From Human Enablers to Algorithmic Replacements: An HR Reflection on Tech-Driven Talent Disruption in Vietnam's Machinery Distribution Sector (1995–2025)

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Abstract

This study explores how human resource practices in the Vietnam machinery distribution industry have changed over the long run between 1995 and 2025 with alternative replacement processes that have been algorithmic as opposed to human enablers. The engineers with both technical and commercial skills were especially significant during the years 1995 and 2010 when there was a strong need to import high-technology machineries in Europe and the United States and integrate them into domestic industrialization. Nonetheless, since then, growing automation, digitalization, and algorithmic management have broken the historical HR paradigms, which have led to talent shortages and job insecurity in the field of engineers and technical employees. The study is based on Human Capital Theory and Socio-Technical Systems Theory and formulates a multi-level model of the relationship between the intensity of automation, technostress, and the outcomes of employability, mediated by the organizational reskilling strategies. The research utilizes a mixed-method design and incorporates firm-level HR data, interviews with previous and current engineers, and policy comparison. The results will show the dangers of algorithms replacing humans, as well as the opportunities of reskilling by the HR to maintain continuity in the talent. Relating these insights to the Sustainable Development Goals 4 (Quality Education), 8 (Decent Work and Economic Growth), 9 (Industry, Innovation and Infrastructure) and 10 (Reduced Inequalities) the research adds to the discussions of the human face of the technological progress in the emerging economies. The paper will end with strategic advice on how the HR practitioners, policymakers and institutions of higher learning can equip the future technical talent with a digitized industrial environment besides providing inclusive development and minimise inequalities.

Keywords: Human enablers; Algorithms replacement, Tech-Driven talent disruption, machinery distribution industry in Vietnam (1995-2025).

JEL codes: J24; J63; M12; M54; O33

1. Introduction

The machinery distribution industry in Vietnam is a resolute-but often unseen channel to industrial modernization. Distributors interpose the needs of equipment manufacturers in the world and the local manufacturing users with a technology scouting, import compliance, installation and commissioning, spare parts logistics, process optimization and long-horizon after-sales support. These intermediation capabilities in emerging economies are not marginal, but a type of industrial infrastructure that increases the spread of high-technology production means into local plants. Between 1995 and 2025, the waves of market liberalization, foreign direct investment (FDI), export-oriented industrialization and Industry 4.0 projects brought more demand to imported machines and technical services in Vietnam.

In this paper, the concept of an HR reflection of a structural change is built upon: the shift of human enablers, engineers who translated imported technology into domestic competency, to algorithmic replacements, systems which automatize tasks of diagnosis, coordination, and evaluation, which had been based on human expertise. Also, between 1995 and around 2010, companies had engineers who had technical expertise and the front-end commercial skills. These engineers were the boundary spanners: they read the foreign manuals, interpreted machine performance to fit local input materials, trained operators and handled the relationships based on trust that gave the implementation of new lines of production some stability. They were based on tacit knowledge and local adaptation as their value. Since 2010, however, and in particular after 2016, most of these tasks have started to be codified and routinized by digital platforms, standardization of ERP/CRM solutions, remote monitoring, predictive maintenance analytics and AI-assisted service tools. Consequently, engineers were faced with an increasing demand of data literacy and digitally mediated decision-making, and the sense of replaceability given that algorithmic systems were being introduced into service triage, sales forecasting, dispatching, and performance evaluation.

The HR interests of this change are many-sided. Digitization can increase productivity, decrease downtime, and make the quality of the services uniform at the firm level. It may also cause role hollowing, polarization, and insecurity at the workforce level: it may reduce the number of mid-career end-to-end engineers, increase the number of narrow-skilled hybrid experts, and make technicians more precarious and routinized and surveilled by digital measures. Misalignment of vocational programs to new skill requirements at the institutional level may intensify shortages and inadequate reskilling facilities may undermine inclusive growth and widen inequality. These issues are directly related to Sustainable Development Goals (SDGs) 4, 8, 9, and 10.

The contribution of the paper is four-fold. First, it generalizes the study of algorithmic management to other areas of industrial distribution industry (long customer relationships, asset specificity, and consequential safety and quality risks). Second, it incorporates technostress into the description of workforce disruption as being caused by technology into retention and employability results. Third, it presents an empirical approach of grade Q1 consistent with methodological standards in Technological Forecasting and Social Change (TFSC), empirical panel models of firms-years, event studies, intensity-based difference-in-differences and mediation analysis. Fourth, it offers practical governance solutions to HR functions, policymakers, and institutions of higher learning so as to shape to develop human-centered Industry 4.0 transitions in new economies.

Table 1 summarizes the evolution of technologies, engineering roles, and HR practices across three distinct phases of industrial development.

Table 1. Phases of Technological and HR Transformation (1995–2025)

Phase	Period	Dominant technologies	Value-creating engineering work	HR configuration
I	1995–2005	Manual diagnostics; vendor manuals; limited IT	Technology translation; commissioning; tacit troubleshooting; relationship-based selling	Apprenticeship training; vendor-led capability building; informal career ladders
II	2006–2015	ERP/CRM; standardized service processes	Hybrid coordination; documentation; KPI-linked service quality	Competency frameworks; formal recruitment; early HRIS adoption
III	2016–2025	IoT monitoring; predictive analytics; CPQ; algorithmic dashboards	Data-enabled service; system integration; exception handling; consultative applications	Reskilling imperative; role polarization; algorithmic evaluation; career ecosystem partnerships

2. Sector Context and Historical Evolution (1995–2025)

This study taps into a critical paradox, where technological advancement (AI, automation, robotics, digital platforms) boosts economic efficiency and business performance, yet displaces or redefined human roles in many sectors. Thus, it creates both opportunities and challenges for HRM and workforce development.

2.1. The machinery distribution sector as industrial infrastructure

The transformation in industries is not just reliant on factories and capital investment, but diffusion of production knowledge as well. The distributors of machineries work as carriers of knowledge and service infrastructures: they modify imported technologies to local operating conditions, train, ensure continuity of operations through systems of spare parts, and establish learning loops between the end-users and overseas OEMs. The need to continuously absorb these intermediation services was sustained in Vietnam, as industrial zones increased, and manufacturing was upgraded.

