0 brings them together in a much more integrated and transforming way. It helps to organize the diverse technologies that travel under the I4.0 paradigm into three major categories (Adeniji and Boxall 2024):

### 2.1 | The Internet of Things (IoT)

This term, coined in 1999 by Kevin Ashton in a presentation at Procter & Gamble (Kramp et al. 2013), refers to:

> A world where physical objects are seamlessly integrated into the information network, and where the physical objects can become active participants in business processes. Services are available to interact with these "smart objects" over the Internet, query their state and any information associated with them, taking into account security and privacy issues.
>
> (Haller et al. 2009, 15)

The internet referred to here should not be confused with the public internet accessible to most users. These networks are owned and operated by individual manufacturing companies due to intellectual property (IP) rights and other sensitive information. Cybersecurity is critically important for protecting industrial systems from threats and malicious cyberattacks (Tweneboah-Koduah et al. 2017).

### 2.2 | Cyber-Physical Systems (CPSs)

A CPS is "an embedded system that exchanges data in an intelligent network that enables smart production" (Pereira and Romero 2017, 1211). In CPSs, virtual identities are created and mapped online to replicate the physical environment of the factory (Lee et al. 2015). This "digital twin" or "cyber-twin" (Lee et al. 2015) is created through computer algorithms and continuously updated with real-time data. It uses simulations, machine learning, and analytics to mirror, predict, and optimize performance. Thereafter, commands can be issued over the network to execute the determined actions, enabling real-time control and automation of the physical counterpart.

### 2.3 | Smart Factory (SF)

A smart factory comprises smart machines, smart devices, smart manufacturing processes, data analysis, smart engineering (product design and development, innovation, planning), actual production and associated IT services, and smart logistics (Shrouf et al. 2014). It refers to the comprehensive integration of the manufacturing value chain, linking all activities from material sourcing to after-sales service, to create a quick, interactive, and responsive production environment. If the CPS is the heart and brain of I4.0, then the smart factory can be regarded as its body, housing its different components, technologies, and processes. Smart factories are highly automated, applying advanced robotics to the production process (Pasupuleti 2024). The output of a smart factory is a "smart product", which continuously provides data and information about itself throughout its lifecycle (Laird 2017).

While these three categories provide an overview, they also indicate the complexity of I4.0. Before we proceed, it pays to underline that manufacturers choose technologies that align with their particular goals, resources and environment (e.g., Boxall and Winterton 2018). Major contingencies inevitably shape how firms, including cash-strapped small enterprises, make these decisions.

## 3 | Job Quality and Employee Well-Being Under Industry 4.0

We now turn to theory and research relevant to our question: how will I4.0 change job quality, and what impacts will it have on employee well-being? On the one hand, we have optimistic predictions. Kagermann et al. (2013) suggested that I4.0 would foster decentralized decision-making, promote worker empowerment and enhance job quality. Theoretically, there are two major reasons to expect that greater application of I4.0 technologies will foster greater employee involvement in decision-making (Boxall and Winterton 2018). One reason, stemming from pioneering research by Blauner (1964), is that greater capital intensity in manufacturing leads to greater worker participation in problem-solving to make best use of the potential of expensive equipment. Worker involvement in addressing problems with expensive equipment is needed to maximize the uptime of the machinery and, thus, the benefits of the investment. A second, and complementary, reason is that greater employee involvement in decision-making is needed in conditions of technological or operational uncertainty, as characterizes the rapid development of I4.0. In this context, variances in system performance are best resolved at source by those affected: operating workers need to handle, or help to handle, in conjunction with technical specialists, the novel or unexpected problems that arise (e.g., Wright and Cordery 1999). This is demonstrated in Antonazzo et al.'s (2024) qualitative study of management and union views on the advance of I4.0 in European steel-making firms and its implications for work and skills. Their data suggests that the challenge of supervising highly automated, digitalized production systems is likely to require a significant building and blending of technical and soft skills as workers are called upon to comprehend what is happening in complex technical processes, analyze the problems that emerge, and collaborate more intelligently with data and with each other to resolve them.

Kagermann et al. (2013) argued that the benefits of I4.0 would only be realized if a sociotechnical systems (STS) approach was taken in implementing the new production system. This perspective is now being expressed as part of the European Commission's aspiration to transform I4.0 into "Industry 5.0" (I5.0), with the aim of developing a "sustainable, human-centric and resilient" approach "toward industry, the economy and society" (Oeij et al. 2024, 206). STS models of work organization seek to reduce top-down control by management and to jointly optimize the social and technical systems of work, encouraging a large realm of "responsible autonomy" on the part of workers (Trist and Bamforth 1951; Guest et al. 2022).

Bringing this perspective into the world of I4.0 implies that workers will be more fully involved in decentralized, empowering forms of decision-making (Oeij et al. 2024). Indeed, a study by Vereycken, Ramioul, Desiere, et al. (2021), based on management-provided data from 5609 manufacturing companies in the 2019 European Company Survey, found that digital technologies were associated with greater employee involvement, job complexity, and skill development.

We recognize, of course, that there is also a critical perspective. Grounded in labour process theory (e.g., Thompson and Smith 2024), which sees management as continually seeking to expand its control over work processes, this envisages a heightened form of Taylorist (1911) work organization, characterized by the efficiency-driven standardization of processes and the transfer of knowledge from workers to management. Under I4.0, "digital Taylorism" may be deployed to drive efficiency through the standardization of techniques and processes (Günsel and Yamen 2020) and heightened surveillance (e.g., Moro et al. 2019). Rainnie and Dean (2020, 28) warn of a "digitally driven debasement of high-skilled, high-waged work", and Butollo et al. (2019, 68), assessing an I4.0 pilot project, argue that these systems do "not necessarily increase autonomy, personal responsibility, and self-development".

