Organizational Workforce Management in the Digital Age: The Role of Technocultural Interventions in Mitigating the Negative Impacts of AI-Driven Technological Change

Abstract

This study explores the impact of AI-driven technological change on workforce management, focusing on job displacement, employee satisfaction, and productivity. A mixed-method approach was employed, including logistic regression, K-means clustering, and multivariate regression analysis, to evaluate the effectiveness of technocultural interventions (upskilling programs, ethical AI frameworks, and innovation culture). Data was sourced from the U.S. Bureau of Labor Statistics (BLS) and survey questionnaires. Logistic regression revealed that routine AI adoption showed a weak positive relationship with job displacement ($B = 0.013$, $p = 0.111$), but the overall model was not statistically significant. The K-means clustering identified three distinct organizational patterns in adopting technocultural interventions. Multivariate regression highlighted the significant role of leadership commitment in increasing employee satisfaction ($B = -0.067$, $p = 0.039$) but found limited direct effects of upskilling programs and AI frameworks on productivity. Based on the findings, the study highlights the importance of customized, sector-specific interventions, and recommends that organizations integrate leadership and ethical considerations to effectively manage AI-driven changes.

Keywords: AI-driven workforce management, Technocultural interventions, Job displacement, Upskilling programs, Employee satisfaction

1. Introduction

In the technological age, the rapid advancement of artificial intelligence (AI) technologies is reshaping organizational workforce management, presenting both opportunities and challenges. AI's increasing sophistication promises enhanced efficiency, productivity, and innovation across various industries, yet it introduces significant risks such as job displacement, skill obsolescence, and decreased employee morale; to effectively navigate these issues, organizations must adopt technocultural interventions that aim to mitigate the negative impacts of AI while promoting a positive and adaptive work environment [1]. The incorporation of AI into organizational processes has greatly transformed workforce dynamics, large corporations like Microsoft and Google have implemented substantial layoffs, often attributing them to economic conditions and operational streamlining. However, these layoffs reflect a deeper shift driven by AI-powered solutions that automate tasks that were otherwise traditionally performed by humans. For instance, the increasing use of AI-driven customer service bots and manufacturing robots has led to the replacement of human workers, raising concerns about job security and displacement [2]; this changing development towards AI-powered job replacements points to the need for strategic measures that address the social and economic impacts of technological change, ensuring that employees are not marginalized in the process.

Moreover, while AI offers considerable benefits, it raises critical ethical concerns, particularly regarding algorithmic bias. According to Al-kfairy et al. [3], AI systems are perpetuating biases in hiring, lending, and criminal justice decisions and this have garnered widespread attention, prompting calls for greater transparency and accountability; bias in AI can lead to the unfair treatment of certain groups, perpetuate inequalities, and erode trust in technology, and to address these concerns, organizations are increasingly developing ethical frameworks to guide AI deployment. For example, IBM's establishment of an AI Ethics Board exemplifies proactive efforts to ensure that AI technologies are developed and used responsibly [4], such initiatives help build trust with both customers and employees. AI might be welcomed by many, but it is still being resisted by a few. Some employees often exhibit resistance to technological change, and this is driven by fears of job loss, skill redundancy, and reduced job satisfaction; this resistance can manifest as decreased morale, reluctance to adopt new technologies, and even active opposition to AI-driven changes, and so this digital divide worsened these challenges, as disparities in access to technology create inequalities within the workforce. Employees lacking necessary digital skills or tools may find themselves at a disadvantage, which can increase feelings of job insecurity and reduce overall productivity, hence, addressing these technocultural challenges requires a comprehensive approach that considers both technological solutions and the cultural and social dimensions of workforce management [5]. In order to combat these challenges, Chong and Lee [6] states that organizations are increasingly investing in upskilling and reskilling initiatives to mitigate the adverse effects of AI-driven technological change; these programs aim to equip employees with the skills required to thrive in the AI era, enabling them to transition into new roles and remain relevant in a rapidly evolving job market. Governments and corporations are focusing on training and development programs to prepare the workforce for AI's challenges and opportunities, for instance, Salesforce's Trailhead platform offers a range of courses and certifications designed to enhance digital skills, promoting a culture of continuous learning and adaptation [7].

Furthermore, the COVID-19 pandemic has quickened the adoption of remote and hybrid models of working, and this has led to significant changes in organizational culture and employee expectations. While remote work offers benefits like flexibility and autonomy, it also presents challenges such as isolation, burnout, and difficulties in maintaining work-life balance [8]; organizations must address these challenges while capitalizing on the benefits of remote work. Garcia-Perez et al. [5] opines that technocultural interventions that promote digital well-being, foster a sense of belonging, and encourage collaboration are crucial for creating a positive remote work environment. Given the diverse challenges presented by AI-driven technological change, technocultural interventions provide a strategic response to mitigate its negative impacts. These strategies are, ethical AI frameworks, upskilling programs, and the promotion of an innovative and adaptable culture, such as IBM's AI Ethics Board, Google's AI Impact Challenge, and Salesforce's Trailhead [4][7]. Zhang and Chen [9] posit that as the digital age continues to evolve, the importance of these interventions will only grow, making them indispensable components of effective workforce management strategies. Therefore, this paper investigates the effectiveness of technocultural interventions in mitigating the negative impacts of AI-driven technological change on organizational workforce management. The study achieves the following objectives:

1. Identify the specific negative impacts of AI-driven technological change on organizational workforce management, focusing on job displacement, skill obsolescence, and decreased employee morale.

2. Analyse the various technocultural interventions that organizations can implement to address these negative impacts, including upskilling programs, ethical AI frameworks, and fostering a culture of innovation.

3. Evaluate the effectiveness of different technocultural interventions in mitigating the negative impacts of AI-driven technological change, considering key factors such as employee satisfaction, productivity, and overall organizational performance.

4. Develop recommendations for organizations on implementing technocultural interventions, ensuring a positive and equitable transition to the AI era tailored to specific organizational needs and contexts.