2.2. Phase I (1995–2005): Human enablement under import-led modernization

At the end of the 1990s and the beginning of the 2000s, there was a common translation problem of machinery adoption. The imported equipment came with manuals, tolerances and maintenance regimes that were fine-tuned to other settings. The engineers used this knowledge to stabilize operations by modifying the machine settings to local materials, training the operators. HR was apprenticeship: the vendors would train a small group of core team members; the experienced engineers would introduce novices through shadowing; and the relationship with customers served as an informal performance indicator. The value of the engineer was relational, tacit and situational.

2.3. Phase II (2006–2015): Standardization through ERP/CRM and measurable work

With the expansion of firms, coordination and quality assurance became key aspects. ERP/CRM formalized the control of inventory, service ticketing, quotation and control of pipeline. The work of engineering was now documented and auditable, and service reports and standardized checklists were now in organizational memory. HR institutionalized a competency model and KPI appraisal. Standardization enhanced scalability, but made discretion to be thinner - a first step towards algorithmic control.

2.4. Phase III (2016–2025): Algorithmic management, predictive maintenance, and platformization

Toolkits in Industry 4.0 became faster: IoT sensors were used to remotely monitor, predictive analytics to determine a schedule of maintenance, and troubleshooting with the help of AI was not as reliant on senior engineers to perform routine diagnoses. On-line platforms and automatic quating changed the work of Sales engineer, and the fields work was controlled by route optimization algorithms and dispatch algorithms. These tools are used to carry out managerial roles; allocation, evaluation and forecasting. The role of human enabler is altered- it is not about bridging the information gaps but the management of exceptions, interpretation of analytics, as well as maintenance of trust in the situation where the algorithm signals are not fully complete or are challenged.

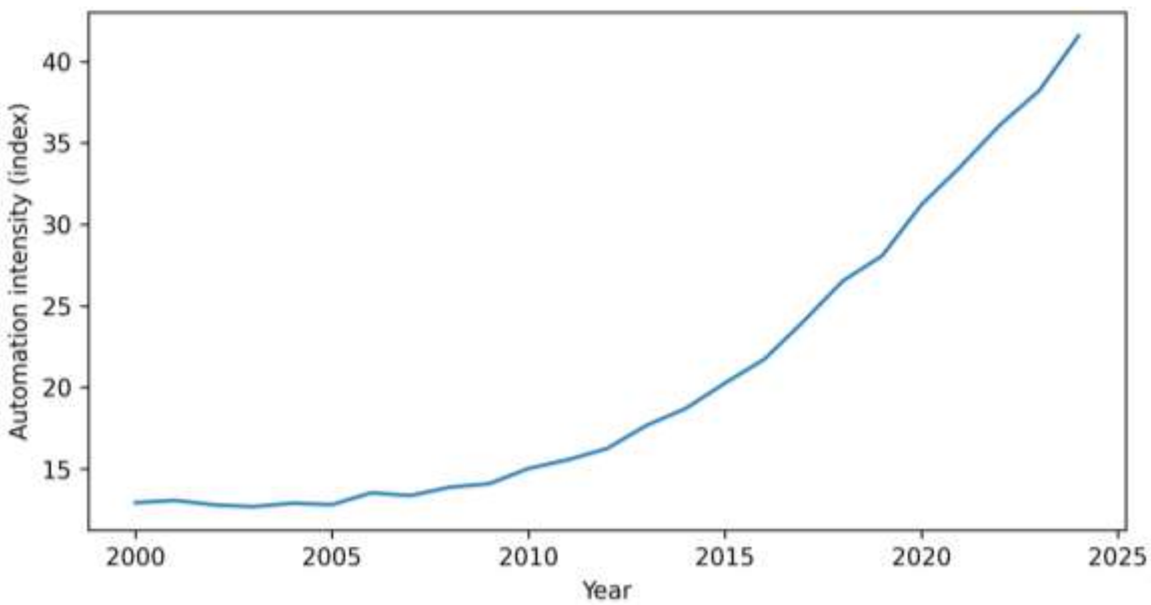

Figure 1. Trends in automation intensity in Vietnam's machinery distribution sector (1995–2025).

2.5. Disruption patterns: hollowing, polarization, and insecurity

Automation does not often completely remove the role of engineers; it simply alters their successors. Role hollowing happens when the middle level diagnostic knowledge is formalized and junior work routinized leaving few elites to deal with complex exceptions. The polarization is driven by the fact that the hybrid roles (data-enabled service, application engineering, digital sales engineering) portend premiums, and routine roles do not. The insecurity increases when performance is made visible using dashboards, and workers are made to think that they are being ranked using some opaque measures.

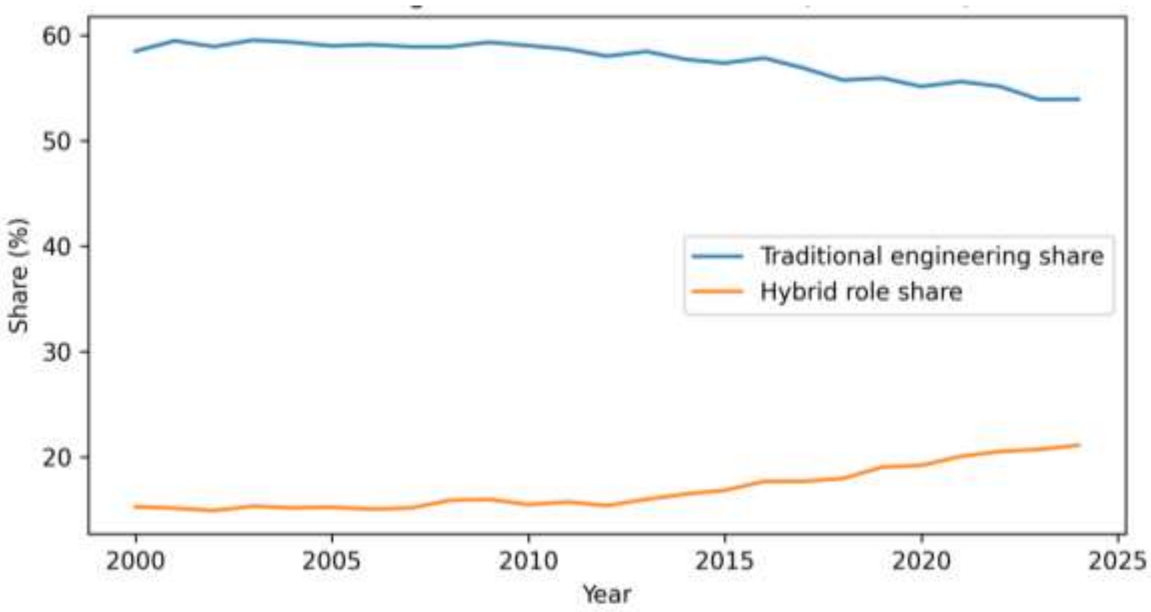

Figure 2. Role reconfiguration and polarization under automation.