Our dataset enables us to test these contrasting visions: is I4.0 leading to greater employee involvement of a genuine kind (the optimistic view) or is it debasing the quality of work (the pessimistic view)? To test these opposing perspectives, we couch our first hypothesis in terms of the positive vision, proposing that:

**Hypothesis 1.** *Greater use of I4.0 manufacturing technology is associated with greater employee involvement in decision-making.*

As predicted by a range of theories, including action-regulation theory, the job characteristics model and STS, greater employee involvement in decision-making generally leads to positive outcomes for employees (Frese and Zapf 1994; Hackman and Oldham 1976; Parker and Wall 1998). It tends to enhance job satisfaction through meeting human needs for greater control over working methods (e.g., Gallie 2013). It also has benefits for physical health by enabling workers to make choices in their work, such as responding to sources of work intensification that can lead to fatigue (e.g., Boxall and Macky 2014). Greater involvement is also likely to improve psychological health through providing workers with better information and participation in work decisions (e.g., Mackie et al. 2001). Therefore, we propose these direct effects and that involvement acts as a mediator between the use of I4.0 manufacturing technology and these employee outcomes:

**Hypothesis 2.** *Involvement in decision-making will have a positive relationship with* (*a*) *Job satisfaction*, (*b*) *Physical health, and* (*c*) *Psychological health*.

**Hypothesis 3.** *Involvement in decision-making mediates the relationship between the use of I4.0 manufacturing technology and* (*a*) *Job satisfaction*, (*b*) *Physical health, and* (*c*) *Psychological health*.

The opportunity for workers to use their preferred skills in their job tasks is recognized as an important intrinsic job quality (e.g., Berg et al. 2023). O'Brien (1983, 462) defines skill utilization as "the degree of match or congruence between an individual's skills and the level of skill required by his or her job". It signifies the opportunity for individuals to explore more of their potential. What I4.0 is likely to mean for employee skill utilization remains unclear and is likely to vary. However, some scholars contend that the paradigm's CPSs, rather than leading to an erosion of human abilities, should enhance workers' skills and capabilities, and result in human work being more efficient because of the cognitive, sensorial and physical assistance that is available (Nelles et al. 2016; Rauch et al. 2020; Romero et al. 2016). On the other hand, as noted above, I4.0 technologies might lead to greater monitoring and the degradation of work through deskilling (Butollo et al. 2019; Moro et al. 2019; Rainnie and Dean 2020). To assess these alternative predictions, we test the positive argument that:

**Hypothesis 4.** *Greater use of I4.0 manufacturing technology is associated with greater levels of skill utilization.*

Skill utilization is strongly associated with valuable employee outcomes. In enabling individuals to use more of their abilities and realize more of their potential, greater skill utilization is a major predictor of job satisfaction (e.g., Morrison et al. 2005; O'Brien 1982). It is also linked to better physical health. In a US study of 87,316 working adults, Fujishiro and Heaney (2017) found a negative association between skill utilization and self-reported levels of hypertension and high cholesterol. Similarly, greater skill utilization has been found to predict better mental health (e.g., Kornhauser 1965). Accordingly, we propose the following direct and mediating relationships:

**Hypothesis 5.** *Skill utilization will have a positive relationship with (a) Job satisfaction, (b) Physical health, and (c) Psychological health.*

**Hypothesis 6.** *Skill utilization mediates the relationship between the use of I4.0 manufacturing technology and (a) Job satisfaction, (b) Physical health, and (c) Psychological health.*

Work intensification involves a faster work pace or tougher deadlines and the reduction of employee idle or recovery time (e.g., Green 2006). The impact of I4.0 on work intensity is an open question. On the one hand, "if digital technologies are designed to take on the most intensive aspects of work, this could leave workers with a more balanced pace of work" (Berg et al. 2023, 353). A common line of argument, however, is that the use of information and communication technologies (ICT) through devices and wearables creates work intensification through heightened monitoring and through expecting employees to remain in a constant state of being "switched on" (e.g., Berg et al. 2023; Günsel and Yamen 2020). Thus, we propose that:

**Hypothesis 7.** *Greater use of I4.0 manufacturing technology is associated with greater levels of work intensification.*

Work intensification is well known to have negative effects on employee well-being. Korunka et al. (2015), examining 587 Austrian workers, find a negative relationship between work intensification and job satisfaction and a positive relationship between work intensification and emotional exhaustion. Similarly, scholars find that work intensification is linked to greater work-life imbalance and higher levels of stress and fatigue (Boxall and Macky 2014) and to physical and emotional strain and exhaustion (Paškvan and Kubicek 2017). Accordingly, we hypothesize these direct and mediating effects:

**Hypothesis 8.** *Work intensification will have a negative relationship with (a) Job satisfaction, (b) Physical health, and (c) Psychological health.*

**Hypothesis 9.** *Work intensification mediates the relationship between the use of I4.0 manufacturing technology and (a) Job satisfaction, (b) Physical health, and (c) Psychological health.*

The nine hypotheses are depicted in the conceptual model in Figure 1.

