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“I’m stressed!”: The work effect of process innovation on mental health

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ABSTRACT

Objectives: The prevalence of unmet mental healthcare needs is a common challenge faced by many developing countries. This situation may worsen if more attention is not paid to the dramatic changes in the industrial workplace because of the diffusion of new automation and robotisation in the process of production.We aim to examine whether mental health problems are associated with frontline workers’ direct experience of process innovation in the firms where they operate and verify whether/which of these mechanisms are involved in this relationship.

Methods: Our data were obtained from the Foshan Workplace Employee Survey (FWES). Mental health was proxied by the subjective assessment of workers’ need to receive psychological counselling or treatment. To address endogeneity concerns, this study employed an extended ordered probit model and the two-stage least squares (2SLS) method.

Results: Frontline workers employed in innovative manufacturing firms are significantly more likely than those in firms taking no such action to experience psychological difficulties and to seek psychological counselling or treatment. Firms with a higher likelihood of upgrading their production process are more capable of taking a range of measures to significantly but not sufficiently mitigate the psychological problems of their workers induced by process innovation. In workplaces with a new advanced automation environment, workers believe that they face higher job insecurity (JI) and work stress, which in turn is partially and effectively linked to the deterioration in their mental health and further increases treatment-seeking behaviours.

Conclusion: This study suggests that carrying out process innovation is associated with increased psychological distress and, hence, more needs for mental healthcare services. To narrow the treatment gap originally subject to existing obstacles, it is necessary to face the new challenges posed by automation-induced change in the workplace, which policies should be particularly attentive to.

1. Introduction

Recent years have witnessed technological progress occurring at an unprecedented pace. The diffusion of new automation and robotisation in the process of production has resulted in dramatic changes in the industrial workplace, reviving intense discussions about the various consequences of this technological progress. Undoubtedly, workers’ health should fall within the scope of these discussion. The meaning of health contains multiple dimensions (e.g., physical, mental and social well-being) (Rosini, 2002), and the relationship between technological change and workers’ health is complex. In the case of physical health, many believe that the introduction of automation technology plays a positive role by improving work conditions and because such technology undertakes dangerous tasks. Indeed, recent studies provide straightforward evidence on this point (see Gihleb et al., 2020; Gunadi & Hanbyul, 2021). Meanwhile, authors have also emphasised serious concerns about the non-negligible influence of new technologies on increased stress, anxiety and other varieties of mental health problems. Thus far, however, this issue has received limited attention in empirical studies and even less attention in developing countries, which provides the direct motivation for this study to explore whether/how the adoption of technological innovation correlates with workers’ mental health in China.

China is the fastest growing country worldwide in terms of robotics adoption, and the Chinese government is continuously providing comprehensive support for the development and application of new

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automation technologies. To combat the rapid rise in labour costs, many manufacturing firms have been motivated by giant subsidies and support policies and have implemented industrial upgrades by introducing more advanced automated systems and facilities into their workplaces. In contrast to the rapid deployment of automation in the manufacturing sector, the insufficient and maldistributed mental healthcare resources and capacity[1] in China (Liang et al., 2018; Liu et al., 2011; Shang et al., 2019), together with other barriers, cannot satisfy the pressing service needs for mental health-related inquiries (in particular, stress and anxiety), leading to a large gap between the high prevalence of mental disorders and the low counselling rate (Lin, 2018; Qin & Hsieh, 2020; Que et al., 2019). In fact, this mental health burden may be worsened in the new era of automation. Thus, understanding the detrimental impact of automation-induced change in the workplace on the mental health of workers is of special interest. To some extent this study has timely implications for policy-makers and business managers regarding human–machine coexistence.

The introduction of superior technology or the adoption of a new process in production is known as process upgrading (Barrientos et al., 2010; Humphrey & Schmitz, 2002) or process innovation (Dosi et al., 2021; Vivarelli, 2013). Due to its labour-saving nature (Barbieri et al., 2019; Feldmann, 2013; Harrison et al., 2014), process innovation may cause technological unemployment, which repeatedly raised in the face of each new technological wave (Du & Wei, 2020; Smids et al., 2020). Because of the unprecedented capability of robots and intelligent automation to threaten the jobs held by humans in the current wave (Antón Pérez, Fernández-Macías, & Winter-Ebmer, 2021; Mauro et al., 2021), some dire predictions show that millions of jobs and many occupations are at high risk of being wiped out (Frey & Osborne, 2017; Manyika et al., 2017; World Bank, 2016), shaping the pessimistic views of workers who worry about becoming “victims” of rapid technological change, eroding their confidence in their career planning and increasing fear of automation. Fear of automation is closely related to job insecurity (JI), which is found to be negatively correlated with mental health. De Witte et al. (2016) obtained strong evidence for such a relationship from 57 longitudinal studies published since 1987. Recent works (Ganson et al., 2021; Gasparro et al., 2020; Green, 2020; Khubchandani & Price, 2017; Watson & Osberg, 2018; Wilson et al., 2020) have directly shown that psychological distress and symptoms (including depression, anxiety and emotional exhaustion) significantly increase with the threat of unemployment or fear of job loss.

