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 substantial 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 manage AI-driven changes effectively.

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

1. Introduction

In the digital era, the swift emergence of artificial intelligence and advanced technologies is transforming organizational workforce management, offering both benefits and obstacles. The escalating sophistication of AI's offerings has led to substantial gains in efficiency, productivity, and innovative capabilities throughout multiple industries. However, this also poses substantial risks, including job displacement, skills obsolescence, and diminished employee morale [1]. Hence, to successfully address these challenges, organizations must implement techno-cultural strategies that alleviate the adverse effects of AI while advocating for a favorable and flexible work environment [1]. The integration of Artificial Intelligence into organizational processes has significantly altered workforce dynamics, with major corporations such as Microsoft and Google undertaking extensive restructuring, citing economic pressures and operational efficiency. The recent layoffs, however, signal a more fundamental change, propelled by AI-driven automation of tasks that were originally executed by human personnel. Notably, the escalating adoption of AI-driven customer service platforms and industrial robots has led to the substitution of human labor, promoting concerns about job stability and employee displacement [2].

Furthermore, despite its numerous advantages, AI also poses significant ethical dilemmas, notably concerning algorithmic bias and its far-reaching implications. According to Al-kfairy et al. [3], Artificial intelligence systems have been found to perpetuate biases in recruitment, loan, and financing, and criminal justice decisions, sparking widespread concern and demands for enhanced transparency and accountability. These algorithmic biases can result in discriminatory treatment of specific demographics, exacerbate existing inequalities, and undermine confidence in technological systems [3]. In response to these concerns, organizations are increasingly establishing comprehensive ethical frameworks to inform and govern AI development. IBM's creation of an AI Ethics Board serves as a paradigmatic example of proactive measures to guarantee the responsible development and utilization of AI technologies [4]; by implementing such measures, organizations can establish and maintain trust with their customer base and workforce.

While AI has garnered widespread acceptance, a minority still expresses reservations and resistance to its adoption. A subset of employees frequently demonstrates a reluctance to embrace technological advancement, primarily motivated by concerns regarding job security and potential displacement, skill redundancy, and decreased job satisfaction. Resistance to AI-driven change can lead to diminished employee morale, reluctance to embrace new technologies, and, in extreme cases, overt opposition, and so this technological diversion worsens these problems; inequities in technology access create unequal opportunities for workforce development, hindering organizational equity. Employees without access to digital tools or possessing inadequate digital skills may experience a significant disadvantage; this can heighten job insecurity concerns and decrease productivity levels; therefore, a holistic approach integrating technological innovations and cultural/social workforce management strategies is essential to tackle these techno-cultural challenges[5].

According to Chong and Lee[6], organizations are increasingly investing in upskilling and reskilling programs to counteract the negative consequences of AI-driven technological change; these programs focus on enabling employees with the skills necessary to succeed in the artificial intelligence period, this allows them to seamlessly transition into emerging roles and maintain relevance within a dynamic job market. Governments and corporations are investing in comprehensive training and development initiatives to equip the workforce with the skills necessary to navigate AI-driven challenges and capitalize on emerging opportunities [7]. For example, Salesforce's Trailhead platform delivers a comprehensive range of educational resources and certifications specifically designed to enhance digital skills, encouraging a culture of ongoing learning and professional growth [7].