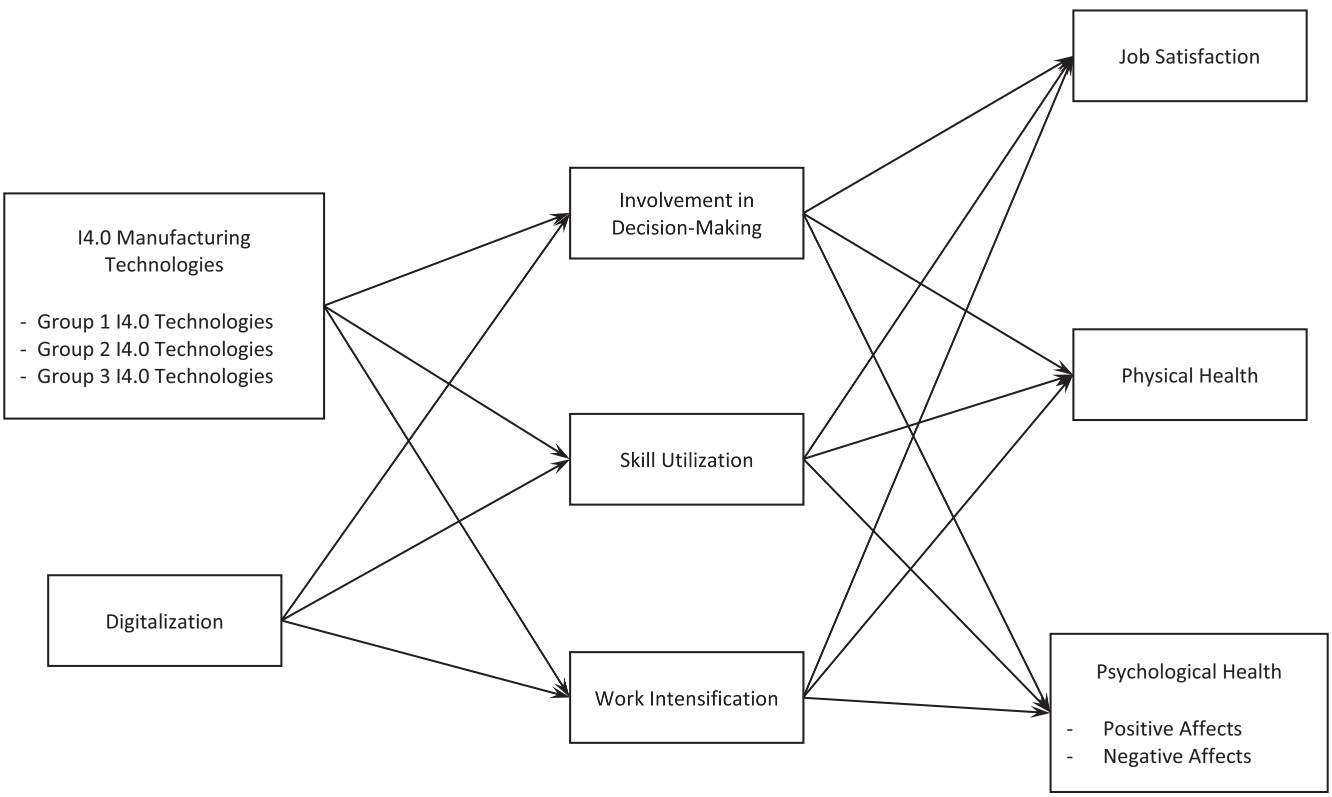


**FIGURE 1** | Conceptual model.

## 4 | Data, Methods and Analysis

The study is based on an international survey of manufacturing workers conducted in 2020. Respondents were sourced from the Prolific platform. The parameters were a non-management manufacturing worker, aged 18 to 65, currently working in one of 19 manufacturing sub-sectors (Table S1). Prolific has controls in place to verify participants, ensure reliable demographic information, and prevent fraudulent activity (Palan and Schitter 2018). The survey instrument, which covered a range of questions on working conditions, HR practices, and employee outcomes, was written in straightforward, concise language. It was pilot-tested before deployment and provided assurances of anonymity and confidentiality. To alleviate common-method bias, the Likert response scales varied in terms of type, number of scale points, and anchor labels for the questions (Podsakoff et al. 2003).

Once the survey was closed, the response of each participant was checked for completeness and to weed out those who engaged in satisficing (i.e., the random selection of answers with little or no thought), and submissions (11) completed in less than a third of the allocated time were not included in the final sample (DuHadway et al. 2018). This left 147 respondents (70 operations workers and 77 technical specialists and professional engineers), as described in Table S1. The largest respondent groups are in the USA (64), the UK (34) and Australia (11).

The mean age of the respondents is 36.9 years, and, as expected in the manufacturing sector, males dominate the sample. Two-thirds hold a degree, a technical qualification, or an apprenticeship. The average tenure with the current employer is 7.43 years. 31.3% of plants are unionized, but only 15.6% of respondents are trade union members. Around 70% of plants are at least 20 years old. The main manufacturing subsectors are electronics and electrical equipment, other manufacturing, metal and metal products, and industrial and commercial machinery.

The extent of uptake of I4.0 technologies was measured using 12 items based on responses to an earlier employer survey and suggestions from a group of I4.0 engineering experts. Values of 0 (no) and 1 (yes) were assigned to the non-use and use of the technologies, respectively, and these were averaged for each respondent to give a score for technologies used. As a second measure of I4.0 implementation, respondents were asked about the extent of digitalization in their plant: 4% reported complete digitalization, 31% reported a lot of digitalization, 42% reported that digitalization was used for stand-alone processes, 16% reported very little and 7% reported none. Overall, then, while only a small number have experienced a total takeover by I4.0, three-quarters of the sample are experiencing I4.0 technologies to some extent.

Involvement in decision-making was measured by asking the respondents how often they were involved in the decision-making process for methods of work, adoption of new technologies, pace of work, quality of work, and work schedule or roster, on a 7-point Likert scale, ranging from 1 (never) to 7 (always).

Skill utilization was assessed using the six-item measure from Morrison et al. (2005) on a 5-point scale, ranging from 1 (not at all) to 5 (a great deal). A sample item is "To what extent does your job provide you with the opportunity to use all of the skills, talents and abilities you possess on a regular basis?"