However, many studies argue that the displacement effect of automation could be counterbalanced by different forces,[2] although their efficacy is much affected by different parameters and institutional and economic contexts (Du & Wei, 2020; Van Roy et al., 2018). Some studies have also failed to find significant negative impact of automation on employment conditions (Caselli, Fracasso, Scicchitano, et al., 2021; Dottori, 2021; Feldmann, 2013). More directly, Caselli, Fracasso, Scicchitano, et al. (2021) found that as a signal of a firm's health and commitment to maintaining its production levels, the introduction of new machines tends to reduce the level of perceived JI. Therefore, the inconclusive relationship between process innovation and workers' JI still cannot be used to ascertain whether process innovation negatively affects mental health by inducing JI, which calls for more empirical assessments in this respect.

Some scholars have also noted that the process of introducing new technology into the workplace is positively associated with increasing task complexity (Galy et al., 2012; Yamamoto, 2019), a perceived lack of autonomy (Fukumura et al., 2021; Katherine et al., 2019)] and physical isolation in a mechanised workflow (Hayes, 2015), all of which correspond to a combination of key dimensions (namely, heavy job demand, low job control and poor workplace social interaction, among others) proposed in the job strain model of Karasek (1979) and Karasek and Theorell (1990). Therefore, they cause heightened levels of work stress among workers (Demerouti et al., 2001; Lazarus & Folkman, 1984). Following the work of these scholars or other extended models, a large body of literature presents solid evidence of the negative association between work stress and mental well-being (see the recent systematic review by Law et al. (2020)). However, similar to the case of JI, the adverse effect of technological innovation on work stress is not predetermined (Baldry, 2012). In some studies, positive effects were found as well, such as less strenuous work (Raisch & Krakowski, 2021; Ramboarison-Lalao & Gannouni, 2019) and a safer and healthier working environment (Gihleb et al., 2020), which will reduce fatigue and stress and improve mental health.

The extant literature has investigated the health-related impact of technological innovation either by combining information (at the county, city and sectoral levels) on robot installation with recent micro survey data or by measuring occupational automation possibilities to identify who are the most likely to be “victims” of the growing penetration of automation technologies. However, research cannot ascertain whether the firm where the surveyed worker is employed has virtually introduced process innovation and, therefore, whether the worker has or has not been directly exposed to technological innovations in the workplace. In this study, we exploit a unique survey covering Chinese frontline factory workers in the city of Foshan, Guangdong Province, to examine whether mental health problems are associated with frontline workers' direct experience of process innovation in the firms where they operate. To the best of our knowledge, this study is the first analysis of mental well-being and technological innovation among the Chinese labour force. In addition, this study enriches the literature by examining the potential connections between technological innovation and selected dimensions of jobs (namely, JI, work stress, working hours and social interaction) and verifying whether/which of these mechanisms are involved in the relationship between mental health issues and technological innovation.

The remainder of this paper proceeds as follows. Section 2 describes the dataset and outlines the empirical methodology. Section 3 presents an analysis of the empirical results, including the baseline results, the results controlling for endogeneity, and the results of further examinations of the channelling effects. Section 4 concludes the present paper.