2. Literature review

The integration of AI-driven technologies into workforce management has significant negative implications, which includes job displacement, skill obsolescence, decreased employee morale, and ethical concerns related to algorithmic bias. According to Fayad [1], AI automation has substantially contributed to job displacement, particularly in sectors such as manufacturing, customer service, and finance; AI technologies are replacing human roles, especially those involving routine or predictable tasks, which significantly reduces the need for manual labour in manufacturing and replaces traditional roles in finance with AI systems that process large data sets more efficiently [10]. Reports from organizations like McKinsey & Company suggest that up to 30% of activities in approximately 60% of occupations could be automated, signalling a transformative change in workforce dynamics [11][12]. However, Bazargani and Deemyad 13] state that this shift raises concerns about the readiness of industries and governments to manage the socioeconomic repercussions of widespread job displacement. Apart from job displacement, AI advancements have also rendered specific skills obsolete, necessitating continuous skill development. Pasko et al. [14] opines that employees in fields such as information technology, healthcare, and finance must acquire new skills to remain relevant, as AI demands develop gradually. For example, traditional customer service roles now require managing AI-powered chatbots, while AI-driven diagnostic tools are changing the nature of medical expertise needed in healthcare [15][16][17]. The World Economic Forum emphasizes the growing demand for skills that complement AI, such as creative problem-solving, emotional intelligence, and advanced data analysis [18], and while some skills may become redundant, Bobitan et al. [19] proposes that human-AI collaboration presents new opportunities for workforce augmentation, highlighting the need for balanced skill development strategies.

Furthermore, Mirbabaie et al. [20] opines that the need to adapt to new technologies also affects employee morale, leading to increased anxiety, stress, and decreased job satisfaction, employees concerned about being replaced by AI may experience a diminished sense of job security, reducing organizational productivity and employee retention. Therefore, organizations must prioritize employee well-being by offering support systems and continuous learning opportunities [21][22]. This raises ethical concerns, particularly in relation to algorithmic bias, as AI algorithms can perpetuate existing biases, leading to discriminatory outcomes in hiring, lending, and law enforcement, and so addressing these concerns requires the development of ethical frameworks and regulatory measures to ensure transparency, accountability, and fairness in AI applications [23][24]. Also, organizations are increasingly investing in upskilling and reskilling initiatives (technocultural Interventions) to mitigate the adverse effects of AI-driven technological change; these programs aim to equip employees with the skills required to thrive in the AI era, enabling them to transition into new roles and remain relevant in a rapidly evolving job market [6].

Technocultural Interventions in Mitigating AI's Negative Impacts

The integration of AI into organisational processes necessitates various technocultural interventions to mitigate its negative impacts on workforce management; key strategies include upskilling and reskilling programs, the development of ethical AI frameworks, the promotion of an innovative culture, and the promotion of digital well-being, are all essential for harnessing AI benefits without compromising workforce stability [25]. According to Fenwick et al. [26], the implementation of upskilling and reskilling programs in organisations are vital as the nature of most work evolves with AI advancements, and continuous learning initiatives, such as Salesforce's Trailhead and Microsoft's Global Skills Initiative, aim to equip employees with the necessary skills in AI, data analysis, and cloud computing, thereby enabling them to remain competitive in an ever-changing job market [4][27][28]. However, Randriamiary et al. [29] argues that these programs may not be universally accessible or adequately tailored to meet diverse employee needs, which potentially leads to unequal opportunities for skill development. Therefore, Rajaram [30] proposes that organisations must ensure inclusivity in their upskilling efforts by tailoring programs to accommodate various learning styles and capabilities, recognizing that upskilling should be viewed as a dynamic and adaptive process rather than a one-size-fits-all solution.

Another critical intervention is the establishment of ethical AI frameworks, these are designed to address concerns related to algorithmic bias, privacy, and accountability [31], companies such as IBM have created AI Ethics Boards to oversee ethical considerations, ensuring compliance with standards that prioritise fairness, transparency, and accountability [4][32]. Similarly, initiatives like Google's AI Impact Challenge promote ethical AI by funding projects that explore responsible AI applications [33], but despite these growing emphasis on ethical AI, practical challenges still remain, as the implementation and enforcement of these frameworks often lack robust oversight mechanisms, and Diaz-Rodriguez et al. [34] argues that without effective accountability measures, ethical guidelines may remain theoretical and insufficiently in address the intricate issues of AI, emphasising the need for ongoing evaluation and refinement of ethical standards. Fostering an innovative culture is equally essential in mitigating AI's potential negative impacts, Adrian and Everett [35] posits that organisational culture significantly influences employee perceptions and responses to technological changes; an environment that encourages innovation, adaptability, and collaboration can help alleviate the fears and uncertainties associated with AI-driven transformations. However, Rozman et al. [36] asserts that fostering such a culture requires strategic commitment from leadership, active employee engagement, and alignment of organisational values with technological objectives.

Most especially, Alahi et al. [37] contends that it has become expedient that organisations address digital well-being, particularly with the rise of remote work which are facilitated by AI-powered tools; though these tools can enhance collaboration and productivity, they also raise concerns about employee privacy, burnout, and work-life balance, and so, organisations must adopt strategies that support digital well-being, such as flexible work arrangements, clear communication channels, and robust employee support systems [38][39]. A comprehensive approach to remote work management should consider not only productivity metrics but also the overall well-being of employees, ensuring a sustainable balance between technological efficiency and human needs [38][40][41].

Evaluation of Technocultural Interventions

Though technocultural intervention programs are good initiatives, it is also essential that they be evaluated in order to optimise workforce management strategies amidst AI-driven technological changes, this evaluation can be conducted through various methodologies, including employee satisfaction surveys, productivity metrics, and performance evaluations, each providing unique insights into the impact of these interventions on organisational outcomes [42][43]. According to Soetjipto et al. [44], employee satisfaction surveys are essential for capturing employees' subjective experiences and attitudes towards technocultural interventions, these surveys offer valuable data on morale, engagement, and job satisfaction, directly linking interventions with employee perceptions; these insights are able to showcase the critical impacts of technocultural changes on organisational culture and ethical AI practices, and while surveys provide subjective insights, they are critical for understanding the broader implications of technocultural interventions, as they help identify areas where improvements may be needed [45][46]. Productivity metrics are another key tool for assessing the impact of technocultural interventions, as posited by Fraile et al. [47], they allow organisations to measure changes in work output and efficiency before and after implementing specific strategies. For example, Google's Project "Aristotle" used a data-driven approach to evaluate team productivity, identifying factors such as psychological safety and dependability as critical to high-performing teams; these findings highlights the importance of technocultural elements like trust and open communication in enhancing productivity, thereby emphasising the value of these metrics in evaluating intervention success [48][49].