Moreover, the COVID-19 pandemic has accelerated the implementation of remote and hybrid work arrangements. Consequently, this shift has resulted in profound transformations in organizational culture and employees. Working remotely offers several benefits, prominently flexibility and autonomy, but it also presents obstacles, which include isolation, burnout, and difficulties in maintaining work-life balance [8]; organizations must strike a balance between mitigating the challenges and leveraging the advantages of remote work. Garcia–Perez et al. [5] argue that techno-cultural interventions focused on digital well-being, belonging, and collaboration are essential for establishing a productive and positive work environment. Given the different obstacles presented by AI-driven technological change, technocultural interventions offer a targeted solution to alleviate the adverse effects. These tactics include ethical AI culture, such as IBM's AI Ethics Board, Google AI Impact Challenge, and Salesforce's Trailhead [4][7]. According to Zhang and Chen [9], the escalating digital transformation underscores the increasing significance of these interventions, rendering them essential elements of successful 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 assimilation of AI-driven technologies into human capital management has substantial adverse effects such as job loss, competency degradation, diminished motivation, and moral dilemmas related to artificial intelligence prejudice. In accordance with Fayad [1], the advent of AI-driven automation has significantly exacerbated job displacement, especially in industries such as manufacturing, customer service, and finance. Human professions are being substituted by artificial intelligence technologies, particularly those comprising routine or predictable tasks; the integration of AI technology substantially diminishes the requirement for manual labor in manufacturing and supplants conventional financial roles with automated systems capable of processing vast data sets with enhanced efficiency [10]. Analysis from organizations such as McKinsey & Company proposes that up to 30% of operations in approximately 60% of professions could be mechanized, indicating a paradigm shift in workforce dynamics [11][12]. Nevertheless, Bazargani and Deemyad [13] announce that this change increases concerns about the preparedness of industries and government to mitigate the socioeconomic impacts of extensive job displacement. Aside from job displacement, the rapid development of artificial intelligence has rendered specific skills redundant, requiring perpetual skill enhancement. Pasko et al. [14] express that employees in industries such as information technology, healthcare, and finance, to remain competitive, must obtain new skills as artificial intelligence requirements increase gradually. For instance, the integration of AI-powered chatbots has redefined traditional customer service roles, while AI-driven diagnostic tools are transforming medical expertise in healthcare [15][16][17]. The World Economic Forum stresses the increasing request for skills that enhance AI, such as innovative problem-solving, emotional intelligence, and modern data analysis [18]. While some skills may be unnecessary, Bobitan et al. [19] suggest that human-AI cooperation presents novel opportunities for workforce enhancement, necessitating a balanced approach to skill development.

Additionally, Mirbabaie et al. [20] suggest that the demand to adjust to modern technologies also influences employee morale, resulting in enhanced anxiety, stress, and diminished job satisfaction; employees worried about being substituted by artificial intelligence might undergo a decreased sense of job security, decrease organizational efficiency and employee maintenance. Consequently, organizations have a critical responsibility to prioritize employee well-being through the provision of comprehensive support systems and ongoing learning opportunities [21][22]. This increases ethical worries, especially in association with algorithmic bias. AI systems can inadvertently reinforce and propagate existing biases, resulting in discriminatory outcomes in hiring, lending, and the justice system. Therefore, handling these fears demands the advancement of ethical frameworks and standards to guarantee transparency, accountability, and fairness in AI applications [23][24]. Furthermore, organizations are ramping up investments in upskilling and reskilling programs (technocultural interventions) to counteract the negative consequences of AI-driven technological transformation; these initiatives are designed to enhance employees' skills, enabling them to excel in an AI-driven environment, empowering them to change into fresh positions and remain pertinent in a swiftly developing job market [16].

Technocultural Interventions in Mitigating AI's Negative Impacts

The incorporations of artificial intelligence into oganizational processes requires targeted technocultural interventions to alleviate its adverse effects on workforce management; critical approaches include upskilling and reskilling programs, the advancement of ethical frameworks, the advocacy of creative culture, and the promotion of digital well-being, are all important for utilizing AI advantages without negotiating workforce balance [25]. In accordance to Fenwick et al [26], the execution of upskilling and reskilling projects in organization are essential as the nature of most work develops with artificial intelligence developments and constant training project which include Salesforce's Trailhead and Microsoft's Global Skills Initiative, designed to prepare employees with the significant skills in AI, data analysis, and cloud computing, consequently allowing them to stay contending in a dynamic job market [4][27][28]. Nevertheless, Randriamiary et al. [29] dispute that these programs might not b globally obtainable or effectively personalized to meet different employee demands, which probably result into disproportionate opportunities for skill advancement. Consequently, Rajaram [30] suggests that organizations must secure equality in their upskilling efforts by modifying programs to adapt different learning ways and capabilities, acknowledging that upskilling should be seen as a dynamic, flexible process instead of a universal approach.

A further crucial initiative involves the development and implementation of ethical artificial intelligence frameworks, specifically crafted to mitigate issues stemming from algorithmic bias, privacy, and accountability [31]. Organizations such as IBM have established AI Ethics Boards to supervise ethical thought, securing conformity with standards that prioritize fairness, transparency, and accountability [4][32]. Likewise, projects like Google's AI influence obstacles and promote ethical AI by financing projects that investigate reliable AI applications [33]. Still, regardless of this growing emphasis on ethical AI, several practical hurdles persist, as the execution and enforcement of this framework frequently lack thorough evaluation procedures, and Diaz et al. [34] dispute that without a robust accountability mechanism, ethical frameworks for AI may remain abstract and inadequate in addressing complex challenges, highlighting the necessity for continuous assessment and enhancement of ethical norms. Cultivating an innovative environment is vital to counterbalance AI's potential adverse effects; Adrian and Everett [35] propose that organizational culture substantially affects employee views and replies to technological modifications. A culture fostering innovation, adaptability, and cooperation can mitigate apprehensions and uncertainties surrounding AI-driven change. However, Rozman et al. [36] claim that developing such a culture demands tactics and dedication from leadership, dynamic employee participation, and coordination of organizational values with technological aim.

