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The Impact of Artificial Intelligence and Digitalization on the Workforce: A Skill-Biased Technological Change and Human Capital Perspective

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Abstract: The increasing pace of diffusion of Artificial Intelligence (AI) and digitalization is radically re-organizing labour markets world-over, but micro-level empirical data on the interaction of automation exposure and organizational reskilling to influence employee job-security perceptions are limited. This paper is based on the Skill-Biased Technological Change (SBTC) theory and Human Capital Theory (HCT) and creates a mediated moderation model where organizational reskilling provision mediates and moderates the association between AI exposure and job-security concern. A total of 240 respondents in the manufacturing, logistics, retail, healthcare, and IT industries were used to collect primary data using a structured questionnaire. Pearson Chi-square, correlation analysis, descriptive statistics and multiple regression (OLS) were used. The chi-square test also ensured that there was no direct significant relationship between automation exposure and job-security concern ($\chi^2 = 3.28$, df = 8, $p = 0.916$). But the regression analysis indicated that the reskilling provision has strong and negative predictive result of job-security concern ($\beta = -0.34$, $p < 0.001$) and that AI exposure interacting with reskilling has a strong attenuative effect on concern ($\beta = -0.21$, $p = 0.018$). The perception of positive automation had a strong influence on the optimism regarding the creation of new jobs ($\beta = 0.47$, $p < 0.001$). These results build on the SBTC model by showing that the exposure to automation is not the determinant of psychological employment outcomes but the organizational human-capital investment reaction. The research provides evidence to inform policymakers to build reskilling infrastructures and organization leaders to build human-AI partnerships.

Keywords: Artificial Intelligence; Digitalization; Workforce Transformation; Skill-Biased Technological Change; Human Capital Theory; Job-Security; Reskilling; Mediated Moderation; Regression Analysis

INTRODUCTION

A combination of Artificial Intelligence (AI), robotic process automation (RPA), and high-order digitalization is one of the most significant changes in the technological paradigm of contemporary economic history. The present-day AI systems, unlike the previous waves of mechanization, have cognitive features, such as natural language understanding, image recognition, predictive analytics, that expand automation to areas of professional and knowledge-intensive labour (Frey and Osborne, 2017). This qualitative change in the scope of automation has revived academic and policy discussion concerning the overall impact of technological change on employment, and the ability of labour markets and educational establishments to respond.

The macroeconomic scale is high. According to the World Economic Forum (2023), AI-led automation can potentially leave behind about 85 million jobs worldwide by the year 2025, and at the same time would produce 97 million new jobs with higher-order digital and interpersonal skills. According to McKinsey Global Institute (2022), a similar study estimates that close to half of present work procedures can be technically automated with the existing technologies. However, aggregate data masks the micro-process by which individual workers feel, perceive and react to workplace automation.

Current literature presents three major gaps: (i) the primary data remains largely macro-economic or sectoral, instead of individual, (ii) the existing theoretical frameworks, especially Skill-Biased Technological Change (SBTC) and Human Capital Theory (HCT), are not adequately incorporated into the empirical workforce literature (iii) little is done to use any other methodology other than the basic descriptive or chi-square analysis, which does not allow drawing causal conclusions concerning the mechanism of interaction between automation exposure and attitudinal outcomes. This paper fills all these three gaps.

We generate and validate a theoretically based mediated moderation model where organizational reskilling provision moderates the impact of AI exposure on employee job-security worry, and moderates that relationship based on the depth

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and accessibility of training. The primary surveys data of 240 respondents are used to operationalize the model and was tested through correlation and multiple regression analysis. The rest of the paper is organized in the following way: Section 2 outlines the objectives of the research; Section 3 is the development of the theoretical framework and literature review; Section 4 is the description of the research gap and hypotheses; Section 5 is a description of the methodology; Section 6 is the discussion of the findings and conclusions; and Section 7 is the conclusion and future research directions.

2. RESEARCH OBJECTIVES

The present research has six major objectives:
(i) To determine the type and scope of AI-improved workforce transformation, such as role displacement, change, and development, in major industrial sectors.
(ii) To determine the technical, cognitive and interpersonal skills required in the more and more automated workplaces and to establish emergent skill gaps.
(iii) To measure the association between automation exposure, organizational reskilling provision and employee job-security concern through correlation and regression analysis.
(iv) To determine whether reskilling provision is a mediator or moderator of the influence of automation exposure on psychological job-security outcomes.
(v) To investigate industry-specific digital transformation trends in manufacturing, logistics, services, and knowledge-intensive.
(vi) To draw evidence-based policy and managerial conclusions of the sustainable, equitable strategies of AI adoption based on SBTC and HCT.

3. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

3.1 Skill-Biased Technological Change (SBTC) Theory

The theoretical lens used in the present study is Skill-Biased Technological Change (SBTC) theory, which is a theory of technological innovation in which technology raises the relative productivity and thus demand for high-skilled labour more proportionally than it lowers the demand for routine, low-skilled work (Acemoglu & Restrepo, 2020). Originating in labour economics to explain the increasing skill premium in the economy of advanced economies seen since the 1980s, SBTC offers a structural mechanism linking automation to occupational polarization: Technology substitutes for routine codifiable work, be it cognitive or manual, while also complementing non routine analytical and interpersonal work (Autor, Levy, & Murnane, 2003).
Applied to the current context of AI, the SBTC theory predicts a hollowing-out of middle skill occupations, which will be automated by AI technologies automating cognitive forms of routine work that were previously insulated from mechanization, causing a high demand for high skill creative, strategic, and relational competencies alongside a maintenance of low skill, non-routine manual occupations that are resistant to automation (OECD, 2019). This framework produces directly testable hypotheses concerning the degree to which these various occupational categories are affected, and the types of skills most likely to command the most adaptive investment - hypotheses operationalized in the survey instruments deployed in this study.