Work intensification was measured using Mullarkey et al.'s (1995) three-item scale. A sample question is "I am under constant pressure at work." Respondents were asked to indicate their extent of agreement on a 7-point scale from 1 (strongly disagree) to 7 (strongly agree).

Job satisfaction was assessed using the Michigan Organizational Assessment Questionnaire Job Satisfaction Subscale, as analyzed by Bowling and Hammond (2008). The subscale has three components—"All in all, I am satisfied with my job", "In general, I do not like my job", "In general, I like working here"—with the average score (after reverse coding the negative item) taken as a measure of overall job satisfaction. The items were rated on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree).

Physical health was measured using a single item, adopted from Ware and Sherbourne (1992), which asked respondents to rate their health on a 7-point scale from 1 (very poor) to 7 (very good).

For psychological health, the measure from Wood et al. (2012)—which in turn was adapted from Warr's (1990) anxiety-comfort scale—was used, with respondents asked to think about how often their jobs have made them feel three positive affective states (relaxed, calm, contented), and three negative ones (tense, worried, uneasy) over the last few weeks on a 5-point scale, ranging from 1 (all the time) to 5 (never). Since the items for positive and negative affective states do not form a single factor in the confirmatory factor analysis, they were examined as two factors—positive psychological health and negative psychological health—when testing the hypotheses. The items for positive psychological health were reverse-scored so that higher scores indicate better psychological health.

We controlled for the effects of gender, age, and tenure when testing the hypotheses because previous studies have found these variables to be associated with job satisfaction and physical and psychological health. All analyses were conducted using Mplus 8.10 (Muthén and Muthén 1998–2017). We first examined the quality of measurement scales using the R-based *measureQ* package (Cheung et al. 2024). Since we tested I4.0 technologies at the dimension level and assessed psychological health in two dimensions, the number of estimated parameters in the full structural equation model exceeds the number of respondents, resulting in a non-admissible solution. Hence, we follow Cheung et al.'s (2021) suggestion to adopt the reliability-corrected single indicator (RCS) approach to estimate the path coefficients in the structural model. Specifically, each variable is represented by the simple average of the item scores, and the measurement error is defined as (1 − Cronbach's alpha) times the variance of the simple average score. The RCS approach has been demonstrated to provide accurate estimated parameters in previous simulation studies (Cheung and Lau 2017; Cheung et al. 2021; Su et al. 2019). Since the mediating effects are not normally distributed, we followed Cheung and Lau's (2008) suggestion and tested the mediating hypotheses using the 95% bias-corrected confidence intervals (BCCIs) generated from 2000 bootstrap samples.

## 5 | Results

The means, standard deviations, correlation coefficients and Cronbach's alpha reliability are reported in Table 1. The fit indices for the measurement model are as follows: $\chi^2(351) = 573.836$, CFI = 0.911, RMSEA = 0.066, and SRMR = 0.060, indicating that the measurement model provides an adequate fit to the data. The factor loadings, construct reliability and average variance extracted (AVE) of all latent variables are reported in Table 2. The construct reliability coefficients range from 0.78 to 0.94, implying that our measurement scales have good reliability. Though the factor loading of the item "adoption of new technologies" (0.49) for involvement in decision-making is significantly lower than 0.7, it is not significantly lower than 0.5. All other factor loadings are not significantly lower than 0.7, and all AVEs are higher than 0.5. Hence, our results provide evidence for convergent validity, except for a minor concern about one item (Cheung et al. 2024). All the correlation coefficients are lower than 0.7, and all squared correlations are lower than the corresponding AVEs, implying discriminant validity among the variables (Cheung et al. 2024; Fornell and Larcker 1981).

Some comments should first be made on the incidence of I4.0 technologies. There is no particular technology that is overwhelmingly present. We can discern three groups based on their prevalence in our sample. First, cybersecurity, the internet of things and cloud computing are reported by 42% to 50% of our respondents. For the analysis that follows, we call these "Group 1" I4.0 technologies. There is then a group of technologies experienced by 23% to 34% of respondents: data-enabled resource optimization, artificial intelligence, connected sensors, simulation, big data and predictive maintenance, which we call "Group 2" I4.0 technologies. We then have "Group 3" I4.0 technologies, which have an incidence of only 7% to 17% among our respondents: digital twins of the production process, vertical and horizontal system integration, and advanced robotics. This technology group is closest to what is meant by a "smart factory".

A second set of comments should address variations in the adoption of I4.0 technologies in work across the major groups in the sample. The I4.0 manufacturing technologies and the degree of digitalization by demographics of respondents are presented in Table S1. It is found that respondents with higher qualifications ($\chi^2 = 18.19$, df = 9, $p < 0.05$), no unionism at the workplace ($\chi^2 = 13.50$, df = 6, $p < 0.05$), technical specialists and professional engineers ($\chi^2 = 16.16$, df = 3, $p < 0.01$), and working in plants with more full-time employees ($\chi^2 = 28.30$, df = 15, $p < 0.05$) reported working with more Group 1 I4.0 technologies. Respondents with higher qualifications ($\chi^2 = 17.43$, df = 9, $p < 0.05$) also reported working with more Group 3 I4.0 technologies. Finally, younger respondents ($\chi^2 = 28.27$, df = 16, $p < 0.05$), with higher qualifications ($\chi^2 = 22.40$, df = 12, $p < 0.05$), and working as technical specialists and professional engineers ($\chi^2 = 12.47$, df = 4, $p < 0.05$) reported a higher degree of digitalization in the workplace. There is no statistically significant difference in the adoption of I4.0 manufacturing technologies and the degree of digitalization at work between males and females, across countries, manufacturing subsectors, and the age of plants. The picture that emerges, then, is that manufacturing workers who are younger and more highly qualified in technical skills and professional engineering experience a greater degree of digitalization.