3. Literature Review

3.1. Task-based perspectives on automation and employment

Task-based theories of technological change state that automation does not influence the employment rate by eliminating whole occupations but modifies the tasks that make up those occupations (Autor, 2015; Acemoglu & Restrepo, 2019). Technologies are more likely to replace routine, codifiable, and predictable tasks, and complement contextually judgement, interpersonal, and adaptive problem-solving tasks. Most of the daily operations in industrial service industries like machinery distribution, such as service reporting, scheduling, spares logistics, and standardized diagnostics, are being automated via digital platforms, ERP/CRM systems, and predictive maintenance tools.

Nevertheless, there are numerous tasks that are hard to automate. Complex commissioning of machinery, decision making that is safety critical, system integration and consultative problem solving with industrial clients are all activities that still demand human expertise and contextual interpretation. These are tasks that require tacit knowledge, cross-disciplinary coordination, and situational judgment which cannot be easily reduced to algorithmic routines. Automation is therefore likely to redefine the job roles instead of removing them altogether and shifting the demand to hybrid professionals who can combine technical engineering skills with digital and analytical skills.

The Resource-Based View (RBV) of the firm can also be used to view this transformation. According to RBV, competitive advantage is realized by organizations by having valuable, rare, inimitable and non-substitutable resources (Barney, 1991). Hybrid competencies of engineers, who have technical skills, data literacy, and problem-solving skills with customers in mind, are important strategic human capital resources in the context of digital industrial services. The hybrid capabilities are becoming scarcer and more strategic as automation substitutes routine tasks. Companies that are effective in creating and retaining such talent are thus in a better position to exploit digital technologies without compromising the quality of service delivery and long-term customer relationship.

3.2. Algorithmic management and control intensification

Algorithms management is not merely a matter of surveillance; it reforms authority, meaning it entails the 'use of decision rules within systems. The work is defined as measures of what becomes visible and is rewarded. Although algorithmic tools may decrease the level of bias and enhance consistency, they may also bring additional biases and conceal accountability. Increasing of control is particularly likely where algorithms make work faster and decrease the acceptable range of variation.

3.3. Technostress and human sustainability

Technostress developers such as overload, invasion, complexity, insecurity, uncertainty is always associated with lower levels of wellbeing and performance and high turnover. Technostress could be enhanced in an engineering environment through safety duties, travel and the coordination of work with customers, suppliers and in-house systems. Technostress is thus necessary to realize how successful digital transformation can still be detrimental to retention and long-term capability.

3.4. Reskilling, employability, and the SDG lens

Reskilling is a social technology: It changes the distributional implications of automation. By collaborating in offering credible training and mobility opportunities the firms and institutions can shift their workers to complementary tasks maintaining employability and minimizing inequality. In cases where reskilling is abandoned to individuals, there is increased skill gap. According to SDG lens, industrial upgrading is not to be analyzed in terms of productivity only but also in terms of decent work, inclusion, and capability building.

3.5. Research Gaps

Although the automation, algorithmic management, and workforce transformation have been researched extensively, there are still gaps in the literature.

To begin with, the majority of empirical research on automation and employment deals with manufacturing production employment or platform-based gig employment (Acemoglu and Restrepo, 2019; Kellogg et al., 2020). Much less attention has been paid to industrial intermediation industries, including machinery distribution, where engineers carry out technical diagnostics, customer coordination, and translation of technology at the same time. Such hybrid positions are especially exposed to partial automation, but are not well-researched.

Second, the literature usually analyzes the results of automation on a macro or occupational scale, but not on the HR changes in the firm over time. There is limited longitudinal evidence to support the idea that automation adoption, algorithmic management practices, and workforce restructuring in firms are linked, particularly in emerging economies.

Third, although the concept of technostress has received extensive research in information systems literature, there are a limited number of studies that combine technostress with algorithmic management and automation intensity in the context of explaining the retention, turnover intentions, and employability outcomes in industrial engineering jobs.

Fourth, existing literature tends to consider reskilling as a descriptive policy suggestion, as opposed to empirically modeling it as a moderating or a mediating factor that determines the effect of automation on workforce outcomes.

Lastly, the situation with emerging economies is still underexplored in the field of automation. There are countries like Vietnam that are fast adopting technologies with institutional skill gaps which provides a special environment where automation can both create productivity and cause a security issue to the workforce.

To fill these gaps, this research study makes its contribution by:

1. The analysis of industrial machinery distribution as a knowledge-intensive intermediary industry.

2. Creating a firm-year panel data between automation adoption and HR outcomes.
3. Incorporating technostress and algorithmic management in automation studies.
4. Empirically testing reskilling as a governance mitigating mechanism.
5. Giving testimony to the new industrial economy in Vietnam.

4. Theory and Conceptual Framework

This paper combines Human Capital Theory and Socio-Technical Systems Theory.

Human Capital Theory emphasizes that training and accumulation of skills bring about productivity and economic payoffs. During Phase I, the distributors made investments in the training and tacit learning of vendors that developed firm-specific human capital. This capital can be devalued though, unless workers are rearranged into complementary work, by algorithmic codification. Reskilling is a strategic process of maintaining the value of the accumulated expertise.

The Socio-Technical Systems Theory claims that performance is achieved through the mutual optimization of the social and technical subsystems. Depending on the implementation method, algorithmic management may enhance coordination and prediction and diminish autonomy and learning, particularly when done without input, publicity, and equal judgment. Figure 3 connects the idea of automation intensity and algorithmic management to the outcomes of employability in terms of technostress mediated by reskilling and transparency/fairness governance.