2. Data and methodology

2.1. Data

The data used in this study are obtained from the Foshan Workplace Employee Survey (FWES) conducted by the postdoctoral innovation practice base of South China Normal University in December 2016. The survey was carried out in the city of Foshan, Guangdong Province. As the most dynamic industrial city in China, Foshan was designated as a pilot area for the reform, transformation and upgrading of the national manufacturing base in 2015 and, along with other cities in Guangdong, enjoyed a subsidy of $150 billion from the provincial government for advanced automation upgrading (Giuntella & Wang, 2019). In response to these pecuniary and policy incentives, many manufacturing firms may have started or even completed the rebuilding and upgrading for advanced automated production lines in the survey period. With the help of the local government, the FWES surveyed 125 randomly sampled manufacturing firms and approximately 2600 workers randomly

[1] According to the World Health Organization (2018), in high-income countries, the number of psychiatric beds, psychiatrists and registered nurses is 7.13 beds (per 10,000 population), 13.06 and 23.49 (per 100,000 people), respectively. Correspondingly, those figures in China are far lower: 3.15 beds, 2.19 and 5.51, respectively (Que et al., 2019).

[2] Vivarelli (2013) summarised market compensation mechanisms, including new investments and the increase in incomes, among others. Acemoglu and Restrepo (2019) proposed the productivity effect of automation, i.e., increasing the demand for workers performing non-automated tasks, and the reinstatement effect, i.e., creating new tasks for laid-off workers.

selected based on the proportion of posts. Our sample is restricted to firms with information about process innovation and their workers without missing data for a series of variables considered.

The dependent variable depends on the following subjective measure based on a question from the FWES: "Do you think it is necessary that firms provide psychological counselling or related services to you?". Workers evaluated their need to receive counselling or treatment on a scale from 1 = very unnecessary to 4 = very necessary. Due to data availability, this study is unable to obtain some traditional indicators.[3] We also must admit that, due to stigma (Link et al., 2001; Rüsch et al., 2005), the respondents may have felt reluctant to carry out self-assessments on the need to receive treatment, even though they only had to provide an answer to a question in a survey rather than actually making a decision on participating in mental health treatment. From another perspective, for those who clearly answered this question with "necessary" and above, the deterioration in their mental health, when they were aware of it, may actually have involved a series of symptoms or substance abuse, or it may even have reached a more severe level. Our results can not only serve as the lower bounds of the mental health impact but also, more importantly, reflect the increase in mental healthcare needs induced by automation-related changes in the respondents' workplaces.

The independent variable of interest in this study is process innovation. Employers were asked to indicate whether the firms have optimised their production lines or introduced advanced automated systems and facilities. We created a binary variable that takes the value of 1 if the firm completed process innovation and 0 otherwise. For our multivariate model, a set of control variables was selected for the analysis based on their relevance to mental health, as shown by previous studies. These variables include common sociodemographic (gender, age, education, marital status, household registration (urban vs. rural) and local language proficiency) and job-related characteristics (monthly wage, tenure, occupation, union membership). This study also controlled for several firm-level variables (including firm age, firm performance, overseas business, employers' gender and educational level, entertainment and fitness facilities provided). The specific definitions/measurements of these variables are presented in Table 1.

Table 2 presents the summary statistics of the considered variables. In the pooled sample (Column 1), over 81% of frontline production workers worked in firms completing process innovation. On average, female workers slightly outnumbered male workers by a few percentage points. Workers had a mean age of approximately 32 years average and 11.9 years of schooling. The majority of them held rural hukou (80%) and were married (73%). The mean job tenure of workers was nearly 5 years; only 38% were members of unions, and more than half were able to basically understand and speak the local dialect for daily life and at work. When we split the sample based on whether firms have completed or not completed process upgrading (Columns 2 and 3), frontline workers in firms completing process innovation reported a higher level of needing to receive counselling or treatment relative to those working in firms taking no such action. However, there is no significant difference between the means of the two groups for most individual variables, which can be observed by the t values in Column 4. In contrast, there are significant differences in many firm characteristics between the two groups. Firms adopting process innovation tend to be older with higher involvement in overseas business and better operational performance, and unsurprisingly, they are more likely to provide entertainment and fitness facilities for their workers.

Table 1
Description of variables used.