Performance evaluations provide a focused method for assessing the effectiveness of technocultural interventions by examining individual and team achievements against predefined goals, this is able to offer concrete evidence of the success or failure of interventions, enabling organisations to refine their strategies to better align with desired objectives [42][44]. While, continuous performance assessments allow organisations to adapt their approaches to ensure that technocultural interventions meet both employee needs and organisational goals [50]. There are case studies of organisations that have effectively implemented technocultural interventions into their operations and they serve as valuable examples of best practices. For instance, AT&T's Future Ready initiative emphasises upskilling and reskilling, demonstrating how comprehensive approaches can mitigate job displacement and maintain a competitive advantage, and Unilever's commitment to ethical AI practices through its involvement in the Partnership on AI highlights the importance of prioritising transparency and ethical considerations to build trust and foster responsibility [51][52][53]. Analysing these different technocultural interventions will unravel varying effectiveness depending on the industry and context; upskilling programs are particularly beneficial in sectors experiencing rapid technological change, while ethical AI frameworks are crucial in industries where algorithmic bias could have significant consequences [25][54][55]. Promoting fairness, accountability, and transparency through these frameworks is essential for maintaining public trust and ensuring ethical AI deployment.

Dua [56] opines that the success of technocultural interventions also depends on promotion of an innovative culture, one that encourages adaptability and resilience in response to technological change. Zhao et al. [57] posits that leadership commitment, employee involvement, and alignment of organisational values with technological objectives are key factors in creating a supportive environment for innovation, and most especially, paying of attention to digital well-being and work-life balance is vital, as seen in organisations like Buffer, which prioritise employee satisfaction and retention by emphasising these aspects [58][59][60].

Challenges and Barriers to Implementation

The implementation of technocultural interventions to manage AI-driven technological changes in organisations often encounters substantial challenges, including organisational resistance, resource constraints, and the digital divide; these barriers must be strategically addressed to ensure effective adoption and sustainability of these interventions. Organisational resistance is a common obstacle, which arises from both leadership and employees that are reluctant to embrace changes that disrupt established norms and practices; this resistance often stems from fear of the unknown, loss of control, or concerns over job security [61][62][63]. McGuinness et al. [64] states that employees may fear that new technologies will render their existing skills obsolete or lead to increased workloads and job displacement, and leaders, particularly in traditional and hierarchical organisations, may resist deviating from proven strategies due to concerns about failure or loss of authority [65][66]. Zhang et al. [67] contends that overcoming this resistance requires strong leadership commitment, transparent communication, and active employee involvement in the decision-making process, and by prompting a sense of ownership and demonstrating the benefits of technocultural interventions, organisations can reduce resistance and enhance acceptance [68][69].

According to Tominc et al. [70], resource constraints are another significant barrier, particularly for small and medium-sized enterprises (SMEs) with limited budgets; financial limitations can hinder investments in upskilling programs, ethical AI frameworks, and other necessary initiatives, and while continuous learning and development programs are essential, they are often costly and time-consuming, leading organisations to prioritise short-term profitability over long-term employee development [71][72]. Additionally, establishing ethical AI frameworks requires investment in specialised staff and advanced compliance tools, further straining resources, and to address these challenges, organisations may need to explore innovative funding models, seek partnerships, or reallocate resources to support comprehensive training and ethical AI initiatives [34][36]. The digital divide also complicates the implementation of technocultural interventions, as differences in access to technology can impact their effectiveness [73]; differences in technological infrastructure and digital literacy can create inequality within a globalised and diverse workforce, with employees in regions lacking access to digital tools facing significant barriers to participation in technocultural initiatives [74]. This divide can worsen existing inequalities, especially for those who would benefit most from upskilling and ethical AI initiatives To bridge this gap, organisations must adopt inclusive strategies that ensure access to technology and training for all employees, regardless of location or technological proficiency; these strategies may involve providing offline learning resources, mobile-friendly platforms, or investing in local infrastructure to guarantee equitable access [[73][75][76].

These existing challenges highlight the intricate issues found in integrating technocultural interventions within organisational structures, and addressing organisational resistance necessitates a comprehensive change management approach that includes leadership endorsement, employee engagement, and clear communication of the interventions' benefits [68][71]. According to Colding et al. [77], overcoming resource constraints requires strategic financial planning and leveraging on existing resources effectively, because bridging the digital divide demands a commitment to digital inclusivity, ensuring that all employees possess the necessary skills and access to participate in technocultural initiatives [78]. Ruiu et al. [79] contends that the development of holistic strategies that consider both human and technological aspects of change is essential for the successful implementation of technocultural interventions, as these strategies will improve workforce resilience and adaptability, ensuring that organisations remain competitive and sustainable in this ever-changing digital economy [80][81].

Policies and Regulations for Successful Technocultural Interventions

As AI technologies become deeply rooted in workplace practices, there is a growing emphasis on aligning these innovations with ethical standards, transparency, and employee empowerment [82]. According to Taylor et al. [83], integrating AI with human-centric approaches requires developing systems that enhance human capabilities and uphold human values and rights. This ever-changing model is evident in the design of AI systems that support rather than replace human decision-making, thereby promoting a partnership between technology and human expertise, and ethical considerations, with transparency, accountability, and fairness, are an integral factor to AI development, this is to prevent unintended negative consequences and ensure responsible use. Badghish and Soomro [84] asserts that government policies and regulatory frameworks play a critical role in shaping the adoption and impact of these technocultural interventions, while Huang et al. [85] affirms that regulatory measures emphasising ethical standards and data protection create an environment conducive to the responsible use of AI, encouraging organisations to adopt best practices. The European Union's General Data Protection Regulation (GDPR) serves as a global benchmark for data privacy, influencing AI system development and deployment worldwide [86]. While these policies guide organisations in using AI ethically, balancing innovation with societal interests, some studies highlight the potential roles strict regulations play in stifling innovation, highlighting the need for adaptive policies that grow alongside technological advancements to support responsible AI use while enabling innovation [34][86][87].