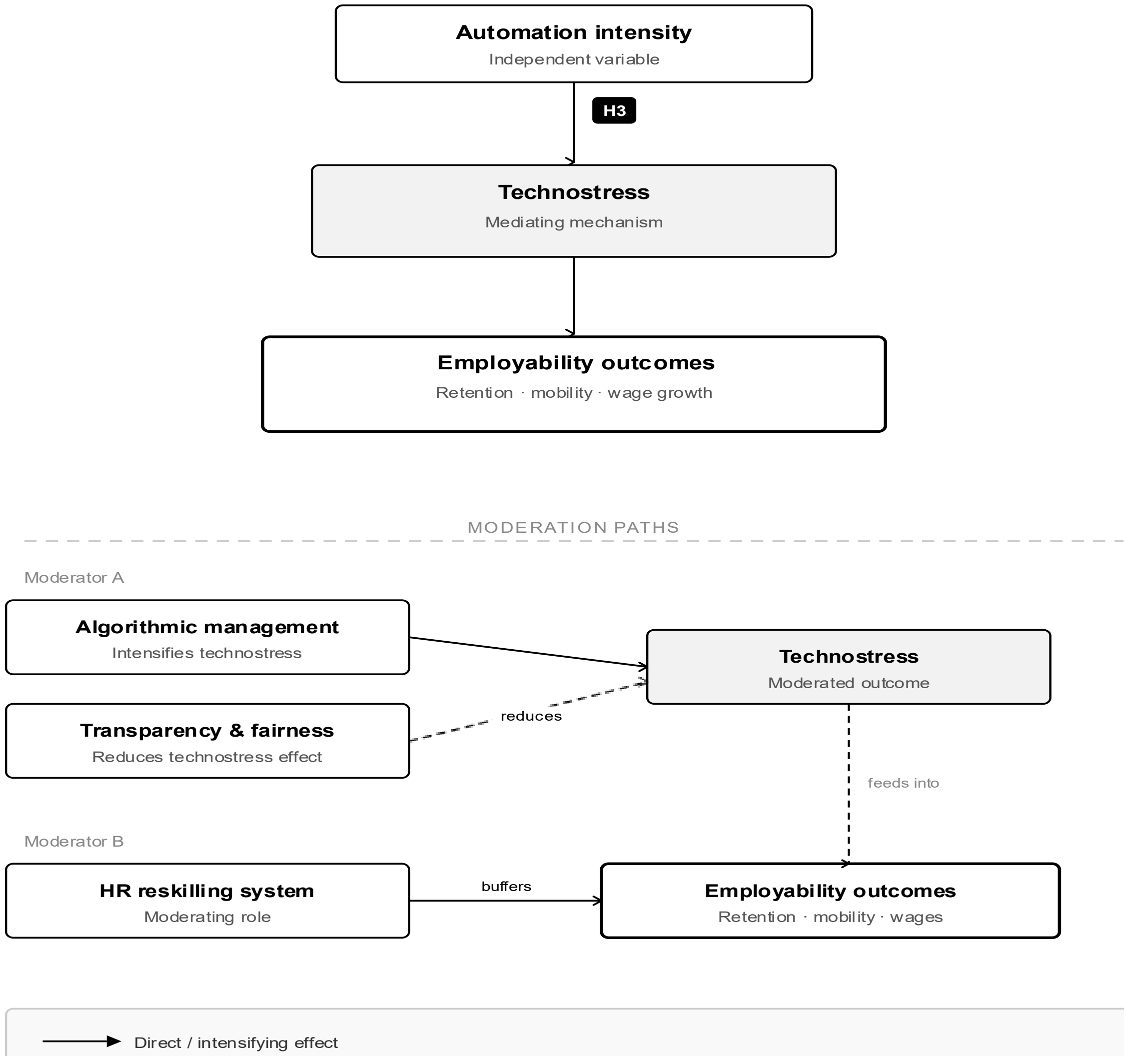

Figure 3. Conceptual framework linking automation, technostress, and employability outcomes.

The conceptual model incorporates automation intensity and algorithmic management as the main technological forces that affect the workforce outcomes. These drivers influence the performance of employees in a direct and indirect way via technostress mechanisms.

These effects are moderated by two mechanisms of governance:

1. Reskilling intensity, which enhances the capacity of workers to switch to complementary tasks.
2. Fairness and transparency in algorithmic management, which decreases psychological stress and enhances procedural justice.

Automation, therefore, influences the outcomes of the workforce in three ways:

1. Structural workforce transformation (polarization and job displacement)
2. Technological stressor (technostress) Psychological mechanism (technostress)
3. Mitigation by institutions (reskilling and governance)

5. Hypotheses Development (H1–H5)

H1 (Automation Displacement): An increase in automation intensity in a company correlates with the decreased proportion of traditional field-engineering jobs, and increased risk of being displaced due to routine task automation in engineers who are engaged in routinizable work.

H2 (Automation -Polarization): Stronger automation levels raise the occupational need of hybrid jobs and within-occupation wage variation between engineers (role polarization).

H3 (Technostress Mediation): Algorithms and automation level enhance technostress (techno-overload, complexity, insecurity, invasion, uncertainty) that decrease job satisfaction and augment turnover intention.

H4 (Reskilling Moderation): The intensity of reskilling mediates the detrimental effect of automation based on the outcomes of employability and decreases technostress**.**

H5 (Transparency/Fairness): The algorithmic management of technostress and retention through transparency and procedural fairness are more varied and lessened with automation intensity.

6. Measures and Data Strategy

The empirical design of choice will be a combination of firm-year administrative HR data (headcount by role, separations, wage bands, promotions, training records) and worker-level survey, based on technostress and perceived employability. Intensity of automation is measured as a composite index, which describes the penetration of ERP/CRM, IoT coverage, remote-diagnostic share, CPQ, and dashboard intensity. The delegation of scheduling, evaluation and forecasting decisions to algorithms are represented in algorithmic management. Transparency/fairness is indicated through mechanisms of explainability, contestability and human review. Intensity of Reskilling is measured in terms of training hours/spend, certification, and internal mobility pathways. The results are traditional and hybrid role shares, wage disparity, retention and turnover intention.