Variables	Definition/Measurement
Mental health	Respondents evaluated their need to receive counselling or treatment on a scale from 1 = very unnecessary to 4 = very necessary.
Job insecurity	Respondents evaluated how much they worry about job security on a scale from 1 = not at all to 3 = very much.
Job stress	Respondents evaluated how stressful they feel at work on a scale from 1 = not at all stressful to 4 = very stressful.
Working hours	Respondents reported how many hours per day they normally work; a continuous variable
Social interaction	Respondents evaluated how frequently they communicate with other colleauges at work on a scale from 1 = very frequently to 5 = very rarely
PI	Process innovation; 1 if the firm completed process innovation and 0 otherwise
Male	Sex of respondent; 1 if male, 0 if female
Schooling years	Educational level of respondent; a continuous variable
Tenure	Duration of employment at current employer; a continuous variable
Union	1 if respondent is a member of union; 0 otherwise
Age	Age of respondent at the time of interview; a continuous variable
Age2_100	Age squared term divided by 100
Rural	Location of residence of respondent: 1 if rural, 0 if urban
Married	Marital status of respondent; 1 if married; 0 otherwise
General worker	1 if respondent is a general worker; 0 otherwise
Skilled worker	1 if respondent is a skilled worker; 0 otherwise
Foreman	1 if respondent is a foreman; 0 otherwise
Others	1 if respondent is unspecified; 0 otherwise
lnwage	Monthly wage in log form
LLP	Local language proficiency of respondent
Employer's gender	Sex of employer; 1 if male, 0 if female
Employer's education	Education level of employer; a continuous variable
Firm age	The number of years since the firm was established; a continuous variable
Oversea business	1 if the firm conducts business overseas, 0 if no
Entertainment facilities	Employers evaluated the completeness of entertainment facilities provided by the firm on a scale from 1 = barely equipped to 5 = fully equipped
Fitness facilities	Employers evaluated the completeness of fitness facilities provided by the firm on a scale from 1 = barely equipped to 5 = fully equipped
ROA	Return on assets calculated by dividing a firm's net income by its total assets
External business environments	Employers evaluated external business environments over the last three years on a scale from 1 = being improving to 3 = being worsening
Pressure of rising labour costs	Employers evaluated pressure of rising labour costs over the last three years on a scale from 1 = lower than peer enterprises to 3 = higher than peer enterprises

2.2. The empirical model

To fulfil the objectives of this study, the empirical strategy of this study adopted an ordered probit model, which has the following reduced form:

$$MH_{i,j} = \alpha + \beta PI_j + \gamma X^{'}_{i,j} + \varphi D^{'}_j + \varepsilon_{i,j} \tag{1}$$

where $MH_{i,j}$ is an ordinal variable denoting the overall level of needing to receive counselling or treatment reported by worker i employed in firm j. PI_j is a dummy variable indicating whether firm j completed process innovation. $X^{'}_{i,j}$ and $D^{'}_j$ denote the set of sociodemographic variables and firm characteristics shown in Table 2, respectively. $\varepsilon_{i,c,t}$ is the error term. The parameter of interest, β, represents the estimated overall effect on workers' mental health status in the comparison between the two groups of firms. Notably, Panel B of Table 2 shows that compared to firms taking no such action, firms with process innovation perform better on various observable indicators. In addition to these observable

[3] The mental health status adopted by the previous literature in different fields is constructed based upon several components reflecting various symptoms (including depression, anxiety, stress and so on) (del Pilar Sánchez-López & Dresch, 2008; Goldberg & Williams, 1988; Hansen et al., 2020) or proxied by excessive tobacco and alcohol consumption and drug misuse, which are found to be strongly associated with psychological issues (Ferreira et al., 2019; Indig et al., 2007; Miller & Brown, 1997).

Table 2
Summary statistics and comparison between two groups.

Panel A: workers	Pooled		PI = 0		PI = 1		*t*-test for diff. in means
	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.	
PI	0.819	0.385					
Mental health	2.637	0.912	2.522	0.943	2.663	0.903	−0.141**
Male	0.486	0.5	0.475	0.5	0.488	0.5	−0.013
Schooling years	11.874	3.039	11.785	3.151	11.894	3.015	−0.109
Job tenure	4.822	4.363	4.863	4.452	4.813	4.344	0.05
Union	0.377	0.485	0.369	0.483	0.378	0.485	−0.01
Age	32.302	7.95	32.593	7.691	32.237	8.007	0.356
Age2_100	11.066	5.592	11.213	5.362	11.033	5.642	0.18
Rural	0.798	0.401	0.743	0.437	0.810	0.392	−0.067***
Married	0.726	0.446	0.737	0.441	0.723	0.448	0.015
General worker	0.532	0.499	0.534	0.5	0.532	0.499	0.002
Skilled worker	0.184	0.387	0.183	0.387	0.184	0.387	−0.001
Foreman	0.196	0.397	0.224	0.418	0.19	0.392	0.035
Others	0.088	0.284	0.059	0.236	0.095	0.293	−0.036**
lnwage	8.176	0.230	8.093	0.233	8.194	0.225	−0.101***
Local Lang. proficiency	2.846	1.126	2.953	1.111	2.823	1.128	0.130*
No. observations	1869		339		1530		
Panel B: firms							
Employer's gender	0.913	0.282	0.894	0.309	0.917	0.276	−0.023
Employer's education	14.783	2.219	14.85	2.439	14.768	2.167	0.082
Firm age	14.685	7.43	11.195	7.044	15.459	7.292	−4.264***
Oversea business	0.587	0.493	0.457	0.499	0.616	0.487	−0.158***
Entertainment facilities	3.271	1.010	2.914	0.846	3.350	1.026	−0.436***
Fitness facilities	3.258	1.025	3.029	0.775	3.308	1.066	−0.278***
ROA	0.070	0.181	0.05	0.163	0.075	0.185	−0.025**
No. observations	105		30		75		