Most especially, Alahi et al. [37] contend that it has become expedient for 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 optimize 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 organizational 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 prioritizing 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:

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

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:

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

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

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:

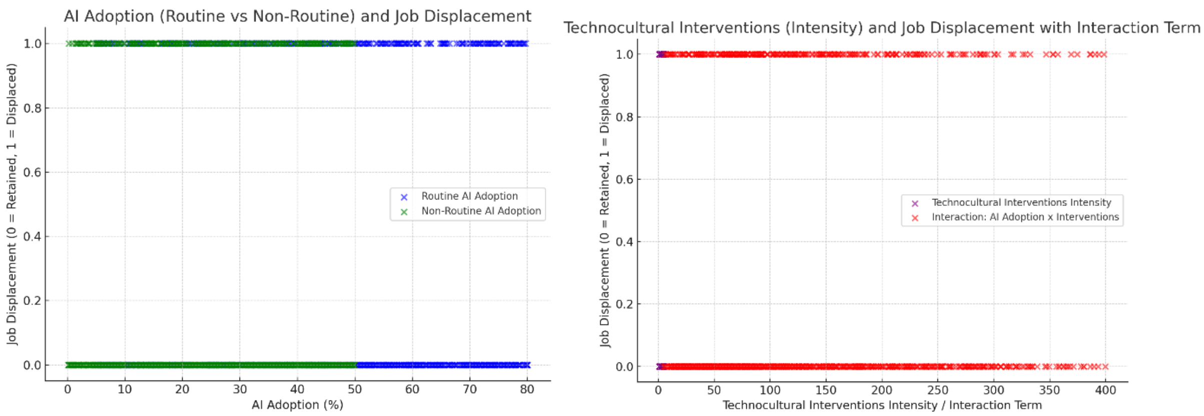
Table 1: Logistic Regression Predicting Job Displacement

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.

Fig 1 Routine AI Adoption



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

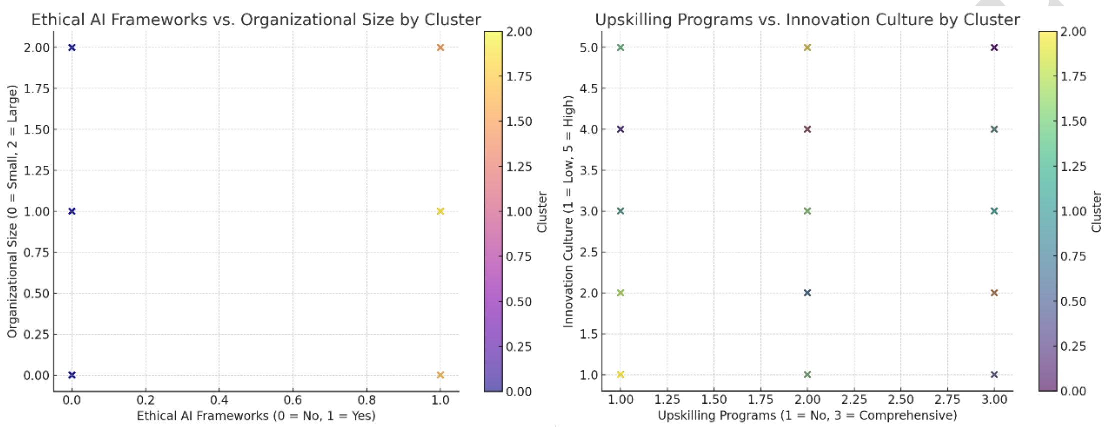
Cluster	**Mean Upskilling Programs**	**Mean Ethical AI Frameworks**	**Mean Innovation Culture**	**Mean Industry Type (Encoded)**	**Mean Organizational Size (Encoded)**	**Mean Geographical Location (Encoded)**
0	2.00	0.00	3.13	2.05	1.00	0.51
1	1.91	1.00	3.03	2.05	1.00	0.00

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).