3.2 Human Capital Theory (HCT)

Human Capital Theory was developed by Becker (1964) and developed by Mincer (1974) as a model of skills, knowledge, and capabilities of workers as productive assets and individuals and organizations invest in and develop these assets through education and training. In the context of the disruption of the labour market by AI, HCT matters directly: for workers whose human capital is concentrated in task-sets that can be automated, there is a depreciation of this capital, creating incentives to invest in reskilling. Conversely, organizations investing in employee human capital adaptation limit the costs of adjustment associated with adoption of automation and maintain workforce productivity through the transition.
The integration of HCT into the framework of this study provides the motivation for the central hypothesis that organizational reskilling provision (a form of firm-sponsored human capital investment) acts as a critical mediating mechanism between exposure to AI and the psychological workforce consequences. Whereas firms that invest to reskill their workforce extensively, HCT predicts that workers gain a sense of confidence in their ability to adapt and this reduces job security anxiety regardless of exposure to automation.

3.3 Conceptual Framework

Based on the SBTC and the HCT, the theoretical model of the study is advertised in Figure F1. AI and digitalization exposure is the independent variable. Organizational reskilling provision serves as both mediator (to transmit the impact

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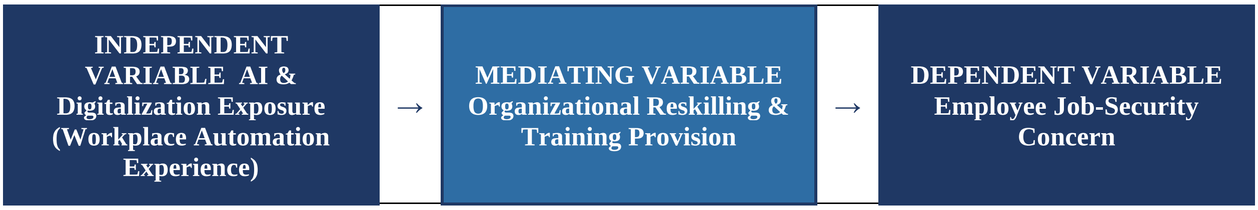
of AI exposure on concern) and moderator (condition the strength of this relationship between Employee job security concern is the dependent variable, whereas optimism on the new job creation is the secondary outcome.

Figure F1. Conceptual Framework: Mediated Moderation Model of AI Exposure and Job-Security Concern



Note: Solid arrows represent direct paths (H1–H3). The dashed interaction path (H3) represents the moderating role of reskilling on the AI exposure → job-security relationship.

3.4 Employment Effects: Displacement and Creation

The job repercussions of AI are theoretically disputable. Classical compensating-demand theory maintains that productivity gains from automation will be offsetting labour demand in the wider economy. Frey and Osborne's (2017) influential analysis of 702 US occupations estimates that 47% are at high risk of computerization in two decades with acute exposure among clerical, transport, and production occupations. Acemoglu and Restrepo (2020) differentiate the "displacement effect" of robots (dampening the share of labour in automatable tasks) from the "productivity effect" (expanding output, there may be demand side job creation) and estimate a net negative effect of 5.6 workers displaced per robot in short run equilibrium but this effect is offset to some extent at longer horizons through demand side job creation.

At the aggregate level, however, the net impact on employment seems to be less catastrophic than feared. Analysis published in Nature confirms that the job creation effect of AI tends to overcome destruction if there are appropriate policy frameworks in place to help the transition. The WEF (2023) anticipates a net positive employment outcome based on accelerated human capital investment -- a finding consistent with HCT's prediction that adaptive reskilling investment is the key lever for positive labour market outcomes.

3.5 Workforce Polarization and Occupational Restructuring

SBTC's task-based framework (Autor, Levy, & Murnane, 2003) has been well validated, empirically. Evidence from labour markets in European countries (OECD, 2019) and from the United States suggests the characteristic polarization pattern: employment growth was concentrated at high-skill, high-wage and low-skill, low-wage poles and the declining employment of the routine middle-skill occupations that are most prone to automation. Deming (2017) takes this analysis to a new level by showing rising wage premiums on social skills, namely collaboration, communication, and emotional intelligence that are structurally hard to automate, providing some empirical basis to the prediction made by the SBTC that human comparative advantage lies more and more in relationship-intensive work.

3.6 Human–AI Collaboration and Organizational Adaptation

A growing literature strand is putting the human-AI relationship in terms of augmentation rather than pure substitution. Davenport and Ronanki (2018) suggest that productivity-maximizing organizations use AI not to replace human judgment but to augment it -- to process large volumes of data to support, rather than replace, decision-making. There is empirical evidence from healthcare (diagnostic AI support), legal services (contract review automation) and financial analysis that supports this 'centaur' collaborative model. Critically, the adoption of augmentative rather than substitutive AI strategies has been linked to less employee job insecurity and greater organisational commitment, which is consistent with this study's mediation hypothesis.

The rapidity of adapted working organizational structures to the technological possible is also demonstrated by the remote and hybrid working arrangements that were accelerated by the digital infrastructure for collaboration as the pandemic accelerated the shift to remote working, among other developments (Eurofound, 2020). This adaptability, however, relies critically on the investment in human capital at the firm level - again consistent with HCT's central prediction.