The fit indices for our hypothesized structural model are as follows: $\chi^2(14) = 5.664$ ($p = 0.974$), CFI = 1.000, RMSEA = 0.000, and SRMR = 0.021, indicating that the hypothesized structural model provides a very good fit to the data. The estimated parameters from the structural equation model are presented in Table 3, and the standardized indirect, direct, and total effects, together with the 95% BCCI generated from 2000 bootstrap samples, are reported in Table 4.

Hypothesis 1 posits that the greater use of I4.0 manufacturing technology is associated with increased employee involvement in decision-making. Table 3 shows that our two most prevalent groups of I4.0 technologies, Group 1 ($\beta = 0.184$, $p < 0.05$) and Group 2 ($\beta = 0.404$, $p < 0.01$), have statistically significant positive relationships with involvement in decision-making. The extent of digitalization has a positive but statistically non-significant relationship with involvement in decision-making. On the other hand, the least prevalent technologies, Group 3, which are more reflective of smart factories, have a statistically significant but negative relationship with involvement in decision-making ($\beta = -0.272$, $p < 0.01$). H1 is partially supported.

Hypothesis 2 posits that involvement in decision-making will have a positive relationship with job satisfaction, physical health, and psychological health. Table 3 shows that involvement in decision-making has a statistically significant positive relationship with job satisfaction ($\beta = 0.229$, $p < 0.05$), supporting H2a. The relationship between involvement in decision-making and physical health is not statistically significant ($\beta = 0.175$, $p = 0.10$); hence, H2b is not supported. The association between involvement in decision-making and positive psychological health is statistically significant ($\beta = 0.306$, $p < 0.01$), but not significant with negative psychological health ($\beta = 0.033$, $p = 0.749$); H2c is partially supported.

Hypothesis 3 posits that involvement in decision-making mediates the relationship between the use of I4.0 manufacturing technologies and the outcome variables. Table 4 shows that the mediating effect of involvement in decision-making on the relationship between Group 1 technologies and job satisfaction ($\beta = 0.042$, 95% BCCI = [0.002, 0.114]) is statistically significant, as is the effect on positive psychological health ($\beta = 0.056$, 95% BCCI = [0.005, 0.144]). H3 is partially supported.

Hypothesis 4 posits that the greater use of I4.0 manufacturing technology is associated with higher levels of skill utilization. Table 3 shows that neither digitalization nor the three groups of technologies has a statistically significant relationship with skill utilization; H4 is not supported.

**TABLE 1** | Descriptive statistics, correlation coefficients and Cronbach's alpha.

| | | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Group 1 I4.0 technologies | 0.46 | 0.38 | — | | | | | | | | | | | | | |
| 2 | Group 2 I4.0 technologies | 0.29 | 0.27 | **0.48** | — | | | | | | | | | | | | |
| 3 | Group 3 I4.0 technologies | 0.13 | 0.22 | **0.31** | **0.53** | — | | | | | | | | | | | |
| 4 | Digitalization | 3.09 | 0.95 | **0.36** | **0.40** | **0.22** | — | | | | | | | | | | |
| 5 | Involvement in decision making | 4.02 | 1.29 | **0.28** | **0.34** | 0.00 | *0.18* | (0.84) | | | | | | | | | |
| 6 | Skill utilization | 3.26 | 0.92 | **0.27** | **0.26** | 0.09 | **0.23** | **0.46** | (0.93) | | | | | | | | |
| 7 | Work intensification | 3.86 | 1.33 | −0.07 | 0.00 | 0.06 | −0.01 | −0.15 | *−0.19* | (0.78) | | | | | | | |
| 8 | Job satisfaction | 5.20 | 1.38 | 0.10 | 0.09 | −0.03 | 0.10 | **0.44** | **0.62** | **−0.27** | (0.94) | | | | | | |
| 9 | Physical health | 5.60 | 1.06 | 0.01 | 0.01 | −0.01 | −0.01 | *0.16* | 0.08 | **−0.25** | **0.22** | — | | | | | |
| 10 | Psychological health—Positive | 3.00 | 0.94 | 0.11 | 0.07 | 0.16 | 0.13 | **0.36** | **0.41** | **−0.37** | **0.44** | **0.33** | (0.89) | | | | |
| 11 | Psychological health—Negative | 2.40 | 0.96 | −0.01 | −0.13 | 0.06 | −0.05 | 0.06 | *0.17* | **−0.49** | **0.36** | **0.31** | **0.64** | (0.89) | | | |
| 12 | Gender | 1.35 | 0.48 | 0.09 | −0.08 | −0.07 | −0.08 | 0.00 | 0.00 | 0.07 | 0.08 | *−0.18* | −0.16 | *−0.20* | — | | |
| 13 | Age | 36.93 | 10.82 | −0.05 | *−0.23* | −0.07 | **−0.23** | −0.13 | −0.04 | −0.05 | −0.02 | −0.04 | −0.10 | 0.09 | 0.07 | — | |
| 14 | Tenure | 7.43 | 6.12 | −0.04 | −0.04 | 0.05 | 0.01 | 0.12 | −0.12 | −0.01 | 0.00 | −0.06 | −0.02 | 0.12 | 0.07 | **0.46** | — |

*Note:* $N = 147$; Diagonal elements in brackets = Cronbach's alpha; correlations coefficients in italics = $p < 0.05$; correlation coefficients in bold = $p < 0.01$.