Fig 2 Ethical AI frameworks



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:

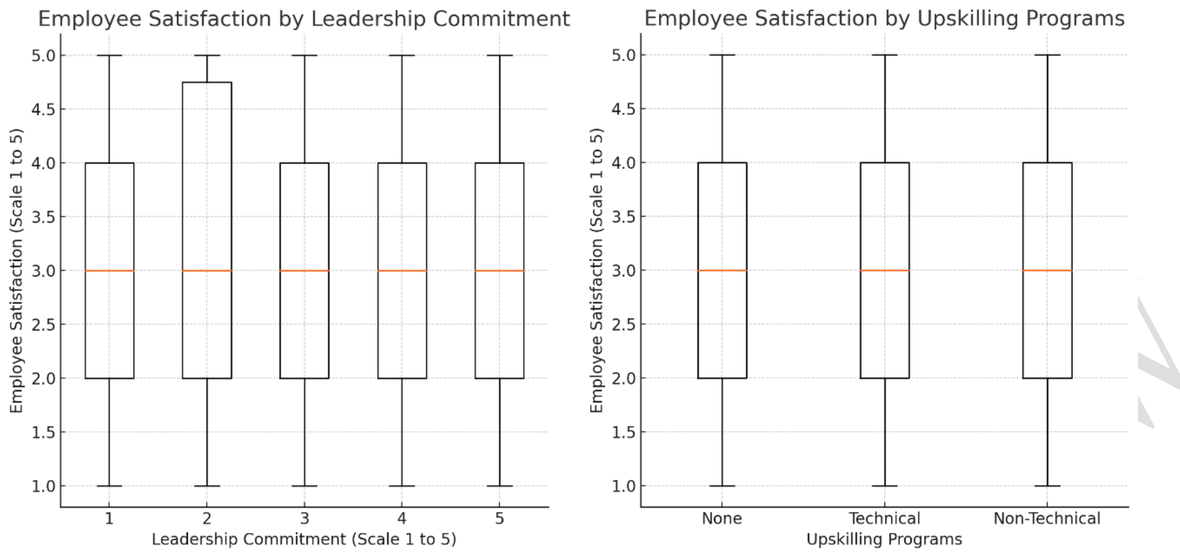
Table 3: Regression Results for Employee Satisfaction and Productivity

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

Fig 3 Employee satisfaction



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.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

References

[1] A. Fayad, "Development and Future Scope of AI in the Workplace," AIJBM, Feb. 2024. Accessed: Sep. 07, 2024. [Online]. Available: https://www.aijbm.com/wp-content/uploads/2024/02/B721120.pdf

[2] Dr. A. Shaji George, "Future Economic Implications of Artificial Intelligence," *zenodo.org*, vol. 2, no. 3, Sep. 2023, doi: https://doi.org/10.5281/zenodo.8347639.

[3] M. Al-kfairy, D. Mustafa, N. Kshetri, M. Insiew, and O. Alfandi, "Ethical Challenges and Solutions of Generative AI: An Interdisciplinary Perspective," *Informatics*, vol. 11, no. 3, pp. 58–58, Aug. 2024, doi: https://doi.org/10.3390/informatics11030058.