factors, some unobservables are equivalently likely to be large assets or driving forces for a firm to enable the upgrading of the production process and may simultaneously affect the way that the workers employed in that firm are treated. In this case, the estimated β in Eq. (1) may suffer from omitted variable bias, which is a common problem in cross-sectional empirical work.

To address endogeneity concerns, this study employed an extended ordered probit model (eoprobit command in STATA), in which an instrumental variable (IV) is used to control for confounding errors when the endogenous covariate is discrete. We considered employers' assessments of two firm-related dimensions as the instruments. Specifically, employers were asked to rate the pressure of rising labour costs and their external business environments over the last three years. Employers' perceptions of whether their external environments have worsened or labour costs have become higher than those of other peer enterprises are unlikely to correlate with frontline workers' perceptions of their mental health status[4]; instead, they are more likely to affect enterprise strategic decisions regarding the adoption of process innovation. The first-stage analysis (Table 3) results show this to be the case, corresponding to instrument relevance. Meanwhile, to address the weak instrument concern, this study further employed the two-stage least squares (2SLS) method as a robustness check. Based on the Sargan–Hansen test of over-identifying restrictions, we cannot reject the null hypothesis that the IVs are uncorrelated with the residuals of Eq. (1). Our F statistic for the first stage is approximately 28, which is well above the value of 10, and the Cragg–Donald Wald F statistic reported for the weak identification test is significant at the 10% level in relation to the Stock and Yogo (2005) maximal IV size, with a critical value of 19.93. Both results help to rule out weak instruments. Therefore, we consider our instruments to be valid.

As mentioned in the introduction, some work-related characteristics may act as important channels through which process innovation affects workers' mental health (i.e., increases the need for mental healthcare services). To identify these potential channels of transmission, we borrow an idea from Abeliansky and Beulmann (2019) and utilise the stepwise regression strategy proposed by Baron and Kenny (1986). In what follows, both equations include the same control variables as shown in Table 1 and the same instruments as shown in Table 4. *TC* refers to several different channels of transmission, including JI, work stress, working hours and social interaction.

$$MH_{i,j} = \alpha_1 + \beta_1 PI_j + \zeta TC_{i,j} + \gamma_1 X'_{i,j} + \varphi_1 D'_j + \mu_{i,j} \tag{2}$$

$$TC_{i,j} = \alpha_2 + \beta_2 PI_j + \gamma_2 X'_{i,j} + \varphi_2 D'_j + \upsilon_{i,j} \tag{3}$$

3. Results

3.1. Econometric results

The baseline results presented in Table 3 were obtained from ordered probit estimations (Columns 1–3) and simple ordinary least squares (OLS) regressions (Columns 4–6) of different specifications. Focusing on the core variable of interest, the results (which are all statistically significant at $p < 0.05$) are consistent and fairly stable across all specifications, with more individual and firm controls gradually being added. However, this initial evidence of the positive relationship between poor mental health and process innovation might be subject to underestimation, as described in the previous section, because process innovation is endogenous. The top row of Panel A of Table 4 further presents the main equation (or second-stage equation) results obtained from the eoprobit approach (Column 1) and 2SLS regression (Column 2). After accounting for unobserved endogeneity bias, the coefficients of the two IV models are 0.903 and 0.717, both of which are statistically significant at the 5% level. These results consistently indicate that the mental health of frontline workers in firms carrying out process innovation is at much

[4] To further safeguard the validity of our IVs, we adopt the approach proposed by Conley et al. (2012) and implement the local to zero (LTZ) procedures (Van Kippersluis & Rietveld, 2018) via the "plausexog" command in STATA (Clarke, 2017; Clarke & Matta, 2017) to examine the robustness of our 2SLS estimators. The results of our sensitivity analysis for both IVs illustrated in Figure A1 suggests that our models are robust under potentially moderate deviations from exclusion restrictions, suggesting that the two instruments are "plausibly exogenous." (Conley et al., 2012). See the online Appendix for further details.