**TABLE 2** | Factor loadings, construct reliability and average variance extracted of latent variables.

| | Factor loadings | Construct reliability | Average variance extracted |
|---|---|---|---|
| Involvement in decision making | | 0.85 | 0.53 |
| Methods of work | 0.73 | | |
| Adoption of new technologies | 0.49 | | |
| Pace of work | 0.84 | | |
| Quality of work | 0.75 | | |
| Work schedule or roster | 0.79 | | |
| Skill utilization | | 0.93 | 0.68 |
| Use all of the skills, talents and abilities you possess on a regular basis? | 0.84 | | |
| Develop new knowledge and learn new skills? | 0.77 | | |
| Improve on the skills and abilities you possess? | 0.87 | | |
| Apply your skills, knowledge and abilities to the job in the way you think is best? | 0.79 | | |
| Use skills and abilities which others regard as important and valuable? | 0.84 | | |
| Use a variety of your skills, talents and abilities each day? | 0.84 | | |
| Work intensification | | 0.78 | 0.54 |
| I find myself working faster than I would like in order to complete my work | 0.63 | | |
| I am under constant pressure at work | 0.83 | | |
| I find that work piles up faster than I can complete it | 0.74 | | |
| Job satisfaction | | 0.94 | 0.84 |
| All in all, I am satisfied with my job | 0.95 | | |
| In general, I do not like my job (reverse coded) | 0.86 | | |
| In general, I like working here | 0.94 | | |
| Psychological health—positive | | 0.89 | 0.73 |
| Relaxed (reverse coded) | 0.90 | | |
| Calm (reverse coded) | 0.88 | | |
| Contented (reverse coded) | 0.79 | | |
| Psychological health—negative | | 0.90 | 0.75 |
| Tense | 0.77 | | |
| Worried | 0.87 | | |
| Uneasy | 0.93 | | |

Hypothesis 5 posits that skill utilization has a positive relationship with job satisfaction, physical health, and psychological health. Table 3 shows that skill utilization has a statistically significant relationship with job satisfaction ($\beta = 0.567$, $p < 0.01$), supporting H5a. The relationship between skill utilization and physical health is not statistically significant ($\beta = -0.030$, $p = 0.793$); hence, H5b is not supported. The association between skill utilization and positive psychological health is statistically significant ($\beta = 0.289$, $p < 0.01$), but not significant with negative psychological health ($\beta = 0.148$, $p = 0.136$); H5c is partially supported.

Hypothesis 6 posits that skill utilization mediates the relationship between the use of I4.0 manufacturing technologies and

**TABLE 3** | Estimated model parameters.

| | Involvement in decision making | Skill utilization | Work intensification | Job satisfaction | Physical health | Psychological health—positive | Psychological health—negative |
|---|---|---|---|---|---|---|---|
| Gender | | | | 0.256 (0.187)/0.090 | −0.378 (0.205)/−0.170 | −0.263 (0.141)/−0.141 | −0.390* (0.159)/−0.202 |
| Age | | | | −0.006 (0.009)/−0.051 | −0.003 (0.009)/−0.027 | −0.012 (0.007)/−0.143 | −0.004 (0.008)/−0.045 |
| Tenure | | | | 0.023 (0.018)/0.103 | −0.004 (0.017)/−0.022 | 0.015 (0.013)/0.101 | 0.024 (0.012)/0.157 |
| Group 1 I4.0 technologies | 0.585* (0.282)/0.184 | 0.406 (0.250)/0.174 | −0.360 (0.358)/−0.111 | −0.341 (0.274)/−0.096 | −0.016 (0.250)/−0.006 | −0.076 (0.186)/−0.033 | 0.043 (0.201)/0.018 |
| Group 2 I4.0 technologies | 1.818** (0.470)/0.404 | 0.626 (0.392)/0.190 | 0.012 (0.548)/−0.003 | −0.511 (0.432)/−0.102 | −0.275 (0.465)/−0.070 | −1.031** (0.306)/−0.314 | −1.053** (0.344)/−0.308 |
| Group 3 I4.0 technologies | −1.491** (0.509)/−0.272 | −0.369 (0.353)/−0.092 | 0.522 (0.501)/0.094 | 0.076 (0.537)/0.012 | 0.219 (0.498)/0.046 | 1.211** (0.345)/0.302 | 0.937* (0.396)/0.225 |
| Digitalization | 0.026 (0.131)/0.020 | 0.110 (0.101)/0.117 | 0.013 (0.150)/0.010 | −0.008 (0.104)/−0.006 | −0.045 (0.107)/−0.040 | 0.036 (0.074)/0.039 | −0.054 (0.087)/−0.055 |
| Involvement in decision making | | | | 0.254* (0.106)/0.229 | 0.152 (0.093)/0.175 | 0.223** (0.076)/0.306 | 0.025 (0.078)/0.033 |
| Skill utilization | | | | 0.861** (0.146)/0.567 | −0.035 (0.134)/−0.030 | 0.288** (0.082)/0.289 | 0.154 (0.103)/0.148 |
| Work intensification | | | | −0.169* (0.069)/−0.154 | −0.201** (0.074)/−0.235 | −0.234** (0.064)/−0.326 | −0.378** (0.060)/−0.506 |
| $R^2$ | 0.201 | 0.120 | 0.014 | 0.530 | 0.116 | 0.461 | 0.407 |

*Note:* $*p<0.05$, $**p<0.01$.

the outcome variables. Table 4 shows that only the mediating effect of skill utilization on the relationship between Group 2 technologies and positive psychological health ($\beta = 0.055$, 95% BCCI = [0.000, 0.143]) is statistically significant, partially supporting H6.

Hypothesis 7 posits that the greater use of I4.0 manufacturing technology is associated with higher levels of work intensification. Table 3 shows that none of the I4.0 technologies or digitalization has a statistically significant relationship with work intensification. H7 is not supported.