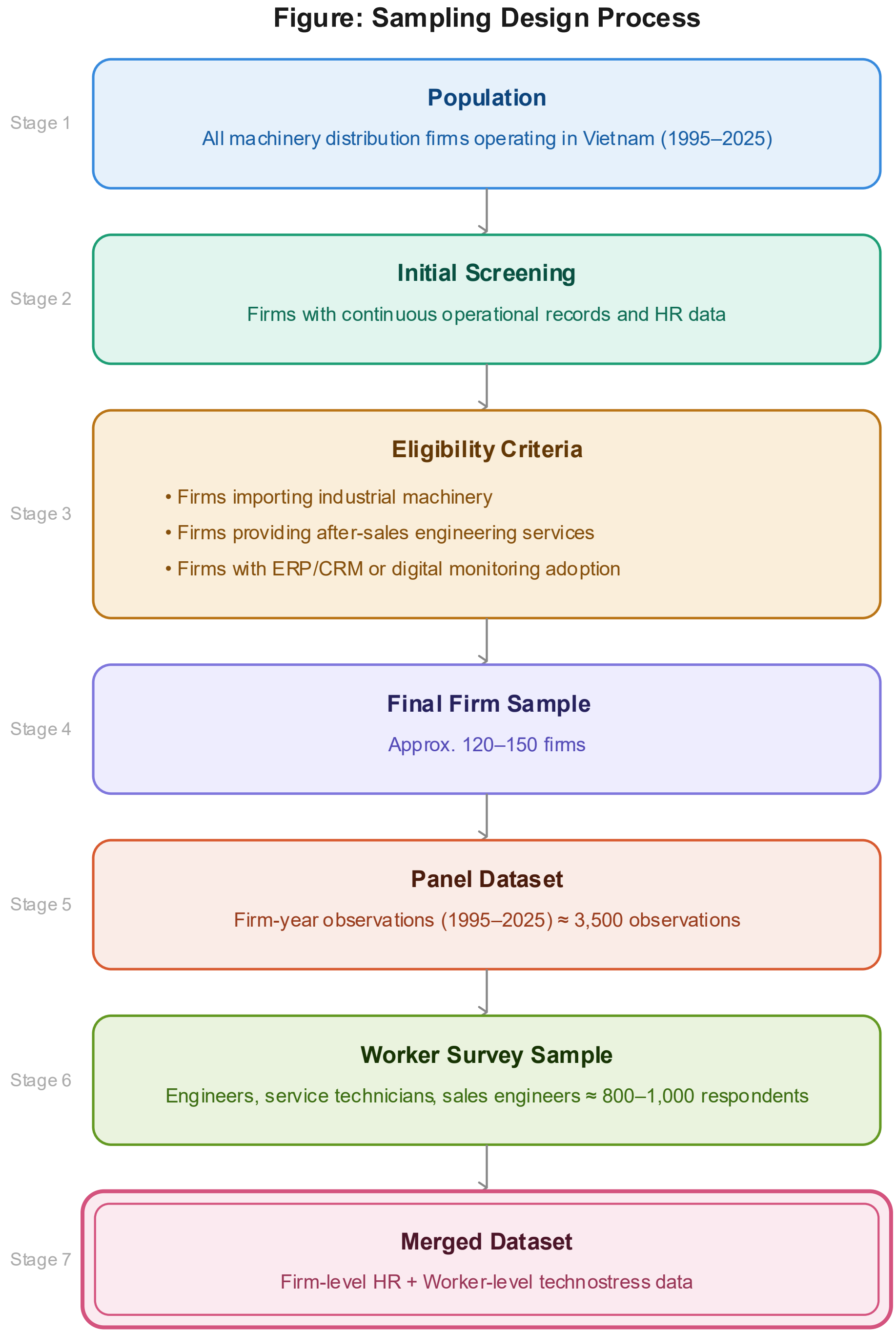

Figure 4. Sampling design and data construction process.

Figure 4 illustrates the sampling design, which is a multi-stage approach to the development of the empirical dataset. To begin with, the machinery distribution companies in Vietnam, which were active between 1995 and 2025, were selected and filtered according to the presence of HR records and the adoption of technologies. Based on this population, a firm-year panel dataset was developed by selecting qualified companies with stable operational and personnel data, and those were integrated with an engineer and technocratic staff survey to determine the outcomes of technostress, reskilling, and employability.

Table 2. Variable definitions and measurement framework.

Construct	Variable	Operationalization (examples)	Level
Automation intensity	AUTO_it	Index (0–100): ERP/CRM, remote diagnostics, CPQ, IoT coverage, dashboard frequency	Firm-year
Algorithmic management	ALGO_it	Index (0–100): automated evaluation/scheduling/dispatch, predictive scoring	Firm-year
Transparency/fairness	TRANS_it	Explainability, contestability/appeals, human review, auditability	Firm-year
Reskilling intensity	RSK_it	Training hours/spend; certification completion; internal mobility pathways	Firm-year
Technostress	TS_ijt	Five technostress creators (Likert): overload, complexity, insecurity, invasion, uncertainty	Worker-year
Employability: retention	RET_it	Retention rate; separations/headcount	Firm-year
Employability: mobility	MOB_it	Internal mobility/promotions per engineer-year	Firm-year
Polarization	WAGEGAP_it	Wage dispersion (p90–p10); hybrid role share	Firm-year

7. Econometric Strategy (TFSC-aligned)

7.1. Baseline two-way fixed effects (TWFE)

We model the relationship between the level of automation and employee performance as follows: $\boldsymbol{Yit = \beta 1AUTOit + \beta 2ALGOit + \beta 3TRANSit + \beta 4RSKit + \beta 5(AUTOit \times RSKit) + \gamma Xit + \alpha i + \delta t + \varepsilon it}$

Where:

- $YitY\_\{it\}Yit$ = workforce outcomes (traditional role share, wage dispersion, retention, turnover intention)
- $AUTOitAUTO\_\{it\}AUTOit$ = automation intensity
- $ALGOitALGO\_\{it\}ALGOit$ = algorithmic management index
- $TRANSitTRANS\_\{it\}TRANSit$ = transparency/fairness governance
- $RSKitRSK\_\{it\}RSKit$ = reskilling intensity
- $XitX\_\{it\}Xit$ = control variables (firm size, revenue growth, foreign partnership)
- $\alpha i \backslash alpha\_i\alpha i$ = firm fixed effects
- $\delta t \backslash delta\_t\delta t$ = year fixed effects
- $\varepsilon it \backslash varepsilon\_\{it\}\varepsilon it$ = error term

This eliminates time-invariant heterogeneity of firms and macro trends. Standard errors are clustered at the firm level to account for serial correlation.