Chowdhury et al. [88] highlights the importance of employee empowerment in AI integration, stating that the involvement of employees in AI-related decision-making processes not only enhances engagement but also utilises the workforce's unique insights to improve AI system design and implementation, and by empowering employees, organisations can create a collaborative culture that sees AI as a tool to augment human capabilities, improving job satisfaction and morale while contributing to ethical AI deployment [88][89].

3. Methodology

This study employed logistic regression, K-means clustering, and multivariate regression analysis to explore the effects of AI adoption, technocultural interventions, and employee change readiness on job displacement, as well as to evaluate patterns in organizational interventions and their impact on employee outcomes.

The logistic regression model was used to predict the probability of job displacement based on AI adoption levels, technocultural interventions, and employee readiness.
The dependent variable was job displacement (0 = retained, 1 = displaced).
Independent variables included:

- BLS data: industry type, organizational size, geographical location
- Survey data: routine AI adoption (% of routine tasks automated), non-routine AI adoption (% of non-routine tasks automated), technocultural interventions (intensity scale: 1 to 5), employee change readiness (scale: 1 to 5).

The logistic regression model was expressed as:

$$\log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \beta^0 + \beta^1 X^1 + \beta^2 X^2 + \ldots + \beta n X n$$

To account for the combined effects of routine AI adoption and technocultural interventions, an interaction term was included:

$$Interaction\ Term\ =\ \beta_{AI} * Routine\ AI\ Adoption\ * Technocultural\ Interventions$$

Model Fit was evaluated using pseudo R-squared and likelihood ratio chi-squared tests. Coefficient significance was assessed via z-scores and p-values. The predicted probability of job displacement was calculated using the log-odds transformation:

$$P(y=1) = \frac{1}{1+e^{-(\beta^0+\beta^1X^1+\cdots+\beta nXn)}}$$

K-means clustering was applied to group organizations based on their adoption of technocultural interventions to identify patterns across different sectors and regions. Independent variables included:

- BLS data: industry type, organizational size, geographical location (all encoded).
- Survey data: upskilling programs (scale: 1 to 3), ethical AI frameworks (binary: 0 = no, 1 = yes), and innovation culture (scale: 1 to 5).

Before clustering, the data was standardized using z-scores to ensure comparability across variables. The K-means algorithm aims to minimize the within-cluster sum of squared distances (WCSS), which can be expressed as:

$$WCSS\ =\ \Sigma_{\{i=1\}}^{\{k\}\Sigma_{\{x\in C_i\}}^{2}(x-\mu_i)}$$

Three clusters were generated based on exploratory analysis. The optimal number of clusters, k, was determined using the elbow method, which plots WCSS against the number of clusters and identifies the point where the rate of decrease in WCSS slows down. The formula for the elbow method is as follows:

$$WCSS_k\ =\ \Sigma_{\{i=1\}}^{\{n\}(x_i-\mu_k)^2}$$

Once the clusters were formed, the characteristics of each cluster were analyzed by calculating the mean values of key variables, including upskilling programs, ethical AI frameworks, innovation culture, industry type, organizational size, and geographical location. The formula used to compute the mean value (x̄) for each variable within a cluster is:

$$\bar{x}\ =\ \left(\frac{1}{n}\right)\Sigma_{\{i=1\}_i^{\{n\}x}}$$

A multivariate regression analysis was conducted to assess the influence of technocultural interventions on employee satisfaction and productivity. The dependent variables were:

- Employee satisfaction (Likert scale: 1 to 5).
- Productivity, measured as revenue per employee.

Independent variables included:

- Upskilling programs (scale: 0 to 2, where 0 = none, 1 = technical skills, 2 = non-technical skills).
- Ethical AI frameworks (binary: 0 = no, 1 = yes).
- Innovation culture (scale: 1 to 5).
- Routine and non-routine AI adoption (expressed as percentages).
- Leadership commitment (scale: 1 to 5).
- Work-life balance (scale: 1 to 5).
- Industry type (encoded categorical variable).

The regression model was formulated as:

$$Y = \beta^0 + \beta^1(Upskilling\ Programs) + \beta^2(Ethical\ AI\ Frameworks) + \dots + \beta n(Industry\ Type) + \varepsilon$$

An interaction term was added to observe the combined effect of upskilling programs and AI adoption on employee satisfaction and productivity:

$$Y = \beta^0 + \beta^1(Upskilling\ Programs) * \beta^2(AI\ Adoption) + \dots + \varepsilon$$

The model was evaluated using R-squared to assess the proportion of variance explained, and p-values to determine statistical significance, with $p<0.05$ considered significant.

4. Results and Discussion

Logistic Regression Analysis Predicting Job Displacement (Objective 1)

The results of the logistics regression to understand how **AI adoption** (routine and non-routine tasks), **technocultural interventions**, and **employee morale** predict job displacement (Objective 1) are presented in Table 1 below:

Table 1: Logistic Regression Predicting Job Displacement

Predictor Variables	**B**	**SE B**	**z**	**p**
Constant	-1.573	0.467	-3.37	0.001
Industry Type (Encoded)	0.019	0.049	0.38	0.705
Organizational Size (Encoded)	-0.070	0.085	-0.82	0.411
Geographical Location (Encoded)	0.097	0.140	0.70	0.487
Routine AI Adoption (%)	0.013	0.008	1.59	0.111
Non-Routine AI Adoption (%)	0.002	0.005	0.38	0.707

Technocultural Interventions (Intensity)	0.156	0.111	1.41	0.159
Employee Change Readiness	-0.005	0.050	-0.10	0.920
Interaction (AI Adoption × Interventions)	-0.003	0.002	-1.32	0.186

R^2 (Pseudo) = 0.0037, $\chi^2(8, N = 1000) = 4.40$, $p = 0.8200$

The logistic regression model, which explained 0.37% of the variance in job displacement (R^2 (Pseudo) = 0.0037), was not statistically significant ($\chi^2(8, N = 1000) = 4.40$, $p = 0.8200$), indicating that the predictors did not reliably distinguish between job retention and displacement.