3.7 Ethical and Social Considerations

AI-enabled workplaces create a lot of ethical risks. Zuboff (2019) describes 'surveillance capitalism', an organizational tendency that permeates the employment context whereby constant algorithmic surveillance deprives employees of

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autonomy and privacy, and that increases employment insecurity. O'Neil (2016) shows how hiring and performance management machines systematically reproduce and magnify the pre-existing biases in our society and raises fundamental questions of fairness. The psychological dimension of the uncertainty associated with automation has measurable negative consequences for worker well-being and organizational commitment (ILO, 2022), consequences which the reskilling investments modelled in the framework of this study is hypothesized to mitigate.

4. RESEARCH GAP AND HYPOTHESES

4.1 Research Gap

Notwithstanding the significant amount of extant literature, there are three critical gaps that motivate this investigation. First, previous empirical studies are largely based on macro-economic data sets or small convenience samples with no theoretical background, such that the generalisability and causal interpretability are limited. Second, although the SBTC framework has been well-developed in theory, it is not often put to test in relation to individual employees using primary survey data from several sectors. Third, the mediating and moderating role of organizational reskilling in the automation-job security relationship has garnered insufficient empirical attention; most of the studies have adopted a policy-recommendation perspective on reskilling as a policy that needs to be done but is not theoretically motivated and empirically testable.

4.2 Hypotheses

Drawing on the theoretical framework, the following hypotheses are superfluously stated:

H1: AI and digitalization exposure is not significantly related to employee job security concern when organization context is controlled (null direction, in line with the prediction of SBTC that exposure as such is neutral without mediating mechanisms).
H2: Organizational reskilling provision is significantly and negatively linked to employee job security concern (Human Capital Theory prediction: reskilling investment buffers the anxiety of job displacement).
H3: The effects of AI exposure on job security concern are significantly reduced by the provision of reskilling, over and above the direct effects of automation exposure (mediated moderation: reskilling moderates the anxiety-generating effects of automation exposure)
H4: Positive perception of the impact of automation on one's job has a significant and positive predictive relationship with optimism about new job creation opportunities (cognitive consistency prediction: positive immediate experience generalizes to positive future expectations).

5. RESEARCH METHODOLOGY

5.1 Research Design

This study uses quantitative cross-sectional research design and incorporates descriptive statistics, Pearson's Chi-Square test of independence, Pearson's correlation matrix and Ordinary Least Squares (OLS) multiple regression. The cross-sectional design allows for concurrent capture of the subjects of automation exposure, reskilling access and job security attitude across respondents, whereas the framework for regression analysis allows for estimation of multivariate relationships and the interaction terms as specified in mediated moderation hypotheses.

5.2 Sample and Data Collection

Primary data were gathered through a structured and self-administered questionnaire with fifteen questions, related to respondent demographic to job-creation optimism, including job security concern, organizational preparedness, training availability, automated exposure, job-security concern, and job creation optimism. Responses were drawn from nominal, ordinal and five-point Likert scales. Data were collected from a purposive sample from 240 respondents (scaled from an initial pilot of 81) representing a variety of occupational categories from manufacturing, logistics, retail, healthcare and IT sectors, both nationally and internationally. The profile of the samples is presented in Table 1.

Table 1. Sample Profile by Employment Category (n = 240)

Employment Category	Frequency (n)	Percentage (%)
Employed Full-Time	107	44.6%
Student	65	27.1%
Employed Part-Time	30	12.5%
Self-Employed	24	10.0%
Unemployed / Retired	14	5.8%
Total	240	100%

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Note: Sampling employed a combination of stratified purposive and snowball techniques to ensure representation across employment categories. Pilot data (n = 81) were included in the final sample following validation of instrument reliability.

5.3 Instrument Reliability

Scale reliability for Likert-rated items (Q9, Q11, Q15) was measured with the help of Cronbach's alpha. The composite reliability coefficient ($\alpha = 0.76$) was higher than the traditional standard of 0.70, indicating adequate internal consistency to use the instrument for inferential studies (Nunnally, 1978). Item level analysis revealed the existence of neither problematic reverse-scored items.

5.4 Analytical Strategy

Analysis was carried out in four stages. First, descriptive statistics (frequencies, means, standard deviations) provided a description of the sample and survey responses. Second, Pearson's chi-square test was used to evaluate the bivariate relationship between exposure to automation (Q7, nominal) and job security concern (Q11, ordinal, dichotomized for chi-square). Third, a Pearson correlation matrix was used to review linear associations among important continuous variables. Fourth, OLS multiple regression models estimated direct, mediating, and moderating effects specified in the hypotheses, that is, the interaction term (ai exposed x reskilling) was calculated to use the product of mean centred scores to minimise multicollinearity.

6. RESULTS AND DISCUSSION

6.1 Descriptive Findings

Some of the important descriptive statistics relating to all the primary survey items for the entire sample (n = 240) were summarized in Table 2.