[4] P. B. de Laat, "Companies Committed to Responsible AI: From Principles towards Implementation and Regulation?," *Philosophy & Technology*, vol. 34, Oct. 2021, doi: https://doi.org/10.1007/s13347-021-00474-3.
[5] L. García-Pérez, M. García-Garnica, and E. M. Olmedo-Moreno, "Skills for a Working Future: How to Bring about Professional Success from the Educational Setting," *Education Sciences*, vol. 11, no. 1, p. 27, Jan. 2021, doi: https://doi.org/10.3390/educsci11010027.
[6] S. Chong and M. F. Lee, "Rethinking Education in the Era of Artificial Intelligence (AI): Towards Future Workforce Competitiveness and Business Success," *Springer Link*, pp. 151–166, Jan. 2024, doi: https://doi.org/10.1007/978-981-97-2211-2_7.
[7] A. Bergman, "What Is Trailhead? All About Salesforce's Free Online Learning Platform," *The 360 Blog from Salesforce*, Apr. 02, 2024. https://www.salesforce.com/blog/what-is-trailhead/ (accessed Sep. 05, 2024).
[8] D. Sengupta and D. Al-Khalifa, "Pandemic Imposed Remote Work Arrangements and Resultant Work-Life Integration, Future of Work and Role of Leaders—A Qualitative Study of Indian Millennial Workers," *Administrative Sciences*, vol. 12, no. 4, p. 162, Nov. 2022.
[9] J. Zhang and Z. Chen, "Exploring Human Resource Management Digital Transformation in the Digital Age," *Journal of the Knowledge Economy*, vol. 15, Mar. 2023.
[10] H. Choung, P. David, and A. Ross, "Trust in AI and Its Role in the Acceptance of AI Technologies," *International Journal of Human–Computer Interaction*, vol. 39, no. 9, pp. 1–13, Apr. 2022, doi: https://doi.org/10.1080/10447318.2022.2050543.
[11] E. Hazan *et al.*, "A new future of work: The race to deploy AI and raise skills in Europe and beyond," 2024. Accessed: Sep. 05, 2024. [Online]. Available: https://www.mckinsey.de/~/media/mckinsey/locations/europe%20and%20middle%20east/deutschland/news/presse/2024/2024%20-%2005%20-%2023%20mgi%20genai%20future%20of%20work/mgi%20report_a-new-future-of-work-the-race-to-deploy-ai.pdf
[12] A. D. Samuel-Okon, O. I. Akinola, O. O. Olaniyi, O. O. Olateju, and S. A. Ajayi, "Assessing the Effectiveness of Network Security Tools in Mitigating the Impact of Deepfakes AI on Public Trust in Media," *Archives of Current Research International*, vol. 24, no. 6, pp. 355–375, Jul. 2024, doi: https://doi.org/10.9734/acri/2024/v24i6794.
[13] K. Bazargani and T. Deemyad, "Automation's Impact on Agriculture: Opportunities, Challenges, and Economic Effects," *Robotics*, vol. 13, no. 2, p. 33, Feb. 2024, doi: https://doi.org/10.3390/robotics13020033.
[14] Ł. Paśko *et al.*, "Plan and Develop Advanced Knowledge and Skills for Future Industrial Employees in the Field of Artificial Intelligence, Internet of Things and Edge Computing," *Sustainability*, vol. 14, no. 6, p. 3312, Mar. 2022, doi: https://doi.org/10.3390/su14063312.
[15] R. Chaturvedi and S. Verma, "Opportunities and Challenges of AI-Driven Customer Service," *Springer eBooks*, pp. 33–71, Jan. 2023, doi: https://doi.org/10.1007/978-3-031-33898-4_3.
[16] A. Shiwlani, M. Khan, A. M. K. Sherani, M. U. Qayyum, and H. K. Hussain, "REVOLUTIONIZING HEALTHCARE: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON PATIENT CARE, DIAGNOSIS, AND TREATMENT," *JURIHUM : Jurnal Inovasi dan Humaniora*, vol. 1, no. 5, pp. 779–790, Feb. 2024, Accessed: Sep. 05, 2024. [Online]. Available: http://jurnalmahasiswa.com/index.php/Jurihum/article/view/845
[17] C. S. Adigwe, O. O. Olaniyi, S. O. Olabanji, O. J. Okunleye, N. R. Mayeke, and S. A. Ajayi, "Forecasting the Future: The Interplay of Artificial Intelligence, Innovation, and Competitiveness