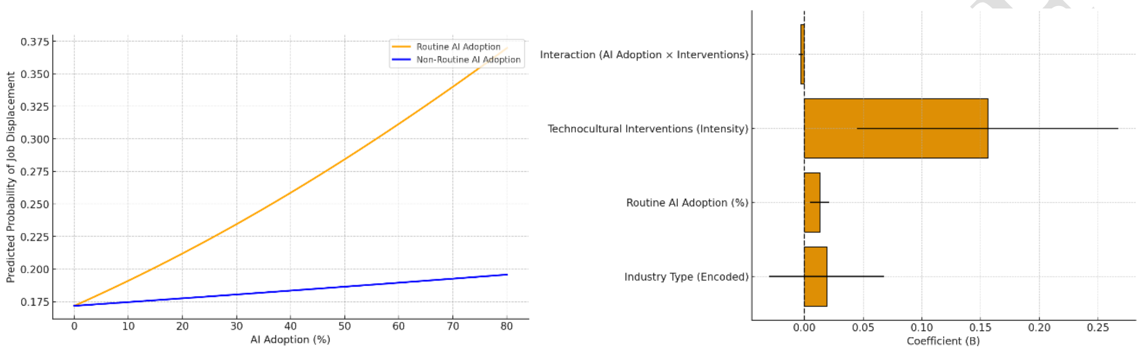

Figure 1. Logistic regression analysis result (a)

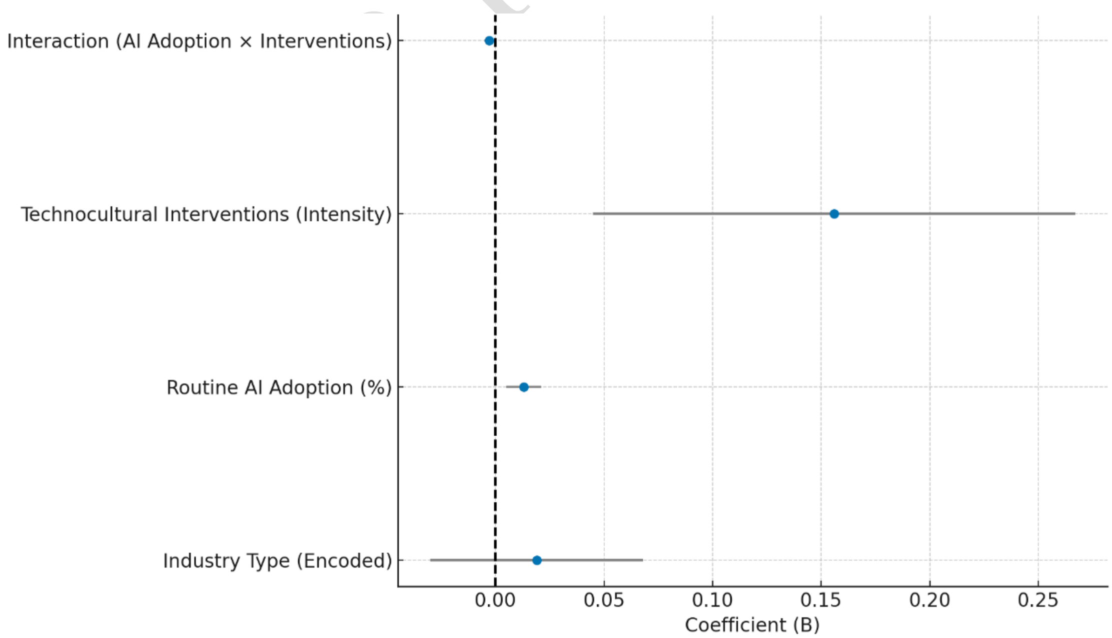

Figure 2. Logistic regression analysis result (b)

Routine AI Adoption had a weak positive relationship with job displacement (B = 0.013, p = 0.111), suggesting a slight increase in displacement as routine tasks are automated, though not statistically significant. Non-routine AI Adoption (B = 0.002, p = 0.707) showed no effect on displacement. Technocultural Interventions (B = 0.156, p = 0.159) had a weak positive relationship with retention, and Employee Change Readiness (B = -0.005, p = 0.920) had no significant effect. The interaction between AI Adoption and Interventions (B = -0.003, p = 0.186) suggested that stronger interventions might slightly reduce displacement in organizations with high AI adoption, but this was not statistically significant.

These findings suggest that while AI adoption and technocultural interventions are relevant, their individual effects on job displacement were weak and not significant in this model.

The results of the K-means cluster analysis conducted to identify patterns in the adoption of technocultural interventions (Objective 2), based on organizational adoption level adoption of upskilling programs, ethical AI frameworks, and innovation culture are presented (evaluated by industry type, organizational size, and geographical location are presented in Table 2 below.

Table 2: Summary of Clusters on Technocultural Interventions

Cluster	**Mean Upskilling Programs**	**Mean Ethical AI Frameworks**	**Mean Innovation Culture**	**Mean Industry Type (Encoded)**	**Mean Organizational Size (Encoded)**	**Mean Geographical Location (Encoded)**
0	2.00	0.00	3.13	2.05	1.00	0.51
1	1.91	1.00	3.03	2.05	1.00	0.00
2	1.99	1.00	2.89	2.04	1.01	1.00

The K-means cluster analysis identified three distinct groups based on the adoption of upskilling programs, ethical AI frameworks, and innovation culture.

Cluster 0 shows organizations with moderate upskilling programs (mean = 2.00) and no ethical AI frameworks (mean = 0.00), with moderate innovation culture (mean = 3.13). These organizations are evenly distributed between urban and rural locations (mean = 0.51) and are balanced in size (mean = 1.00).