Table 3
Baseline Results from the Ordered probit estimations and the OLS regressions.

	Ordered probit estimations			OLS regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
PI	0.164**	0.164**	0.131**	0.141**	0.134**	0.104*
	(0.077)	(0.076)	(0.071)	(0.065)	(0.063)	(0.057)
Constant				2.522***	1.004**	0.852
				(0.086)	(0.492)	(0.519)
Sociodemographic controls	No	Yes	Yes	No	Yes	Yes
Job-related controls	No	Yes	Yes	No	Yes	Yes
Firm Characteristics	No	No	Yes	No	No	Yes
N	1869	1869	1869	1869	1869	1869
Pseudo R2/R2_a	0.001	0.042	0.047	0.004	0.105	0.115

Note: Standard errors clustered at the firm level in parentheses, *p < 0.1 **p < 0.05 ***p < 0.01. Demographic controls are gender, schooling years, age, age_square/100, marital status, household registration and local language proficiency. Job-related characteristics are job tenure, occupation (General worker is the reference group), union membership, log monthly wage. Firm controls are: firm age, firm performance measured by return on asset, overseas business, employers' gender and education level, entertainment and fitness facilities provided.

Table 4
Results from the extend ordered Probit estimation and the 2SLS regression.

A. Main results Dependent variable: Mental health Issues	Eoprobit		2SLS	
	Coeff.	Robust std. err.	Coeff.	Robust std. err.
PI	0.903**	(0.426)	0.717**	(0.360)
male	−0.233***	(0.060)	−0.191***	(0.052)
Schooling years	−0.062***	(0.013)	−0.054***	(0.011)
tenure	−0.022***	(0.008)	−0.019***	(0.006)
union	−0.102*	(0.058)	−0.089**	(0.048)
age	−0.050*	(0.027)	−0.047**	(0.024)
age2_100	0.079**	(0.041)	0.072**	(0.037)
rural	0.085	(0.067)	0.039	(0.061)
Married	−0.078	(0.078)	−0.056	(0.066)
Skilled worker	−0.196***	(0.069)	−0.160***	(0.055)
Foreman	0.055	(0.079)	0.043	(0.065)
Others	−0.026	(0.101)	−0.072	(0.087)
lnwage	−0.032	(0.137)	−0.280	(0.228)
Local Lang. proficiency	−0.040*	(0.023)	−0.039*	(0.021)
Employer's gender (male = 1)	0.170*	(0.070)	0.024	(0.081)
Employer's education	−0.020*	(0.014)	−0.016	(0.016)
Firm age	−0.001	(0.004)	−0.004	(0.005)
ROA	−0.000	(0.007)	−0.003	(0.007)
Oversea business	0.020	(0.059)	−0.033	(0.056)
Entertainment facilities	−0.081*	(0.042)	−0.090**	(0.038)
Fitness facilities	−0.000	(0.057)	−0.041	(0.059)
Constant			0.437	(0.691)
B. First stage results Dependent variable: PI				
External business environments	0.022**	(0.011)	0.025**	(.012)
Pressure of rising labour costs	0.113***	(0.031)	0.121***	(0.030)
Corr. (e.PI, e.Mental health)	−0.308**	(0.156)		
Endogeneity test		3.193*	[0.073]	
Hansen J statistic		0.179	[0.672]	
Kleibergen-Paap rk LM statistic		25.887***	[0.000]	
Cragg-Donald Wald F statistic		28.114		
N	1869			
C. Summary statistics of IVs	Mean	Std. Dev.	*t*-test for diff. in means	
External business environments	1.984	0.865	−0.074*	
Pressure of rising labour costs	2.393	0.505	−0.333***	

Note: Standard errors clustered at the firm level in parentheses, *p < 0.1 **p < 0.05 ***p < 0.01. The values in the [ ] are p-values.

higher risk of deterioration than that of frontline workers in firms taking no such action.