and its Effect on the Global Economy," *Asian journal of economics, business and accounting*, vol. 24, no. 4, pp. 126–146, Feb. 2024, doi: https://doi.org/10.9734/ajeba/2024/v24i41269.
[18] World Economic Forum, "Future of Jobs Report 2023," May 2023. Accessed: Sep. 07, 2024. [Online]. Available: https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf
[19] N. Bobitan, D. Dumitrescu, A. F. Popa, D. N. Sahlian, and I. C. Turlea, "Shaping Tomorrow: Anticipating Skills Requirements Based on the Integration of Artificial Intelligence in Business Organizations—A Foresight Analysis Using the Scenario Method," *Electronics*, vol. 13, no. 11, p. 2198, Jan. 2024, doi: https://doi.org/10.3390/electronics13112198.
[20] M. Mirbabaie, F. Brünker, N. R. J. Möllmann, and S. Stieglitz, "The rise of artificial intelligence – understanding the AI identity threat at the workplace," *Electronic Markets*, vol. 32, no. 1, pp. 73–99, Oct. 2021, doi: https://doi.org/10.1007/s12525-021-00496-x.
[21] G. Sorensen, J. T. Dennerlein, S. E. Peters, E. L. Sabbath, E. L. Kelly, and G. R. Wagner, "The future of research on work, safety, health and wellbeing: A guiding conceptual framework," *Social Science & Medicine*, vol. 269, no. 1, p. 113593, Jan. 2021, doi: https://doi.org/10.1016/j.socscimed.2020.113593.
[22] S. O. Olabanji, T. O. Oladoyinbo, C. U. Asonze, C. S. Adigwe, O. J. Okunleye, and O. O. Olaniyi, "Leveraging FinTech Compliance to Mitigate Cryptocurrency Volatility for Secure US Employee Retirement Benefits: Bitcoin ETF Case Study," *Asian journal of economics, business and accounting*, vol. 24, no. 4, pp. 147–167, Feb. 2024, doi: https://doi.org/10.9734/ajeba/2024/v24i41270.
[23] N. Gupta, "Artificial Intelligence Ethics and Fairness: A study to address bias and fairness issues in AI systems, and the ethical implications of AI applications," *Revista Review Index Journal of Multidisciplinary*, vol. 3, no. 2, pp. 24–35, Jun. 2023, doi: https://doi.org/10.31305/rrijm2023.v03.n02.004.
[24] O. O. Olaniyi, O. O. Olaoye, and O. J. Okunleye, "Effects of Information Governance (IG) on Profitability in the Nigerian Banking Sector," *Asian Journal of Economics, Business and Accounting*, vol. 23, no. 18, pp. 22–35, Jul. 2023, doi: https://doi.org/10.9734/ajeba/2023/v23i181055.
[25] F. A. Ajayi and C. A. Udeh, "REVIEW OF WORKFORCE UPSKILLING INITIATIVES FOR EMERGING TECHNOLOGIES IN IT," *International Journal of Management & Entrepreneurship Research*, vol. 6, no. 4, pp. 1119–1137, Apr. 2024, doi: https://doi.org/10.51594/ijmer.v6i4.1003.
[26] A. Fenwick, G. Molnar, and P. Frangos, "The critical role of HRM in AI-driven digital transformation: a paradigm shift to enable firms to move from AI implementation to human-centric adoption," *Discover Artificial Intelligence*, vol. 4, no. 1, May 2024, doi: https://doi.org/10.1007/s44163-024-00125-4.
[27] G. Li, C. Yuan, S. Kamarthi, M. Moghaddam, and X. Jin, "Data science skills and domain knowledge requirements in the manufacturing industry: A gap analysis," *Journal of Manufacturing Systems*, vol. 60, pp. 692–706, Jul. 2021, doi: https://doi.org/10.1016/j.jmsy.2021.07.007.
[28] O. O. Olaniyi, C. U. Asonze, S. A. Ajayi, S. O. Olabanji, and C. S. Adigwe, "A Regressional Study on the Impact of Organizational Security Culture and Transformational Leadership on Social Engineering Awareness among Bank Employees: The Interplay of Security Education and Behavioral Change," *Asian Journal of Economics, Business and Accounting*, vol. 23, no. 23, pp. 128–143, Dec. 2023, doi: https://doi.org/10.9734/ajeba/2023/v23i231176.