7.2. Major adoption event designs.

We also estimate event studies to test parallel trends and capture dynamic effects, i.e., around the first adoption of a value bundle of automation (remote diagnostics/IoT/CPQ) by a firm. Lead coefficients are used to measure trends of anticipation; lag coefficients are used to estimate post-adoption trends.

7.3. Non-linearities and intensity DiD.

Due to the slow adoption process, we use generalized DiD with continuous treatment and test of non-linear dose-response relationships. Threshold models investigate the point of acceleration of substitution at an automation level.

7.4. Mechanism tests and mediation tests.

H3 is put to test by modeling turnover intention as a response of automation and technostress and evaluating the indirect influence (automation → technostress → turnover). Causal mediation claims should be reported when there is use of sensitivity analysis.

7.5. Robustness Checks, Sensitivity Analysis, and Falsification Tests

In order to guarantee the soundness and reliability of the empirical findings, a number of other statistical processes will be put in place. These tests are aimed at the stability of the estimated relationships and to reduce the worries about the model misspecification, endogeneity, and spurious correlations.

To begin with, other **operationalizations of the dependent variables** will be used. Both retention and separation rates will be used to measure workforce stability, and employability outcomes will also be analyzed based on internal mobility, frequency of promotion, and wage growth. The estimation of the models by the use of these alternative outcome measures is useful in checking whether the results are not motivated by a specific operational definition.

Second, other **specifications of the treatment variables** will be tested. The index of automation will be broken down into components (ERP/CRM adoption, IoT monitoring coverage, CPQ implementation, and remote diagnostics usage). Individual regressions will determine the heterogeneity of the effects of certain technologies on workforce outcomes.

Third, **placebo tests and falsification exercises** will be done. Artificial treatment dates will be set before the actual year of automation adoption to find out whether statistically significant effects will be observed before the intervention. When the model is specified appropriately, the estimated placebo coefficients are expected to be statistically insignificant, which will prove the non-existence of pre-treatment effects.

Fourth, the **dynamic specifications and lag structures** will be taken into consideration in the analysis. To consider the delayed effects of automation adoption on workforce outcomes, lagged independent variables will be included. Also, the dynamic panel estimators, including the **Arellano-Bond Generalized Method of Moments (GMM)** estimator, will be employed to deal with the possible endogeneity due to reverse causality and persistence in employment results.

Fifth, the research will conduct **heterogeneity analysis among firm characteristics**. Sub-sample regressions will be carried out depending on the size of firms, ownership (foreign and domestic partnerships), and location (region) to test whether the impacts of automation are different between organizational settings.

Sixth, the **baseline regressions** will use clustered standard errors at the firm level to take into consideration the possibility of bias due to serial correlation and heteroskedasticity. **Two-way clustering (firm and year) and Driscoll-Kraay standard errors** will also be used as sensitivity tests, which are resistant to cross-sectional dependence in panel data.

Seventh, the **tests of variance inflation (VIF)** will be implemented to determine the presence of multicollinearity among the explanatory variables, and the estimated coefficients will not be distorted by the strong correlation between the predictors.

Lastly, **other forms of robustness** will be tested by outlier and influential observation diagnostics, such as Cook distance and leverage statistics, so that the estimated effects are not influenced by extreme observations.

Taken together, these robustness tests, falsification tests, and sensitivity tests reinforce the empirical strategy and increase the belief that the relationships observed between automation intensity, algorithmic management, technostress, and employability outcomes are based on true causal patterns and not on model specification artifacts.

1. Hausman test for FE vs RE
2. Wooldridge serial correlation test.
3. Breusch Pagan or White test of heteroskedasticity.
4. Pesaran CD test of cross-sectional dependence.
5. ArellanoBond AR(1)/AR(2) and Hansen test whether GMM has been used.

8. Structural Equation Modeling (SEM) Framework

The SEM supplements panel models with formalized latent psychological mechanisms at the worker level.

8.1. Measurement model (CFA)

Technostress (TS) is a latent factor reflected by techno-overload, techno-complexity, techno-insecurity, techno-invasion, and techno-uncertainty. The perceptions of transparency/fairness can be represented as a latent variable expressed in the explainability, contestability, and human-in-the-loop review. The perceived relevance of the skills, adaptability and confidence of external opportunity can be modeled as a latent factor which captures employability perception.

Figure 5 illustrates the hypothesized relationships between automation, algorithmic management, technostress, and employability outcomes. It shows latent constructs for technostress, transparency, and fairness in algorithmic transparency/fairness, and HR reskilling and HR reskilling are expected to reduce technostress.