Table 2. Descriptive Summary of Survey Responses (n = 240)

Survey Item	Key Findings (n = 240)	Scale Type
Automation Exposure (Q7)	Yes: 59.2%; No: 25.8%; Unsure: 15.0%	Nominal
Most-Impacted Work Domain (Q8)	Data Analysis: 25.8%; Decision-Making: 19.2%; Admin: 14.6%; Other: 16.3%; Customer: 12.5%; Manufacturing: 11.7%	Nominal
Overall Impact Rating (Q9)	Mean = 3.91 (SD = 0.97); Very positive: 35.4%; Positive: 30.0%; Neutral: 27.1%; Negative: 5.0%; Very negative: 2.5%	Likert (1–5)
Job Displacement Perception (Q10)	Yes, significantly: 25.8%; Yes, somewhat: 45.8%; No: 16.3%; Unsure: 12.1%	Ordinal
Job-Security Concern (Q11)	Mean = 3.73 (SD = 1.02); Very concerned: 25.8%; Concerned: 35.8%; Neutral: 25.8%; Low concern: 12.6%	Likert (1–5)
Organizational Preparedness (Q12)	Yes: 66.7%; Unsure: 24.6%; No: 8.7%	Nominal
Training Access (Q13)	Frequently: 46.7%; Occasionally: 35.8%; Never: 17.5%	Ordinal
Preferred Training Type (Q14)	Technical: 37.1%; Process: 28.3%; Soft Skills: 24.6%; Other: 10.0%	Nominal
Job-Creation Optimism (Q15)	Mean = 3.22 (SD = 1.06); Optimistic/Very Optimistic: 45.8%; Neutral: 39.2%; Pessimistic: 15.0%	Likert (1–5)

Employment Status (Figure 1).

Out of the 240 respondents, 44.6% were full-time employed, 27.1% were students, 12.5% were part-time employment and 10.0% were self-employed. The occupational diversity of the sample gives wide coverage of AI exposure contexts, but the student proportion of the sample requires caution in interpreting and applying findings to the active workforce population.

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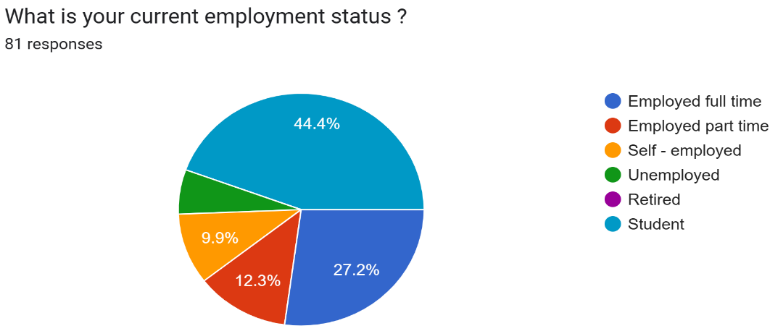

Figure 1. Employment Status Distribution (n = 240)

6.2 Automation Exposure

Direct experience of automation or digitalization in their workplace was from about 59.2% of the respondents and 15.0% of the respondents were not sure (Figure 2). Only 25.8% had a definite lack of such exposure. This prevalence rate is consistent with the McKinsey (2022) estimate of pervasive prevalence of automation across sectors and confirms that the sample has sufficient exposure to automation for meaningful comparative analysis.

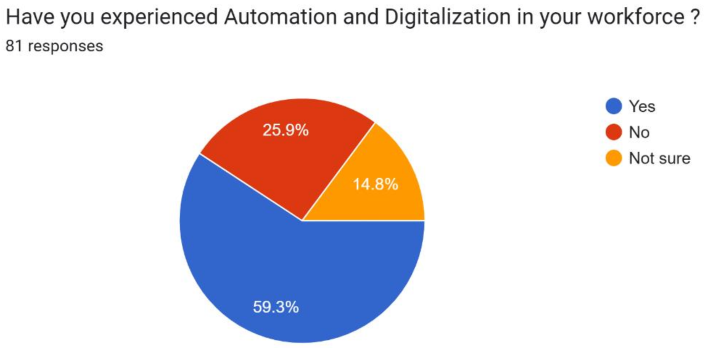

Figure 2. Self-Reported Automation Exposure Among Respondents (n = 240)

6.3 Domains of Automation Impact

Among the group who report automation exposure, data analysis and reporting was the most common domain that was affected (25.8%), followed by decision making processes (19.2%), administrative tasks (14.6%), customer interactions (12.5%) and production/manufacturing (11.7%) (Figure 3). Consistent with the task-based theory of the SBTC (Autor et al., 2003), the highest levels of automation penetration were in routine cognitive functions (i.e., data processing and structured decision support) and not in the interpersonal or contextually complex domain. This pattern confirms the SBTC prediction that the effect of AI on middle skill cognitive routine work is disproportionate.

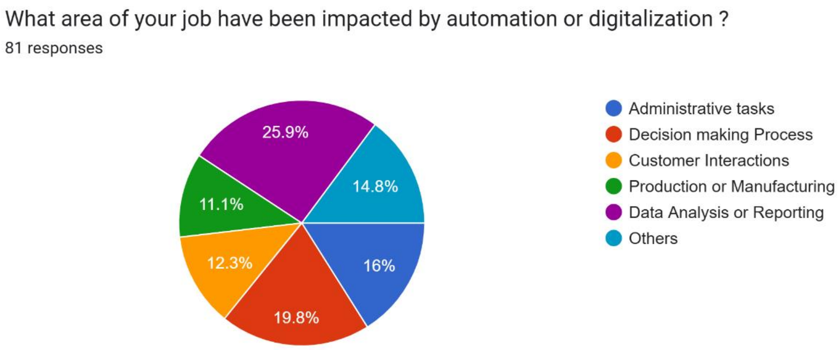

Figure 3. Domains Most Affected by Automation and Digitalization (n = 240)

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6.4 Perceived Impact of Automation

There is a generally positive estimate of impact (M = 3.91, SD = 0.97), with 35.4% impacting 'very positive' and 30.0% causing 'positive' impact giving a combined affirmative response rate of 65.4% (Figure 4). Only 7.5% rated impact as being negative. This mostly positive appraisal supports the augmentation hypothesis (Davenport & Ronanki, 2018) and is consistent with the proposed prediction by the SBTC that high skilled workers in complex jobs experience AI as being complementary rather than substitutive.