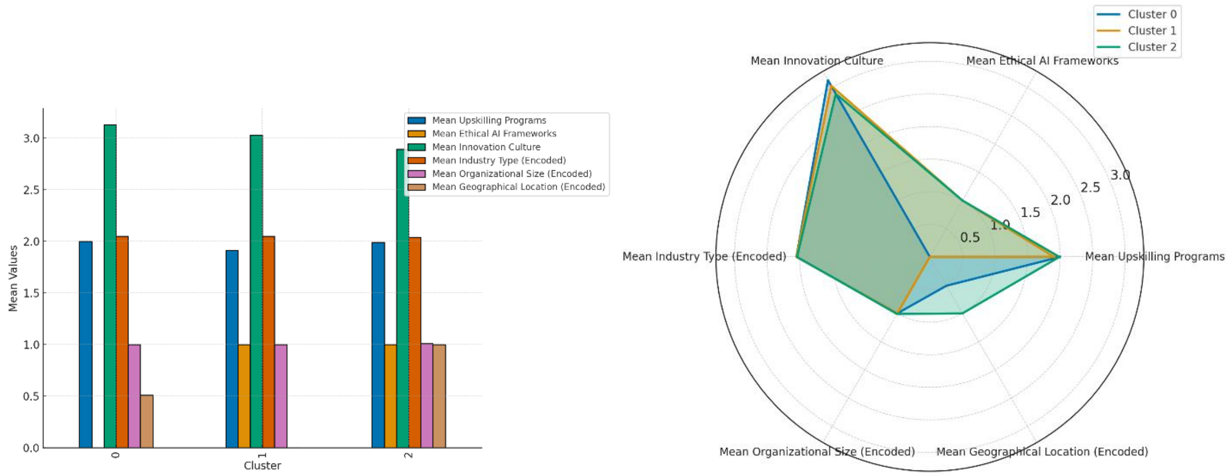

Figure 3: Cluster analysis result showing the various group of adoptions

Cluster 1 has similar upskilling levels (mean = 1.91) but all organizations have ethical AI frameworks (mean = 1.00). These organizations also have moderate innovation culture (mean = 3.03) and are mainly urban (mean = 0.00), with balanced organizational size (mean = 1.00).

Cluster 2 features comprehensive upskilling programs (mean = 1.99) and ethical AI frameworks (mean = 1.00) but lower innovation culture (mean = 2.89). These organizations are primarily in rural areas (mean = 1.00) and are balanced in size (mean = 1.01). This analysis shows how organizations' adoption of technocultural interventions varies by size, industry, and location.

The results the multivariate regression analysis to evaluate the effects of technocultural interventions on employee satisfaction and productivity (objective 3) are presented in table 3 below:

Table 3: Regression Results for Employee Satisfaction and Productivity

Variables	**Coefficient (Satisfaction)**	**p-value (Satisfaction)**	**Coefficient (Productivity)**	**p-value (Productivity)**
Constant	3.4032	0.000	103.4778	0.000
Upskilling Programs (Granular)	0.0054	0.966	1.2690	0.624
Ethical AI Frameworks	-0.1621	0.079	-0.8597	0.649
Innovation Culture	0.0013	0.968	-0.3493	0.602

Routine AI Adoption (%)	0.0003	0.932	-0.0117	0.854
Non-Routine AI Adoption (%)	0.0038	0.221	0.0492	0.435
Interaction (Upskilling × AI Adoption)	-0.0008	0.478	-0.0025	0.919
Leadership Commitment	-0.0672	0.039	0.8646	0.393
Work-Life Balance	0.0327	0.197	-0.3127	0.626
Industry Type	0.0582	0.462	-1.3090	0.047

The results (see Table 5) indicate that leadership commitment significantly affects employee satisfaction (B = -0.067, p = .039), suggesting that strong leadership enhances satisfaction. Ethical AI frameworks approached significance for satisfaction (B = -0.162, p = .079), indicating a potential positive effect, although not conclusive.

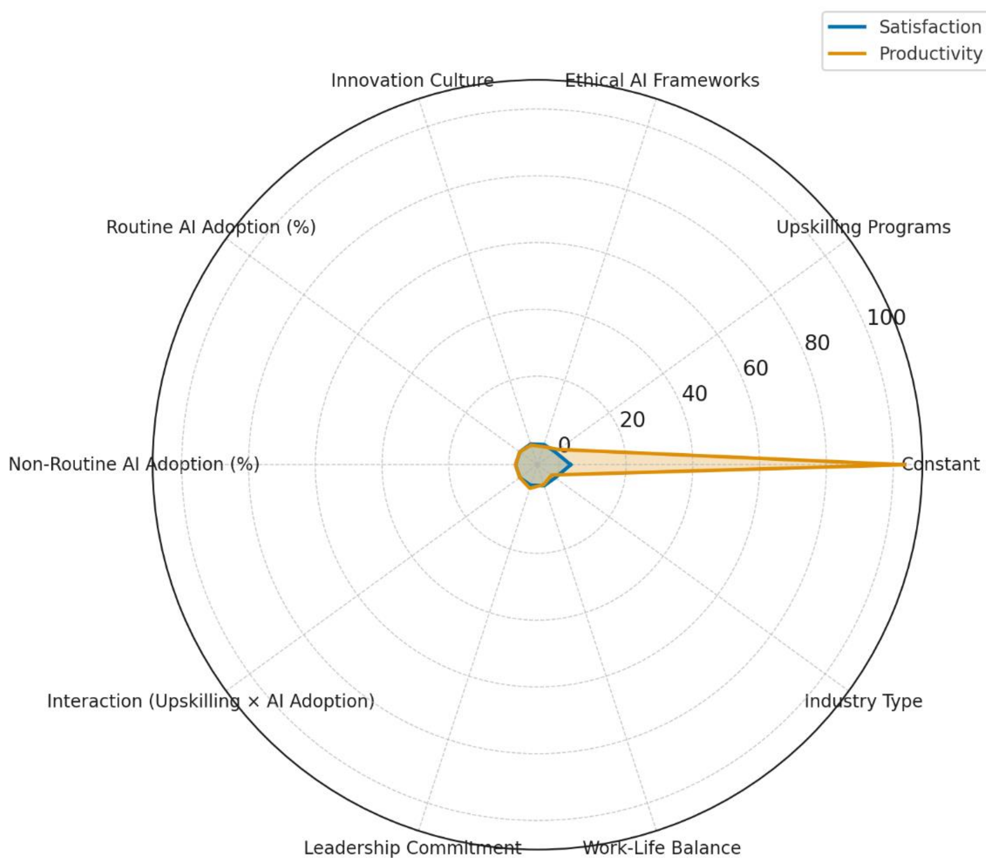

Figure 4. Multiple regression result for employee satisfaction and productivity

Other technocultural interventions, including upskilling programs, innovation culture, and AI adoption, did not significantly influence satisfaction or productivity.