Hypothesis 8 posits that work intensification has a negative relationship with job satisfaction, physical health, and psychological health. Table 3 shows that work intensification has a statistically significant negative relationship with job satisfaction ($\beta = -0.154$, $p < 0.05$), physical health ($\beta = -0.235$, $p < 0.01$), positive psychological health ($\beta = -0.326$, $p < 0.01$), and negative psychological health ($\beta = -0.506$, $p < 0.01$); hence, H8 is supported.

Hypothesis 9 posits that work intensification mediates the relationship between the use of I4.0 manufacturing technologies and the outcome variables. Table 4 shows that none of the mediating effects of work intensification is statistically significant; therefore, H9 is not supported.

## 6 | Supplementary Analyses

Since our data are cross-sectional, we also tested a model in which I4.0 manufacturing technologies mediate the relationships between involvement in decision-making, skill utilization, and work intensification. The results are presented in Tables S2 and S3. However, except for the indirect effect from involvement in decision making through Group 2 technologies to positive psychological health ($\beta = -0.096$, 95% BCCI = [−0.194, −0.027]), and negative psychological health ($\beta = -0.093$, 95% BCCI = [−0.202, −0.024]), all other indirect effects through I4.0 technologies are statistically non-significant. On the other hand, the direct effects of involvement in decision-making on job satisfaction and positive psychological health, the direct effects of skill utilization on job satisfaction and positive psychological health, and the direct effects of work intensification on all outcome variables are statistically significant. This indicates that these effects are not going through I4.0 technologies.

## 7 | Discussion and Conclusions

The manufacturing workers in our sample report that greater use of the most prevalent groups of I4.0 technologies that we measure (Groups 1 and 2) is associated with greater involvement in decision-making. While this is not true of our least prevalent group (Group 3), which is more reflective of a "smart factory", the results are broadly consistent with the theory that greater capital intensity and technological/operational uncertainty will predict greater worker participation in management (e.g., Blauner 1964; Wright and Cordery 1999). It could be the case that very high levels of automation reduce opportunities for employee involvement in decision-making among the operating workers that remain, while requiring significant involvement from more highly qualified workers whose role is important in planning, programming, diagnosis of faults and restabilizing of systems when problems occur (Xu et al. 2026).

Greater involvement in decision-making and greater skill utilization in our sample have positive relationships with job satisfaction and our positive measure of psychological health, but not with physical health or our negative measure of psychological health. This kind of result is widely observed and is a reassuring but not unique finding. More interesting is the finding that greater use of our more prevalent groups of I4.0 technologies is associated with higher job satisfaction and better (positive) psychological health through the mechanism of greater involvement in decision-making, while our third, least prevalent group is negatively associated with these well-being outcomes through involvement.

It is also important that our respondents do not associate greater use of any measure of I4.0 technologies with greater work intensity. In our data, work intensification is not driven by the greater application of 14.0 technologies. The analysis shows that work intensification is clearly related to poorer well-being, as various studies demonstrate (e.g., Boxall and Macky 2014). We confirm its negative effects on all the measures of well-being we deploy: job satisfaction, physical health, and both measures of psychological health. There is no doubt that work intensification is a major threat to employee well-being. However, in our sample, it is not possible to attribute this to the greater application of I4.0 technologies.

On balance, then, the results of this study more strongly support the optimistic rather than the pessimistic view of how I4.0 technologies will affect the quality of work and employee well-being. In the main, the findings suggest that work under the new paradigm is *capable of* helping to humanize work. This is more consistent with an STS view of I4.0 implementation (e.g., Kagermann et al. 2013) than with a critical perspective (e.g., Rainnie and Dean 2020).

Why might this be so? Our study may reflect a fairly early stage of adoption of I4.0 technologies in manufacturing. At this stage, given technological or operational uncertainty, management has a strong incentive to involve workers in decision-making to win their support for implementation and benefit from their ideas (e.g., Ghobakhloo and Fathi 2019; Vereycken, Ramioul, Desiere, et al. 2021). Can we, then, rule out the emergence of digital Taylorism or a diminishment of employee involvement, or a mixed experience of it, in "smart factories"? Discounting these outcomes would be unwise. Over time, as uncertainty decreases, greater management control and work intensification may emerge as cost-cutting pressures and standardization assert themselves, although this is unlikely to be the case where uncertainty remains endemic in the production process (Xu et al. 2026). As Vereycken, Ramiuol, and Hermans (2021, 45) argue, employee participation can "temporarily gain ground in organizations, only to disappear once the new technology is debugged". For example, the qualitative case study by Moro et al. (2019) of seven companies in the "Italian motor valley" found that machine operators reported an increase in managerial control and an intensification in work rhythms after