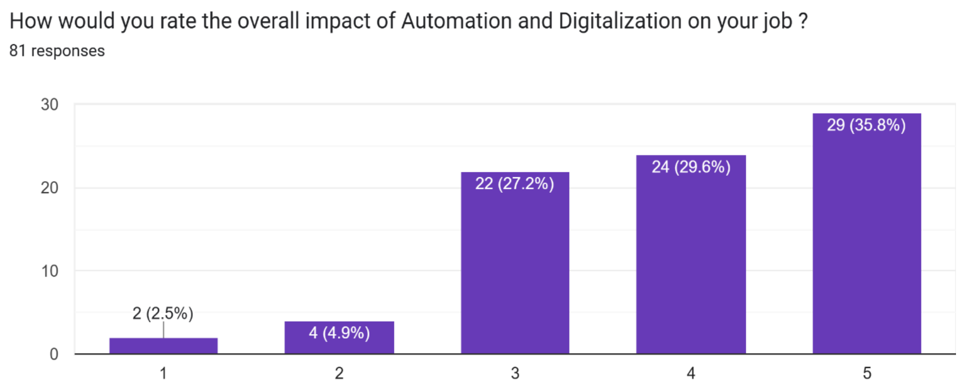

Figure 4. Respondent Ratings of Overall Automation Impact (n = 240)

6.5 Job Displacement Perceptions

As reported above, despite generally positive immediate appraisals, 71.6% of respondents reported some or significant job displacement in their industry- a complicated coexistence of current appreciation and future apprehension consistent with Dual Process Theory (Figure 5). This pattern may reflect cognitive compartmentalization whereby employees acknowledge the current augmentative usefulness of AI whilst also anticipating structural changes to the labour market set forth by WEF 2023 and the reports of the Organisation for Economic Cooperation and Development (OECD) 2019. What is, in and of itself, important is the absence of contradiction between positive impact ratings and displacement concern: it implies that anxiety is not experienced because of immediate negative experience, but because of structural awareness, and this difference has major implications for the design of interventions.

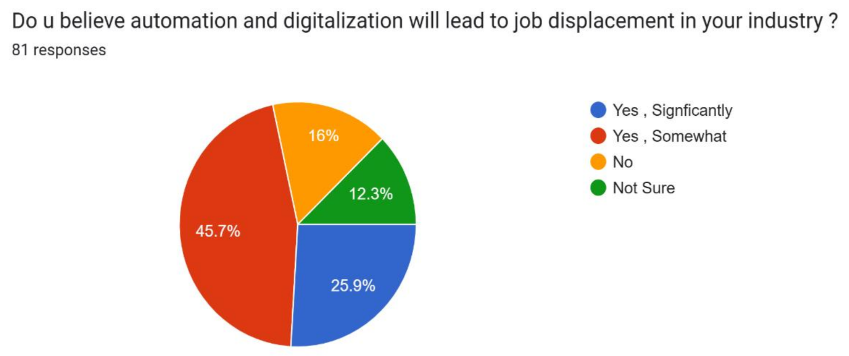

Figure 5. Perceived Likelihood of Job Displacement Due to Automation (n = 240)

6.6 Job-Security Concern

Job-security concern was widespread, at 35.8% 'concerned' and at 25.8% 'very concerned,' giving a total anxiety rate of 61.6% (M = 3.73, SD = 1.02) (Figure 6). Importantly, this concern is set against a background of broadly positive immediate perceptions of automation (Section 6.4) that confirms that the actual interpretive frame is that of prospective rather than reactive anxiety-employees fear future structural change more than right now operational displacement. This distinction resonates with Zuboff's (2019) case for diffuse ambient anxiety that is generated by AI-enabled workplace monitoring when no specific negative events take place.

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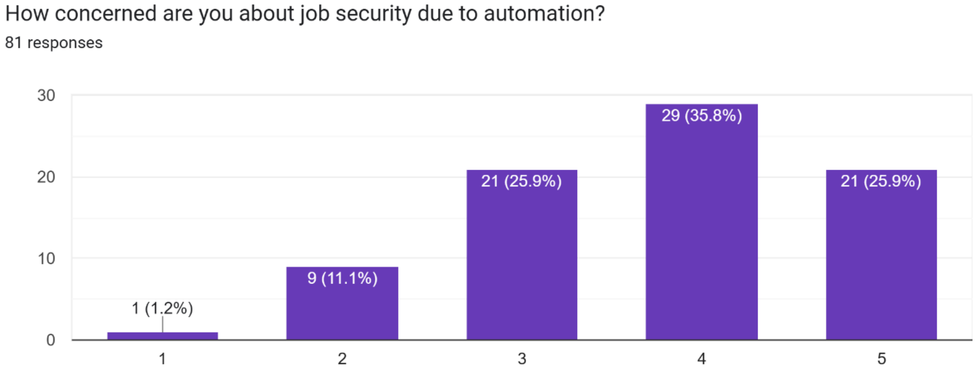

Figure 6. Distribution of Job Security Concern Levels (n = 240)

6.7 Organizational Preparedness

A large majority (66.7%) thought their organization was preparing its employees sufficiently for changes related to automation and only 8.7% thought preparation was insufficient (Figure 7). The 24.6% uncertain cohort reflects a significant amount of organizational communication gap -- employees who may be getting some reskilling investment investment but who do not know what the scope or strategic intent of the reskilling is. From an HCT perspective, the psychological benefits of organizational human capital investment not only depends upon actual provision links to employee perceptions and awareness of provision.