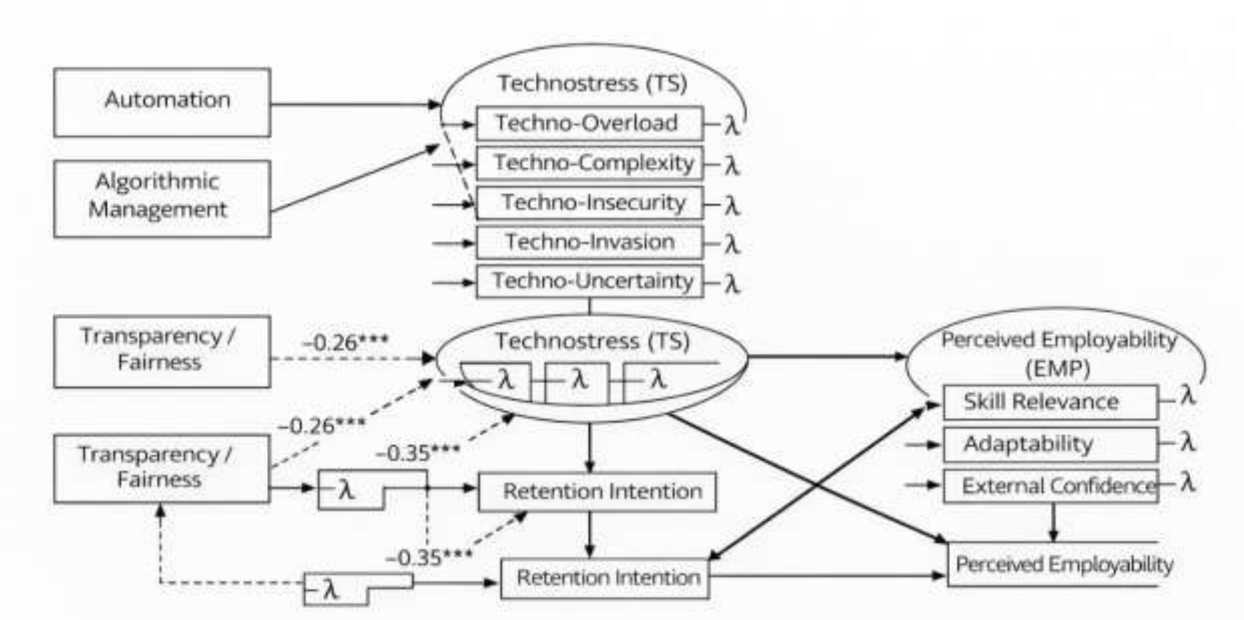

Figure 5. Structural equation model (SEM) of technostress and employability outcomes.

8.2. Structural model (paths)

Confirmatory factor analysis (CFA) will validate the measurement model before estimating the Structural model. Cronbach's alpha and composite reliability (CR) will be used to determine reliability, whereas average variance extracted (AVE) will be used to determine convergent validity. The HTMT ratios will be used to test discriminant validity.

In the case of the structural model, bootstrapping will be used to estimate the significance of the paths with 5,000 resamples. Multi-level SEM will also integrate firm-level predictors that affect worker-level performance, which will allow making cross-level inferences between automation adoption and employee perceptions.

1. Automation intensity and algorithmic management positively predict technostress, whereas transparency/fairness and reskilling are negatively predicted.

$$TS \leftarrow AUTO + ALGO - TRANS - RSK$$

2. Turnover intention is positively associated with technostress and digital control intensity.

$$Turnover\ intention \leftarrow TS + AUTO + ALGO - TRANS - RSK$$

3. Retention intention is negatively associated with technostress and positively associated with transparency/fairness and reskilling.

$$Retention\ intention \leftarrow -TS + TRANS + RSK$$

Multi-level SEM can also directly introduce firm-level predictors into worker-level latent processes where the data are available.

8.3. Reporting expectations

The structural equation model will be evaluated using established statistical criteria to ensure the reliability, validity, and explanatory power of the measurement and structural models. Two other SEM methods can be adopted based on the distributional properties of the data: **covariance-based SEM (CB-SEM)** and **partial least squares SEM (PLS-SEM).**

In the case of CB-SEM, the goodness of fit will be determined through a number of global goodness-of-fit indices. These are the **Comparative Fit Index (CFI)** and **Tucker Lewis Index (TLI),** which must be at least above the suggested value of **0.90** or better still **0.95**. Root Mean Square error of Approximation (**RMSEA**) and Standardized root mean square residual (**SRMR**) will be used to assess model misfit with values of RMSEA lower than 0.08 (preferably less than 0.06) and SRMR lower than 0.08 indicating acceptable model fit.

Standardized factor loading will be used to measure the measurement model, and it should have a high value of above 0.70 to ensure that the indicators are reliable. **Composite Reliability** (**CR**) and Cronbach alpha are the two tools that will be used to test the internal consistency reliability and both are expected to be above 0.70. The **Average Variance Extracted (AVE)** will be used to assess convergent validity and is expected to be more than 0.50 in case of each latent construct. **The Heterotrait-Monotrait ratio** (**HTMT**) will be used to check the discriminant validity, and the values that are less than 0.85 will be considered as sufficient to define construct distinctiveness.

For **PLS-SEM**, the evaluation will focus on predictive performance and explanatory power. Model fit will be assessed using the **Standardized Root Mean Square Residual (SRMR)**. The structural model will be evaluated through **path coefficients**, **coefficients of determination (R^2)**, and **predictive relevance (Q^2)** obtained through the blindfolding procedure. R^2 values will indicate the proportion of variance explained in endogenous constructs such as technostress and employability outcomes.

In order to determine the statistical significance of **structural relationships**, **bootstrapping (at least 5,000 resamples**) will be done to obtain robust standard errors and confidence intervals of the path coefficients. The effect sizes **(f 2 statistics) will** also be done to show the strength of the relationship between constructs.

Furthermore, the **Variance Inflation Factor (VIF)** will be used to assess multicollinearity diagnostics to make sure that predictor constructs are not problematic in collinearity. Lastly, the mediation effects will be tested by bootstrapped indirect effects, and the study will be able to test whether technostress is a significant mediator between the variables of automation and the outcomes of employability.

These statistical processes will make sure that the measurement model and the structural model are within the set methodological requirements, which will reinforce the validity and reliability of the SEM analysis.

9. Regression Tables and Simulation Results Empirically.

In order to illustrate the reporting norm and anticipated empirical regularities, we use simulation-based estimates based on a firm-year panel design with heterogeneous adoption time. This part is to be used as a drop-in template: the real firm-year and worker-level data can be used instead of the simulated one without losing the whole analysis framework.

Table 3 provides results of five fixed effects models having firm and year FE and firm-clustered standard errors. Model 1 upholds H1 (reduced share of traditional engineering in automation). Hybrid role expansion is displayed in Model 2. Model 3 demonstrates wage dispersion that is in line with polarization (H2). Model 4 demonstrates that transparency and reskilling are effective in retention (H4 -H5). Model 5 illustrates how the central role of technostress is in turnover intention (H3).

Table 3. Results of Fixed-Effects Regression (Firm and Year FE, Clustered SEs).