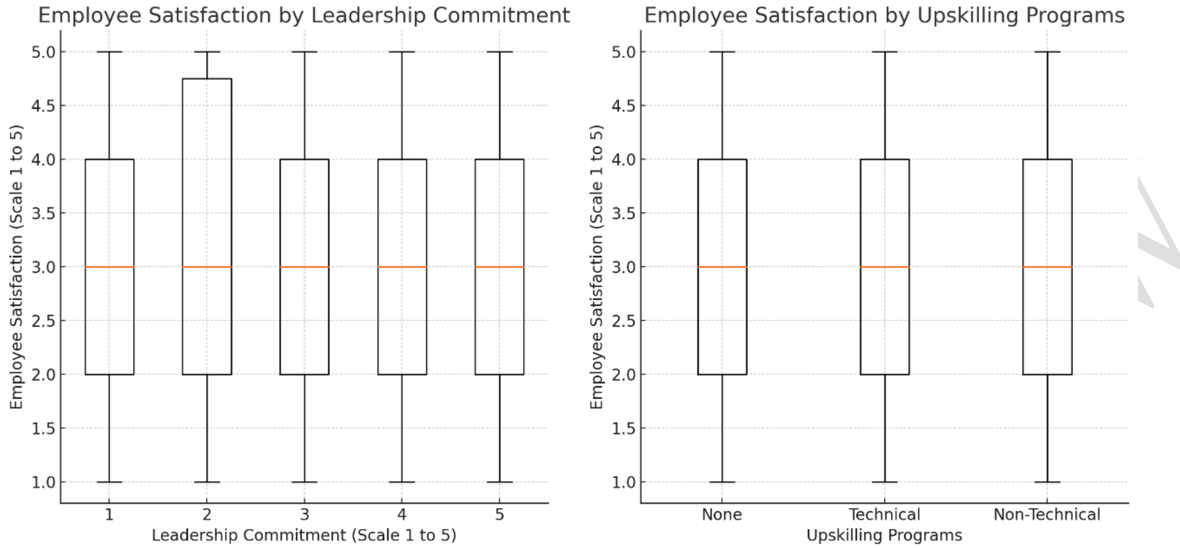

Figure 5. Multiple regression analysis result (a)

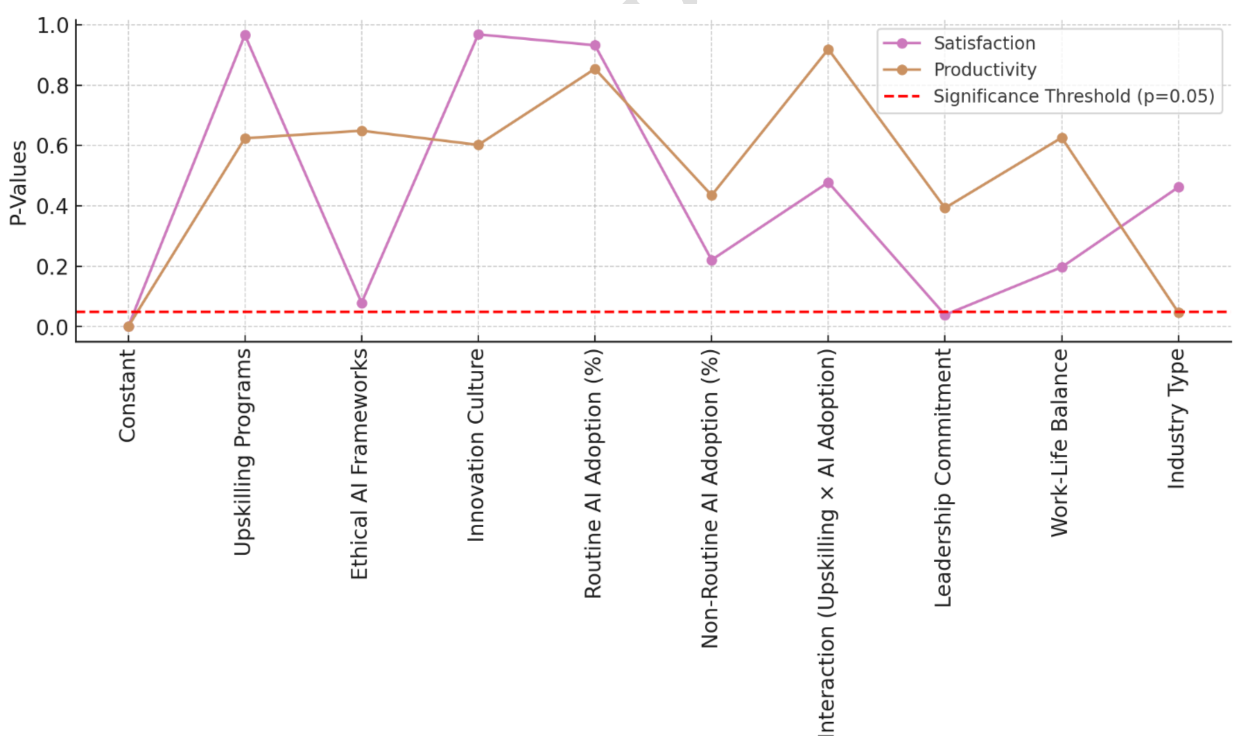

Figure 6. Multiple regression analysis result (b)

For productivity, industry type emerged as a significant predictor (B = -1.309, p = .047), implying that productivity is influenced by sector-specific factors. However, upskilling programs, leadership, and AI adoption did not show significant effects on productivity. These findings suggest that leadership and industry context are critical in shaping outcomes, while other technocultural interventions may require further development or longer-term implementation to demonstrate their impact.

Discussion

The findings from this study provide important insights into the efficacy of technocultural interventions in managing the impacts of AI-driven technological change on organizational workforce management. The results revealed several critical areas where interventions either succeeded or struggled to influence key outcomes like employee satisfaction and productivity, aligning with the background and literature reviewed.