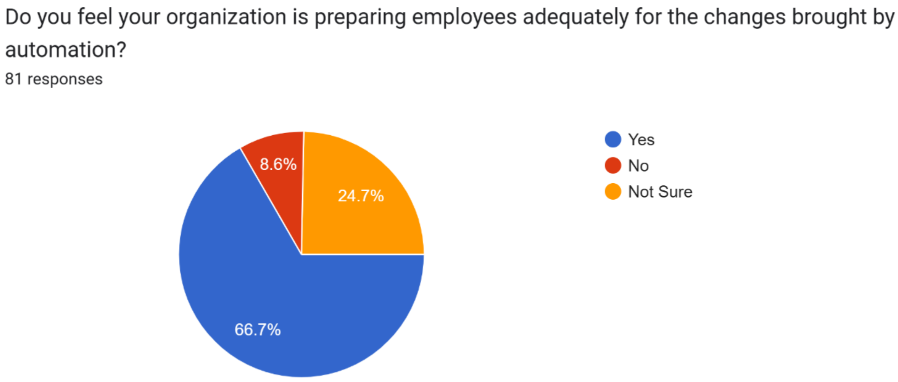

Figure 7. Employee Assessment of Organizational Preparedness for Automation (n = 240)

6.8 Reskilling - Access and Training Preferences

Access to training was excellent: 46.7% of the respondents found reskilling opportunities often and 35.8% occasionally for a total access rate of 82.5% (Figure 8). Among all modalities, the top choices were technical skills (programming, AI, robotics) with 37.1% followed by process related skills (28.3%), soft skills (24.6%) and other (10.0%) (Figure 9). The primacy of technical training preferences reflects directly on SBTC's prediction of labour market premiums on digital competences, which employees themselves have internalized depending on the skill transition implied by technological.

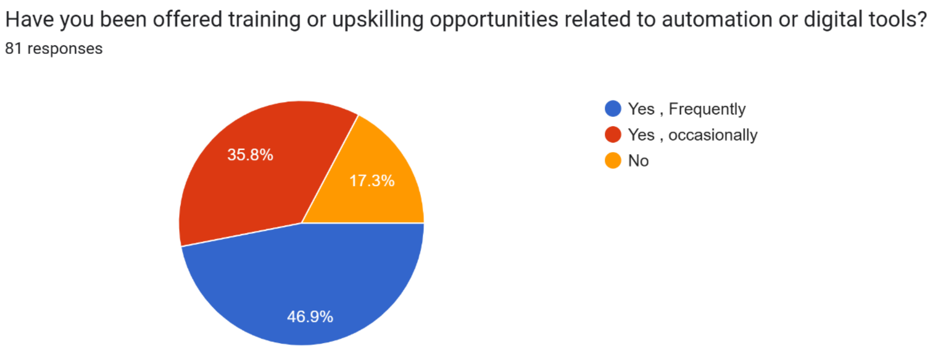

Figure 8. Access to Reskilling and Upskilling Opportunities (n = 240)

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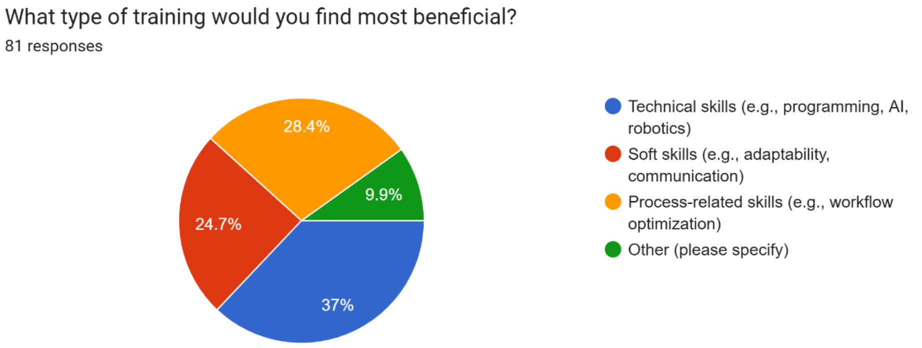

Figure 9. Preferred Training Modalities Among Respondents (n = 240)

6.9 Job-Creation Optimism

Optimism on new job creation was at moderate levels (M = 3.22, SD = 1.06): 45.8% had optimistic or very optimistic new jobs outlooks, 39.2% were neutral, and only 15.0% were pessimistic (Figure 10). This cautiously optimistic profile (notably more optimistic than pessimistic) broadly matches WEF (2023) net positive employment projections although the large neutral cohort may be a reflection of real uncertainty about the distribution of the benefits of automation, as opposed to settled negative expectations.