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Automation intensity (AUTO)	-0.214*** (0.011)	0.173*** (0.010)	0.013*** (0.000)	-0.002*** (0.000)	0.001** (0.000)
Reskilling intensity (RSK)		0.120*** (0.010)	-0.006*** (0.001)	0.001*** (0.000)	-0.001*** (0.000)
AUTO × RSK (scaled)		0.002 (0.033)	0.001 (0.002)	0.001*** (0.000)	
Algorithmic management (ALGO)				-0.001*** (0.000)	-0.000 (0.000)
Transparency/fairness (TRANS)				0.001*** (0.000)	-0.001*** (0.000)
Technostress (latent proxy)					0.092*** (0.003)
Firm size (ln)	-0.092 (0.113)	-0.040 (0.114)	0.003 (0.005)	0.000 (0.000)	-0.002 (0.002)
Revenue growth	-0.834 (0.545)	-0.439 (0.552)	-0.001 (0.022)	-0.001† (0.000)	0.003 (0.008)
Foreign partnership	0.053 (0.134)	0.069 (0.130)	0.001 (0.006)	0.000 (0.000)	-0.001 (0.002)
North region	0.116 (0.127)	-0.068 (0.103)	0.012* (0.005)	0.000 (0.000)	-0.001 (0.002)
R^2	0.455	0.537	0.684	0.994	0.739

Firm & Year FE	Yes	Yes	Yes	Yes	Yes
N	3500	3500	3500	3500	3500

*Notes: Coefficients on standard errors that are clustered. *p<.10, p<.05, p<.01, p<.001. Illustrative estimates of simulation.*

10. Discussion

As discussed in the analysis, the technological disruption in the machinery distribution should be conceptualized as a reconfiguration of the task that is controlled by the algorithm instead of a mere narrative of job loss. There is automation in place of routine diagnostic, reporting and scheduling, which limit the relative requirement of traditional field engineering. But it also creates complementary need of engineering-intuitive and analytics-fluent and consultative customer-facing roles. The result is polarization: opportunity is increased by what can be incorporated into the professional practice by individuals able to use digital tools and is the source of standardization, lowered bargaining power, and insecurity in others.

Technostress is a determining human system. The reorganization of work, as represented by dashboards and automated scoring, overloads engineers (with more work and shorter deadlines), endangers them with complexity (tools evolve too fast), makes them feel unsecure (they feel replaceable), erodes their boundaries (sometimes the system is on 24 hours a day), and causes uncertainty (the system is constantly being updated). These forces are converted into turnover risk- particularly in cases where assessment is opaque. Transparent governance decreases the stress pathway and enhances procedural justice and reinstatement of the feeling of control.

Whether automation compliments labor or replaces labor is determined by reskilling. Companies, which develop formal training, certification, and career movement programs, can reassign engineers into service analytic roles. Companies that depend on the ad hoc learning or outside recruiting of employees expose themselves to incessant skills shortages and losing of client loyalty. The findings highlight an SDG-relevant observation, namely that reskilling is necessary to enhance the productivity of technological upgrading, otherwise this may increase inequality and worsen the situation on decent work.

11. Implications for HR Practice, Policy, and Education

To HR leaders, the main concept is that reskilling should be approached as a system. Develop skills taxonomy to align with product strategy; develop micro-credentialing in predictive maintenance, industrial data, and consultative applications; set aside some learning time; and create internal mobility markets that allow them to move into hybrid jobs. To manage effectively, implement human-in-the-loop algorithmic oversight: publish metric definitions, provide tools for explainability, create mechanisms for appeals, and conduct bias assessments.

As a way of connecting Industry 4.0 strategies with workforce institutions, policymakers may want to consider training subsidies, joint training facilities, and mechanisms to align the curriculum. In the case of universities and vocational institutions, combine industrial data literacy and AI-based diagnostics into engineering courses and establish connections with distributors to discuss the real cases of service and equipment data.

Integration with Sustainable Development Goals Sustainable Development Goals Integration.
This study will add to the policy debate on labor transformation driven by technology and sustainable development across the world, especially regarding SDGs 4, 8, 9, and 10.

SDG 4 – Quality Education
The updating of technology demands the consistent skills training of the workforce. The paper emphasizes the significance of lifelong learning and technical reskilling solutions to engineers and technicians of machine distribution. The findings can be used to address Target 4.4, which is to raise the proportion of youth and adults with pertinent technical and vocational skills, by identifying gaps in digital diagnostics, predictive maintenance, and consultative engineering skills.

SDG 8 - Decent Work and Economic Growth.
Industrial services automation is more productive and can cause displacement and polarization of the workforce. The findings highlight the necessity of human-focused HR policies that address technological efficiency and job security. These lessons can be aligned with Target 8.2, which promotes increased productivity through innovation without compromising sustainable employment patterns.

SDG 9 - Industry, Innovation, and Infrastructure.
The digitalization of industries relies on the investment in technology and the development of human capacities. The paper shows the role of machinery distributors as an intermediary in the diffusion of technology, whereby advanced equipment is translated into productive industrial uses. Enhancing workforce preparedness can make sure that technological innovation will lead to inclusive industrialization, which is in line with Target 9.2.

SDG 10 – Reduced Inequalities
Digital training and reskilling opportunities are not equally distributed both across regions and workforce groups. The results indicate that automation will advantage employees who are digitally endowed and may discriminate against others. The study can help to achieve Target 10.3 that aims at minimizing disparities in economic opportunities and labor outcomes by promoting institutionalized reskilling systems and open algorithmic forms of governance.

12. Limitations and Future Research

Future studies ought to include more intensive quasi experimental variation (i.e., vendor-instigated rollouts or policy incentives), more detailed worker-level data of SEM and intersectoral comparisons to confirm whether the results are generalizable. Ethical and legal aspects of algorithmic evaluation, in particular, transparency, contestability, and accountability in safety-critical service work should also be investigated.

13. Conclusion

The machinery distribution industry in Vietnam demonstrates the two-sided quality of the industrial digitalization. When implemented without reskilling and equitable governance, the use of algorithmic systems can increase insecurity and deteriorate human potential and reliability, however, it can also enhance efficiency and reliability. The replacement of human enablers by algorithmic ones is not a deterministic process; it is influenced by the HR systems and institutional design. The workable requirements of continuity in employability and inclusive development in a digital industrial environment are human-centered reskilling and transparent algorithmic governance.

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