[29] D. Randriamiary, "Reframing the Role of Leaders Navigating the Challenges and Opportunities of Tomorrow's Workplace in the Age of Artificial Intelligence," *Social Science Research Network*, Jan. 2024, doi: https://doi.org/10.2139/ssrn.4716033.
[30] K. Rajaram, "Future of Learning: Teaching and Learning Strategies," *Springer Link*, pp. 3–53, Jan. 2023, doi: https://doi.org/10.1007/978-981-19-9201-8_1.
[31] A. Alam, "Developing a Curriculum for Ethical and Responsible AI: A University Course on Safety, Fairness, Privacy, and Ethics to Prepare Next Generation of AI Professionals," *Lecture notes on data engineering and communications technologies*, vol. 171, pp. 879–894, Jan. 2023, doi: https://doi.org/10.1007/978-981-99-1767-9_64.
[32] O. O. Olaniyi, N. Shah, and N. Bahuguna, "Quantitative Analysis and Comparative Review of Dividend Policy Dynamics within the Banking Sector: Insights from Global and U.S. Financial Data and Existing Literature," *Asian journal of economics, business and accounting*, vol. 23, no. 23, pp. 179–199, Dec. 2023, doi: https://doi.org/10.9734/ajeba/2023/v23i231180.
[33] N. Tomašev *et al.*, "AI for social good: unlocking the opportunity for positive impact," *Nature Communications*, vol. 11, no. 1, May 2020, doi: https://doi.org/10.1038/s41467-020-15871-z.
[34] N. Díaz-Rodríguez, J. Del Ser, M. Coeckelbergh, M. López de Prado, E. Herrera-Viedma, and F. Herrera, "Connecting the dots in trustworthy Artificial Intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation," *Information Fusion*, vol. 99, no. 101896, p. 101896, Nov. 2023, Accessed: Sep. 07, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1566253523002129
[35] C. Adrian and A. Everett, "The Psychology of Digital Transformation: Navigating Change in AI-driven Organizations," *International Journal of Advanced Engineering Technologies and Innovations*, vol. 01, no. 3, p. 3, 2023, Accessed: Sep. 07, 2024. [Online]. Available: https://ijaeti.com/index.php/Journal/article/download/237/257
[36] M. Rožman, P. Tominc, and B. Milfelner, "Maximizing employee engagement through artificial intelligent organizational culture in the context of leadership and training of employees: Testing linear and non-linear relationships," *Cogent Business & Management*, vol. 10, no. 2, Aug. 2023, doi: https://doi.org/10.1080/23311975.2023.2248732.
[37] M. E. E. Alahi *et al.*, "Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends," *Sensors*, vol. 23, no. 11, p. 5206, Jan. 2023, doi: https://doi.org/10.3390/s23115206.
[38] F. A. Ajayi and C. A. Udeh, "COMBATING BURNOUT IN THE IT INDUSTRY: A REVIEW OF EMPLOYEE WELL-BEING INITIATIVES," *International Journal of Applied Research in Social Sciences*, vol. 6, no. 4, pp. 567–588, Apr. 2024, doi: https://doi.org/10.51594/ijarss.v6i4.1010.
[39] C. U. Asonze, O. S. Ogungbemi, F. A. Ezeugwa, A. O. Olisa, O. I. Akinola, and O. O. Olaniyi, "Evaluating the Trade-offs between Wireless Security and Performance in IoT Networks: A Case Study of Web Applications in AI-Driven Home Appliances," *Journal of Engineering Research and Reports*, vol. 26, no. 8, pp. 411–432, Aug. 2024, doi: https://doi.org/10.9734/jerr/2024/v26i81255.
[40] E. Straus, L. Uhlig, J. Kühnel, and C. Korunka, "Remote workers' well-being, perceived productivity, and engagement: which resources should HRM improve during COVID-19? A longitudinal diary study," *The International Journal of Human Resource Management*, vol. 34, no. 15, pp. 1–31, May 2022, doi: https://doi.org/10.1080/09585192.2022.2075235.
[41] O. I. Akinola, O. O. Olaniyi, O. S. Ogungbemi, O. B. Oladoyinbo, and A. O. Olisa, "Resilience and Recovery Mechanisms for Software-Defined Networking (SDN) and Cloud