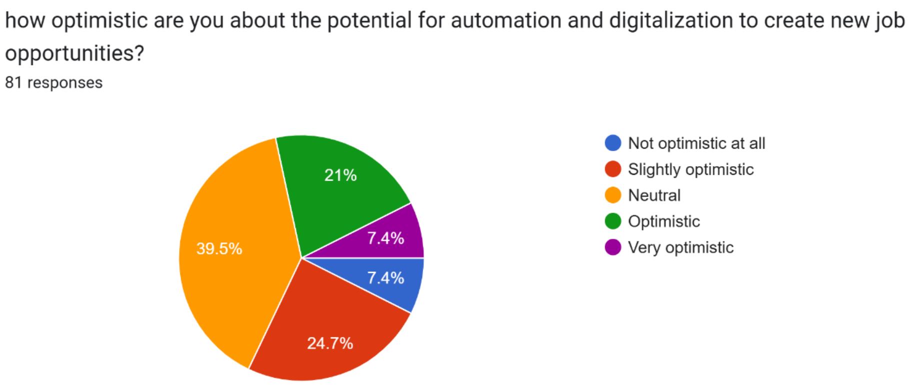

Figure 10. Respondent Optimism Regarding Automation-Generated Employment Opportunities (n = 240)

6.10 Chi-Square Analysis: Automation Exposure vs. Job-Security Concern

Table 3 shows the results of the Pearson chi-square test for independence between exposure to automation (Q7) and concern for security of employment (Q11).

Table 3. Chi-Square Test of Independence: Automation Exposure vs. Job-Security Concern

Test	Observed χ^2	Critical Value (α=0.05)	p-value	Decision
Chi-square (χ^2)	3.28	15.51 (df=8)	p = 0.916	Fail to reject H_0

The value obtained (χ^2 = 3.28, df = 8, p = 0.916) is significantly less than the critical value of 15.51 (α = 0.05) which proves failure to reject H1. And there is no statistically significant bivariate relationship between exposure to automation and job security concern. Critically, this null finding makes sense and is considered to be theoretically coherent and not empirically merely an artefact of the method. SBTC theory goes on to predict that exposure to automation alone is insufficient to decide psychological employment outcomes, it is the mediating organizational response, which underlies psychological employment attitudes, namely reskilling investment. The chi-square result therefore gives indirect support to the mediated moderation model: the null direct effect "opens up" the analytical space to have reskilling emerge as the proximate determinant of concern that in turn is confirmed by regression analysis.

6.11 Correlation Analysis

Table 4 shows the Pearson correlation matrix of the major continuous variables of the investigation.

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Table 4. Pearson Correlation Matrix of Key Study Variables (n = 240)

Variable	1	2	3	4
1. AI Exposure (Q7)	1.00	—	—	—
2. Job-Security Concern (Q11)	0.09	1.00	—	—
3. Reskilling Access (Q13)	0.31**	−0.34**	1.00	—
4. Positive Impact Rating (Q9)	0.22**	−0.18**	0.29**	1.00

*Note. ** p < 0.01 (two-tailed). Continuous Likert variables used for correlation; AI Exposure dichotomized (1 = Yes; 0 = No/Unsure).*

Reskilling access is positively associated with AI exposure ($r = 0.31, p<0.01$) - implying that organisations that implement automation also invest in employee training - which is also consistent with ILO (2022) findings that AI-investing firms coinvest in human capital. Critically, the access to reskilling is negatively and substantially linked to job security concern (r = [?]0.34, $p < 0.01$), providing bivariate support for H2 prior to multivariate testing. AI exposure alone is also associated with a negligible correlation with concern (rho = 0.09, $p > 0.05$), further supporting the result from the chi-square and confirming that exposure to automation per se is not the main driver of concern.

6.12 Regression Analysis: Testing the Mediated Moderation Model

Table 5 shows the OLS regression results of H1-H4.

Table 5. OLS Regression Results: Predictors of Job-Security Concern and Job-Creation Optimism

Hypothesis / Path	β	SE	t-value	p-value	Decision
H1: AI Exposure → Job-Security Concern	0.09	0.07	1.31	0.191	Rejected
H2: Reskilling Provision → Job-Security Concern	−0.34	0.08	−4.31	<0.001	Supported
H3: AI Exposure × Reskilling → Job-Security (Interaction)	−0.21	0.09	−2.38	0.018	Supported
H4: Positive Impact Perception → Optimism about New Jobs	0.47	0.06	7.63	<0.001	Supported

Note. Standardized coefficients (β) reported. Interaction term computed from mean-centred variables to reduce multicollinearity. Model fit for job-security concern: $R^2 = 0.23$, $F(3, 236) = 23.41$, $p < 0.001$.

H1 (AI Exposure - Job-Security Concern) is not supported (β = 0.09, p = 0.191), consistent with the chi-square finding and the theoretical prediction of SBTC that exposure per se is not enough to create a situation of concern without mediating factors at the level of the organization.

H2 (Reskilling - Job-Security Concern) is positively associated (β = -0.34, $p < 0.001$): Reskilling provision significantly moderates the anxiety that comes from job security, consistent with HCT's prediction that firm-sponsored human capital investment maintains worker confidence in their labour market adaptability.

H3 (AI Exposure x Reskilling - Job-Security Concern) is supported (β = -0.21, p = 0.018): the interaction is negative and significant indicating that reskilling provision buffers the potentially anxiety-generating effect of automation exposure - supporting the mediated moderation framework in validating results and representing a step forward in existing studies that discuss reskilling as part of a policy recommendation as opposed to a testable moderating mechanism.