Our auxiliary equation (or first-stage equation) results are shown in Panel B of Table 4. As expected, if employers believed that they have been faced with a tougher outside business environment in recent years and, more specifically, greater upwards pressure on labour costs relative to other peer enterprises in the same sector, they would be significantly more likely to take targeted actions. This study found that carrying out process innovation is one such action. Notably, the correlation coefficient of the residuals of the two equations (the auxiliary and main equation) is −0.308 ($p < 0.05$), which suggests that those unobservable factors would improve workers' mental health. This finding confirms our view on an underestimation of the effect due to unobserved confounders. That is, firms with a higher likelihood of upgrading their production process are more capable of taking a range of measures (e.g., providing retooling programmes and flexible benefit systems to their workers) to significantly but not sufficiently mitigate the psychological problems of their workers induced by process innovation.

Turning to the other controls, our findings for most sociodemographic variables are generally consistent with those of many previous studies. The coefficient for gender is significantly negative, meaning that compared with their male counterparts in the manufacturing industry, female workers are, on average, more sensitive and likely to report mental health problems. The likelihood of suffering from mental health issues decreases with workers' years of schooling, which could provide more psychosocial resources to deal with difficulties detrimental to their mental health. Similarly, relative to general workers, skilled workers are substantially less likely to report that they are in poor mental health because of their technical skills/abilities, which complement machines, their higher wages, and various other benefits from retention strategies. Regarding trade unions, unsurprisingly, union workers are more likely to enjoy better benefits in combating psychological hazards than their non-union counterparts. In addition, although the coefficient on the relationship between job tenure and mental well-being is negative and significant at $p < 0.05$, there is a caveat in interpreting this result due to the reciprocal cause–effect relationship.

3.2. Potential mechanisms

Table 5 presents the relationships between each suspected channel and process innovation and the estimated coefficients of the instrumented process innovation variable after the inclusion of these transmission sources as independent variables. In panel A, process innovation is positively related to an individual's assessment of JI. Setting JI as the independent variable in Eq. (3), we can see that the coefficients of process innovation on mental health problems significantly decrease in absolute magnitude relative to its values in Table 4 (*eoprobit*: 0.785 vs. 0.903; *2SLS*: 0.622 vs. 0.717). Panel B presents the results for work

Table 5
Results from the Eoprobit estimation and the 2SLS regression: Transmission Channels.

A. Dependent variable: Job insecurity				
	Eoprobit	2SLS	Eoprobit	2SLS
	Dependent variable:	Dependent variable:		
	Job insecurity	Mental health issues		
PI	1.258**	0.651**	0.785*	0.622*
	(0.444)	(0.290)	(0.434)	(0.351)
Job insecurity			0.186***	0.137***
			(0.049)	(0.032)
constant		0.966**		0.305
		(0.428)		(0.569)
Sociodemographic controls	Yes	Yes	Yes	Yes
Job-related controls	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes
Observations	1869	1869	1869	1869

B. Dependent variable: Job insecurity				
	Dependent variable:		Dependent variable:	
	Job stress		Mental health issues	
PI	1.071**	0.611**	0.716*	0.564*
	(0.429)	(0.284)	(0.420)	(0.331)
Job stress			0.241***	0.173***
			(0.044)	(0.033)
constant		0.642		0.403
		(0.431)		(0.559)
Sociodemographic controls	Yes	Yes	Yes	Yes
Job-related controls	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes
Observations	1869	1869	1869	1869

C. Dependent variable: Working hours		
	Dependent variable: Working hours	Dependent variable: Mental health issues
PI	1.761**	0.716**
	(0.699)	(0.366)
Working hours		0.006
		(0.023)
constant	8.710***	0.373
	(1.222)	(0.679)
Sociodemographic controls	Yes	Yes
Job-related controls	Yes	Yes
Firm Characteristics	Yes	Yes
Observations	1869	1869

D. Dependent variable: Social interaction				
	Dependent variable:		Dependent variable:	
	Social interaction		Mental health issues	
PI	0.167	0.071	0.897**	0.715**
	(0.503)	(0.266)	(0.404)	(0.341)
Social interaction			0.077**	0.061**
			(0.039)	(0.032)
Constant		1.063**		0.367
		(0.434)		(0.696)
Sociodemographic controls	Yes	Yes	Yes	Yes
Job-related controls	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes
Observations	1869	1869	1869	1869