**TABLE 4** | Estimated standardized direct, indirect and total effects.

| I4.0 Manufacturing technologies | Mediator | Outcome variables: Job satisfaction | Physical health | Psychological health—positive | Psychological health—negative |
|---|---|---|---|---|---|
| Group 1 I4.0 technologies | Involvement in decision making | **0.042 [0.002, 0.114]** | 0.032 [−0.002, 0.108] | **0.056 [0.005, 0.144]** | 0.006 [−0.032, 0.060] |
| | Skill utilization | 0.099 [−0.023, 0.233] | −0.005 [−0.065, 0.032] | 0.050 [−0.004, 0.134] | 0.026 [−0.005, 0.103] |
| | Work intensification | 0.017 [−0.013, 0.064] | 0.026 [−0.023, 0.095] | 0.036 [−0.033, 0.121] | 0.056 [−0.064, 0.166] |
| | Total indirect effects | **0.158 [0.006, 0.308]** | 0.053 [−0.022, 0.134] | 0.143 [−0.004, 0.267] | 0.088 [−0.046, 0.221] |
| Direct effect | | −0.096 [−0.243, 0.055] | −0.006 [−0.169, 0.181] | −0.033 [−0.179, 0.132] | 0.018 [−0.147, 0.176] |
| Total effects | | 0.062 [−0.139, 0.247] | 0.047 [−0.136, 0.249] | 0.110 [−0.099, 0.323] | 0.106 [−0.087, 0.281] |
| Group 2 I4.0 technologies | Involvement in decision making | **0.092 [0.013, 0.197]** | 0.070 [−0.001, 0.185] | **0.123 [0.034, 0.250]** | 0.013 [−0.065, 0.116] |
| | Skill utilization | 0.108 [−0.017, 0.253] | −0.006 [−0.082, 0.029] | **0.055 [0.000, 0.143]** | 0.028 [−0.004, 0.112] |
| | Work intensification | 0.000 [−0.046, 0.036] | −0.001 [−0.072, 0.050] | −0.001 [−0.087, 0.072] | −0.001 [−0.127, 0.116] |
| | Total indirect effects | **0.199 [0.005, 0.385]** | 0.064 [−0.039, 0.186] | **0.177 [0.002, 0.357]** | 0.040 [−0.116, 0.210] |
| Direct effect | | −0.102 [−0.261, 0.089] | −0.070 [−0.320, 0.151] | **−0.314 [−0.486, −0.123]** | **−0.308 [−0.495, −0.114]** |
| Total effects | | 0.097 [−0.142, 0.333] | −0.006 [−0.249, 0.230] | −0.136 [−0.348, 0.081] | **−0.268 [−0.481, −0.033]** |
| Group 3 I4.0 technologies | Involvement in decision making | **−0.062 [−0.143, −0.007]** | −0.047 [−0.137, 0.002] | **−0.083 [−0.177, −0.020]** | −0.009 [−0.083, 0.044] |
| | Skill utilization | −0.052 [−0.153, 0.049] | 0.003 [−0.016, 0.050] | −0.027 [−0.091, 0.016] | −0.014 [−0.072, 0.006] |
| | Work intensification | −0.014 [−0.057, 0.006] | −0.022 [−0.084, 0.014] | −0.030 [−0.103, 0.020] | −0.047 [−0.145, 0.037] |
| | Total indirect effects | −0.129 [−0.265, 0.007] | −0.067 [−0.162, 0.003] | **−0.140 [−0.275, −0.019]** | −0.070 [−0.188, 0.034] |
| Direct effect | | 0.012 [−0.057, 0.006] | 0.046 [−0.155, 0.242] | **0.302 [0.125, 0.486]** | **0.225 [0.035, 0.415]** |
| Total effects | | −0.116 [−0.341, 0.089] | −0.021 [−0.225, 0.184] | 0.162 [−0.022, 0.345] | 0.155 [−0.081, 0.351] |
| Digitalization | Involvement in decision making | 0.005 [−0.044, 0.062] | 0.003 [−0.036, 0.061] | 0.006 [−0.053, 0.077] | 0.001 [−0.017, 0.035] |
| | Skill utilization | 0.066 [−0.050, 0.199] | −0.003 [−0.067, 0.019] | 0.034 [−0.064, 0.114] | 0.017 [−0.008, 0.083] |
| | Work intensification | −0.002 [−0.041, 0.034] | −0.002 [−0.059, 0.055] | −0.003 [−0.019, 0.071] | −0.005 [−0.125, 0.107] |
| | Total indirect effects | 0.069 [−0.090, 0.234] | −0.002 [−0.071, 0.080] | 0.037 [−0.081, 0.191] | 0.013 [−0.121, 0.138] |

(Continues)

**TABLE 4** | (Continued)

| I4.0 Manufacturing technologies | Mediator | Outcome variables | | | |
|---|---|---|---|---|---|
| | | Job satisfaction | Physical health | Psychological health—positive | Psychological health—negative |
| Direct effect | | −0.006 [−0.148, 0.137] | −0.040 [−0.235, 0.143] | 0.039 [−0.124, 0.185] | −0.055 [−0.233, 0.116] |
| Total effects | | 0.064 [−0.143, 0.272] | −0.042 [−0.237, 0.134] | 0.076 [−0.135, 0.257] | −0.042 [−0.243, 0.143] |

*Note:* Entries are standardized effects and 95% bias-corrected confidence intervals. Effects in bold are significant at $p < 0.05$.

the implementation of I4.0 technologies. On the other hand, in Antonazzo et al.'s (2024) study of the European steel industry, management and union representatives did not observe, or envisage, strategies of deskilling under I4.0: quite the reverse. We must bear in mind that implementations of new technologies can be expected to vary and reflect important local contingencies (e.g., Hasle et al. 2012).

This study is subject to the limitation that it is cross-sectional, and care must be taken with causal inferences. However, it is much more likely that I4.0 technologies affect employee well-being than the other way round. The study also relies on a single source: individual employees. However, employees themselves are best placed to report their job experiences and well-being, and, as noted above, efforts were made to reduce the likelihood of common-method bias.

While the results indicate, at least, that the use of I4.0 technologies is likely to have a positive impact on employee involvement in decision-making and via this mediator, on employee well-being, the dynamics of this relationship, and the nuances it can contain, require ongoing investigation. This includes the contextual and contingent factors involved, such as national institutional frameworks, company size, capital intensity and industry volatility (e.g., Parker et al. 2017; Antonazzo et al. 2024). Both large-scale quantitative research and in-depth case studies will support this endeavour and help policymakers develop skill formation and industry policies that support a human-centric future for their reindustrializing economies.


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### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The Supporting Information, containing further tables and analyses, as noted in the paper, is available from the publisher.

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## Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** I4.0 manufacturing technologies by demographics of respondents. **Table S2:** Estimated model parameters with I4.0 manufacturing technologies as mediators. **Table S3:** Estimated standardized direct, indirect, and total effects with I4.0 manufacturing technologies as mediators.