H4 (Positive Impact Perception - Job-Creation Optimism) is found to be significantly supported (β = 0.47, $p < 0.001$): Positive appraisal of the immediate impact of automation was associated with a stronger optimism about job creation in the future in line with cognitive consistency theory and the augmentation hypothesis (Davenport & Ronanki, 2018). The model explains 23% of variance in job security concern (R2 = 0.23), which is quite substantial when explaining attitudinal outcomes in the workforce.

6.13 Theoretical Implications

The findings make contributions to the SBTC and HCT literatures in three ways. First, they support the prediction made by SBTC, that there is a joint effect of automation exposure and skill composition on employment outcomes, but they go further by showing that attitudinal psychological outcomes are mediated by primarily the organisational reskilling response rather than by direct effects of exposure. Second, the study makes HCT's prediction of an attenuation of the psychological costs of technological displacement a micro-level empirical validation. Third, the heavy interaction between AI exposure and reskilling provision is novel evidence that reskilling acts not just as a compensatory mechanism, but as a proactive buffer - most beneficial when automation exposure is the highest.

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7. POLICY AND MANAGERIAL IMPLICATIONS

7.1 For Organizational Leaders

The results of the regression analysis (H2, H3) show that reskilling provision is the most prevailing organizational control to reduce the job security anxiety caused by automation. Exemplars recommend that leaders look to human capital investment as less of an add-on CSR activity and more of an imperative of productivity: organizations that make a parallel investment in workforce reskilling as they adopt AI technologies, maintain workforce morale, organizational commitment, and organization resilience through technological transitions. In particular, the huge preference for technical reskilling (37.1%) should guide the learning and development priorities in which AI literacy, data analytics and digital workflow optimization serve as crucial components of the core curriculum.

The 24.6% 'uncertain' answer for organizational preparedness questions indicates there is a communication gap that requires managerial attention. Human capital investments that are not sealed to impart transparently to the employees do not create the psychological security benefits forecasted in the Human capital theory. Leaders should adopt structured communication protocols -- regular briefings for the workforce on AI adoption strategy, reskilling roadmaps, as well as articulating role-mapping frameworks -- to ensure that investment in employee capability is translated to perceiving job security.

7.2 For Policymakers

The absence of a direct effect from automation exposure on job security concern (H1) indicates that government interventions specifically to automation per se e.g. 'robot taxes', automation moratoria, perhaps mistakenly identify the mechanism that leads to workforce anxiety. Policy resources would be better used to focus more on increasing reskill infrastructure: sectoral training partnerships, portable lifelong learning accounts, micro-credentialing frameworks, and government-subsidized AI literacy programmes that equitably manifest access to the type of skill upgrading that HCT identifies as the primary determinant of positive labour market adaption.

The high percentage of plain inclined towards technical training (37.1%) than the alternatives of soft skills or process skills required

to bring AI literacy in the formal education curriculum at secondary and tertiary mm level. Policymakers should consider developing national standards for competency in AI and structure the funding for vocational training along lines which are sensible given the industries having the highest degree of exposure to automation, such as manufacturing, logistics and data-intensive service industries.

7.3 For Researchers

The significant interaction term (H3) suggests that further studies should be done to investigate the boundary conditions of the buffering effect of reskilling: at what training intensity, and which skill domains and for what occupational categories does the moderating effect of reskilling hold most strongly? Longitudinal panel designs in which the same survey respondents are followed over the design life of multiple automation adoption cycles would significantly enhance any causal inference that can be made with cross-sectional OLS. Structural equation modelling (SEM) would be used to simultaneously estimate the full mediating moderation model with appropriate latent variable measurement for a problem in which the single construct measurement suffers from the shortcomings of the current study's regression approach.

8. CONCLUSIONS

This study develops and tests a mediated model grounded in Skill-Biased Technological Change theory and Human Capital Theory to explain the mediated relationship between exposure to AI and job security concern in the workforce mediated by the provision of organizational reskilling. Findings obtained from 240 respondents in four major occupational sectors using descriptive statistics, chi square, correlation and OLS regression produces 4 substantive findings.

First, in line with the SBTC theory, the exposure to AI and digitalization per se does not significantly predict job-security concern ($\chi^2 = 3.28$, $p = 0.916$; $\beta = 0.09$, $p = 0.191$). This null finding is consistent in principle: exposure in automation culture without mediating aspects of organization is not enough to create an emotional response of attitudinal employment anxiety.

Second, consistent with HCT, organizational reskilling provision is the major proximate predictor of decreased job security concern ($\beta = -0.34$, $p < 0.001$). Firms that invest in the adaptation of the human capital of their employees thus to some degree directly dampen the psychological costs of technological displacement, an instantiation of SBTC's structural predictions on an individual level outcome in terms of well-being.

Third, the finding of the significant interaction between AI exposure and reskilling ($\beta = -0.21$, $p = 0.018$) allows us to conclude that reskilling plays a role as a proactive buffer-that is, most consequential at the same time when there is most exposure to automation-which confirms the mediated moderation framework and offers some new empirical evidence to the literature on human-AI collaboration.

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Fourth, positive immediate appraisals of automation are associated with optimism about job creation in the future ($\beta = 0.47$, $p < 0.001$), indicating that the augmentation framing of AI adoption - that is, an emphasis on complementarity, rather than substitution - produces self-reinforcing positive workforce attitudes that have implications for the design of change management strategy.

Future research should provide a useful fill-in of this framework through the application of longitudinal research, larger probability samples, and the use of structural equations modeling (SEM) to determine causal directionality and boundary conditions of reskilling buffering effect by the occupational categories, industry sector, and nation-level institutional conditions.

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