E. Summary statistics of add. variables	Mean	Std. Dev.	*t*-test for diff. in means
Job security	1.756	0.675	−0.063
Job stress	2.311	0.649	−0.067*
Working hours	8.747	1.378	−0.348***
Social interaction	2.408	0.860	−0.147***

Note: Standard errors clustered at the firm level in parentheses, *p < 0.1 **p < 0.05 ***p < 0.01. All control variables are identical with those in Table 3.

stress. The coefficients of the impact of process innovation on work stress are 1.071 ($p < 0.01$) and 0.611 ($p < 0.05$), and the coefficients of the impact of process innovation on mental health problems, after simultaneously incorporating work stress into the regression equation, become 0.716 and 0.564. Compared to JI, the larger decrease in the magnitude of the coefficient suggests that the increased work stress induced by process innovation is more informative of the deterioration in workers' mental health.

The results for working hours and social interaction are shown in Panels C and D, respectively. There is a statistically significant relationship between working hours and process innovation. However, there is nearly no change in the mental health effect of process innovation after incorporating working hours (0.006; $p > 0.1$) into the baseline model, indicating that working hours are not an effective channel of transmission. In addition, poor social interaction with coworkers is observed to be an effective contributing factor to mental health issues, but it is not significantly affected by process innovation.

4. Discussion and conclusion

On the basis of unique survey data obtained from workers active on the frontline of production in manufacturing firms, we examine whether/how frontline factory workers' mental health is affected by the process innovation implemented by the firms where they operate. This study responds to the serious concern proposed by Gihleb et al. (2020) and Gunadi and Hanbyul (2021) about the influence of technological innovation on mental health issues among workers, and it provides straightforward evidence of a significantly positive relationship between the two. Our results are quite stable across model specifications containing various control variables and different analytical methods. After overcoming the underestimation of the impact caused by potential endogeneity, we confirm that frontline workers employed in manufacturing firms adopting process innovation are significantly more likely than those in firms taking no such action to experience psychological difficulties and to seek psychological counselling or treatment. Our findings are in line with Abeliansky and Beulmann (2019), who found that an increase in sector-level robot intensity is positively related to a decrease in the mental health of workers.

Exploring the potential channels through which process innovation affects the mental health of workers, this study obtains results that show that in workplaces with a new advanced automation environment, workers employed in these innovative firms believe that they face higher unemployment risk and worry about the stability of their jobs, which in turn is partially linked to the deterioration in their mental health and further increases treatment-seeking behaviours. In addition, work stress is found to be another effective channel of transmission that plays an even more important role in the relationship between mental health and process innovation than JI. However, working hours and social interaction at work, which are two contributing factors to work stress, are not effectively involved in this relationship. For the former, one possible reason is that although the automation systems taking over main production tasks are able to efficiently operate over a lengthy period of time, they still need to interact with manpower to complete entire production processes, and the part that workers perform may also become lengthy but relatively effortless.

Our findings may well be applicable to many developing countries that simultaneously face the common challenge of the prevalence of unmet mental healthcare needs and may be committed to introducing technological innovation. The subjective assessment of the need to receive treatment may not be an accurate indicator of workers' mental health problems. However, serving as the lower bounds of the mental health impact, it still reveals a foreseeably enormous increase in the need for mental health services and in the burden on the mental healthcare system.

More importantly, due to the continuously falling cost of new technology adoption, advanced automation deployment has become increasingly pervasive in the current digital era, and it has further extended its reach to service industries. Thus, the treatment gap in mental healthcare tends to be wider, which raises serious policy challenges for the optimisation of healthcare reforms in China. Although the enactment of China's mental health law in 2013 symbolised a milestone step in strengthening mental healthcare, some obstacles apparently remain on the path of mental healthcare industry development. In addition to those frequently mentioned policy options, such as increasing government investment and subsidies and scaling up professional training, policymakers should place some emphasis on pushing more technological innovation for digital healthcare platforms. Such platforms could closely connect with firms, which in turn would provide reasonable financial support and ample feedback, and they could connect with workers in need of more convenience, mental health knowledge and privacy protection.

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Ethical statement

Hereby, we consciously assure that for the manuscript the following is fulfilled:

1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors.
5) The results are appropriately placed in the context of prior and existing research.
6) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

CRediT author statement

Yuhong Du: Data curation, Software,Writing- Original draft preparation, **Hazrul Shahiri**: Software, Validation,Writing- Reviewing and Editing., **Xiahaiwei**: Conceptualization, Methodology, Investigation, Supervision.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2023.101347.

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