The logistic regression analysis aimed at predicting job displacement, given AI adoption and technocultural interventions, produced statistically insignificant results (R^2 (Pseudo) = 0.0037, p = 0.8200). The predictors, including routine and non-routine AI adoption, organizational size, and employee change readiness, failed to reliably distinguish between job retention and displacement. Specifically, routine AI adoption demonstrated a weak positive relationship with job displacement (B = 0.013, p = 0.111), but this effect was not statistically significant. These findings indicate that, although AI adoption is transforming workforce dynamics, its immediate impact on job displacement may not be as pronounced without the presence of other reinforcing factors, such as robust technocultural interventions. This contrasts with prior literature, where AI has been implicated in widespread job displacement, especially in sectors like manufacturing and customer service, due to its capacity to automate routine tasks [1][10]. The absence of a significant impact in this study might reflect the nascent stage of AI integration in many organizations, suggesting that AI-driven job displacement could become more evident as adoption accelerates in the future.

The cluster analysis provided further insights into how organizations are approaching technocultural interventions, particularly upskilling programs, ethical AI frameworks, and innovation culture. Three distinct clusters were identified, demonstrating varying levels of engagement with these interventions. Cluster 0, characterized by moderate upskilling programs and no ethical AI frameworks, showed that a sizable portion of organizations may not yet fully recognize the importance of ethical AI in shaping workforce outcomes. This could align with the practical challenges highlighted by Diaz-Rodriguez et al. [34], where the enforcement of ethical frameworks is often hindered by a lack of robust oversight mechanisms. On the other hand, Cluster 1 featured organizations that adopted both upskilling programs and ethical AI frameworks, which suggests a more proactive approach to managing AI's workforce impact. Cluster 2, with comprehensive upskilling programs but lower innovation culture, further implies the importance of fostering an innovative environment to complement skill development efforts. This finding echoes Adrian and Everett's [35] argument that organizational culture significantly influences employee perceptions of technological change, reinforcing the idea that interventions must be holistic, addressing both technical and cultural dimensions.

The multivariate regression analysis for employee satisfaction and productivity offered critical insights into the varying effectiveness of technocultural interventions. The significant effect of leadership commitment on employee satisfaction ($B = -0.067$, $p = .039$) highlights the pivotal role leadership plays in navigating AI-driven change. Strong leadership can alleviate fears related to job displacement and skill obsolescence by fostering a sense of security and adaptability within the workforce, a theme that has been consistently supported in the literature [57]. Leadership's influence on satisfaction also reinforces the need for a comprehensive strategy, where technocultural interventions like upskilling programs are complemented by strong organizational leadership that actively engages with employees throughout the transformation process. Although leadership commitment did not significantly affect productivity, its influence on satisfaction explains its importance in mitigating the negative emotional and psychological impacts of AI on the workforce.

In contrast, the non-significance of upskilling programs ($B = 0.0054$, $p = .966$) in predicting both employee satisfaction and productivity raises important questions about the design and implementation of these programs. While the literature consistently emphasizes the need for upskilling and reskilling to keep employees relevant in the AI era [6][25][27], the lack of a significant impact in this study suggests that these programs may not yet be sufficiently tailored to meet the diverse and evolving needs of the workforce. Randriamiary et al. [29] previously noted that upskilling programs are often not universally accessible or adequately designed to address the varying levels of employee skills and experiences. This calls for a more inclusive approach, where upskilling efforts are customized to match the specific requirements of different sectors, industries, and employee demographics.

Furthermore, the sector-specific nature of productivity outcomes, with industry type emerging as a significant predictor ($B = -1.309$, $p = .047$), highlights the varying impact of AI and technocultural interventions across different organizational contexts. This finding suggests that while AI adoption may enhance productivity in certain industries, such as technology and finance, it may have a more limited impact in sectors where human skills and creativity are more critical, such as healthcare and education. This aligns with earlier studies that highlighted the importance of tailoring interventions to the unique needs of each sector [54][55]. The finding that ethical AI frameworks approached significance for employee satisfaction ($B = -0.162$, $p = .079$) suggests that organizations prioritizing ethical considerations in AI implementation may foster a more positive work environment. However, the non-significant effect on productivity indicates that ethical AI, while important for trust and fairness, may not immediately translate into higher efficiency or output.

5. Conclusion and Recommendations

The findings from this study highlight the complex relationship between AI adoption, technocultural interventions, and their effects on workforce management outcomes, including job displacement, employee satisfaction, and productivity. While the logistic regression analysis did not find significant predictors of job displacement, the analysis suggested that routine AI adoption and technocultural interventions, when combined, may still play a role in mitigating the risks associated with AI-driven changes. The cluster analysis revealed distinct organizational approaches to adopting technocultural interventions, with ethical AI frameworks, upskilling programs, and innovation culture varying across organizations based on industry type, size, and geographical location. Multivariate regression analysis confirmed the significant role of leadership commitment in driving employee satisfaction but highlighted the limited direct impact of upskilling programs and ethical AI frameworks on productivity. This indicates that, while these interventions are essential, they may need to be tailored and refined to show their full potential over time. Therefore, following the findings these findings, the study recommends that:

1. Organizations should prioritize leadership development as a key part of their strategy for managing AI-driven change. Strong leadership fosters employee satisfaction and can mitigate the negative impacts of technological transformation. Leadership programs should focus on equipping leaders with the skills to communicate effectively about AI-related changes and support employees during the transition.

2. While upskilling programs are essential, they should be customized to the unique demands of different industries and employee groups. Programs should be designed with input from employees and leadership to ensure that they address relevant skills, whether technical or non-technical. Continuous learning initiatives should be flexible and accessible to all employees, ensuring inclusivity.

3. Ethical AI frameworks should be integrated into organizational processes to build trust and ensure fairness, especially in industries where algorithmic bias could have severe consequences. These frameworks must be actively enforced with proper oversight mechanisms, rather than remaining theoretical guidelines, to mitigate potential ethical risks.

4. Considering that industry type was a significant predictor of productivity, organizations should tailor their technocultural interventions to the specific needs

of their sector. This may involve focusing more on automation and AI adoption in industries that benefit from routine task automation while fostering innovation and human-AI collaboration in sectors where creativity and complex problem-solving are more critical.

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