Networks," *Journal of Engineering Research and Reports*, vol. 26, no. 8, pp. 112–134, Jul. 2024, doi: https://doi.org/10.9734/jerr/2024/v26i81234.
[42] K. E. Fox *et al.*, "Organisational- and group-level workplace interventions and their effect on multiple domains of worker well-being: A systematic review," *Work & Stress*, vol. 36, no. 1, pp. 1–30, Aug. 2021, doi: https://doi.org/10.1080/02678373.2021.1969476.
[43] O. S. Ogungbemi, F. A. Ezeugwa, O. O. Olaniyi, O. I. Akinola, and O. B. Oladoyinbo, "Overcoming Remote Workforce Cyber Threats: A Comprehensive Ransomware and Bot Net Defense Strategy Utilizing VPN Networks," *Journal of Engineering Research and Reports*, vol. 26, no. 8, pp. 161–184, Jul. 2024, doi: https://doi.org/10.9734/jerr/2024/v26i81237.
[44] N. Soetjipto, N. Priyohadi, S. Sulastri, and A. Riswanto, "The effect of company climate, organization citizenship behavior, and transformational leadership on work morale through employee job satisfaction," *Management Science Letters*, vol. 11, no. 4, pp. 1197–1204, 2021, Accessed: Sep. 07, 2024. [Online]. Available: http://m.growingscience.com/beta/msl/4439-the-effect-of-company-climate-organization-citizenship-behavior-and-transformational-leadership-on-work-morale-through-employee-job-satisfaction.html
[45] T. Carstensen and K. Ganz, "Gendered AI: German news media discourse on the future of work," *AI & society*, Aug. 2023, doi: https://doi.org/10.1007/s00146-023-01747-5.
[46] O. S. Ogungbemi, "Smart Contracts Management: The Interplay of Data Privacy and Blockchain for Secure and Efficient Real Estate Transactions," *Journal of Engineering Research and Reports*, vol. 26, no. 8, pp. 278–300, 2024, doi: https://doi.org/10.9734/jerr/2024/v26i81245.
[47] F. Fraile, F. Psarommatis, F. Alarcón, and J. Joan, "A Methodological Framework for Designing Personalised Training Programs to Support Personnel Upskilling in Industry 5.0," *Computers*, vol. 12, no. 11, p. 224, Nov. 2023, doi: https://doi.org/10.3390/computers12110224.
[48] C. Duhigg, "What Google learned from its quest to build the perfect team," *The New York Times*, Feb. 25, 2016. Accessed: Sep. 07, 2024. [Online]. Available: https://www.nytimes.com/2016/02/28/magazine/what-google-learned-from-its-quest-to-build-the-perfect-team.html
[49] O. I. Akinola, "Adaptive Location-based Routing Protocols for Dynamic Wireless Sensor Networks in Urban Cyber-physical Systems," *Journal of Engineering Research and Reports*, vol. 26, no. 7, pp. 424–443, Jul. 2024, doi: https://doi.org/10.9734/jerr/2024/v26i71220.
[50] S. Karasvirta and S. Teerikangas, "Change Organizations in Planned Change – A Closer Look," *Journal of Change Management*, vol. 22, no. 2, pp. 1–39, Jan. 2022, doi: https://doi.org/10.1080/14697017.2021.2018722.
[51] T. Mastria, "AT&T Invests $1 Billion in Employee Reskilling," *The Aspen Institute*, Mar. 12, 2018. https://www.aspeninstitute.org/of-interest/upskilling-news-att-invests-1-billion-employee-reskilling/ (accessed Sep. 07, 2024).
[52] T. H. Davenport and R. Bean, "AI Ethics at Unilever: From Policy to Process," *MIT Sloan Management Review*, Nov. 15, 2023. https://sloanreview.mit.edu/article/ai-ethics-at-unilever-from-policy-to-process/ (accessed Sep. 07, 2024).
[53] A. D. Samuel-Okon, "Smart Media or Biased Media: The Impacts and Challenges of AI and Big Data on the Media Industry," *Asian Journal of Research in Computer Science*, vol. 17, no. 7, pp. 128–144, Jul. 2024, doi: https://doi.org/10.9734/ajrcos/2024/v17i7484.
[54] F. Osasona, O. O. Amoo, A. Atadoga, O. Abrahams, O. A. Farayola, and B. Samson, "REVIEWING THE ETHICAL IMPLICATIONS OF AI IN DECISION MAKING PROCESSES," *International journal of management & entrepreneurship research*, vol. 6, no. 2, pp. 322–335, Feb. 2024, doi: https://doi.org/10.51594/ijmer.v6i2.773.

[55] S. O. Olabanji, O. B. Oladoyinbo, C. U. Asonze, T. O. Oladoyinbo, S. A. Ajayi, and O. O. Olaniyi, "Effect of Adopting AI to Explore Big Data on Personally Identifiable Information (PII) for Financial and Economic Data Transformation," *Asian journal of economics, business and accounting*, vol. 24, no. 4, pp. 106–125, Feb. 2024, doi: https://doi.org/10.9734/ajeba/2024/v24i41268.
[56] S. Dua, "Circular horizons: Pioneering sustainable paths in the oil and gas Industry's journey to net-zero resilience," *International Social Science Journal*, May 2024, doi: https://doi.org/10.1111/issj.12509.
[57] D. Zhao, F. Tian, X. Sun, and D. Zhang, "The Effects of Entrepreneurship on the Enterprises' Sustainable Innovation Capability in the Digital Era: The Role of Organizational Commitment, Person–Organization Value Fit, and Perceived Organizational Support," *Sustainability*, vol. 13, no. 11, p. 6156, May 2021, doi: https://doi.org/10.3390/su13116156.
[58] P. smart, "The Influence of Company Culture on Employee Retention and Satisfaction," *Psico-smart.com*, 2019. https://psico-smart.com/en/blogs/blog-the-influence-of-company-culture-on-employee-retention-and-satisfaction-171995 (accessed Sep. 07, 2024).
[59] Ž. Stankevičiūtė, "The Dark Side of Technology Use: The Relationship Between Technostress Creators, Employee Work-Life Balance, and Job Burnout While Working Remotely During the COVID-19 Lockdown," *Intelligent Systems Reference Library*, pp. 119–138, 2022, doi: https://doi.org/10.1007/978-3-031-09928-1_8.
[60] N. R. Mayeke, A. T. Arigbabu, O. O. Olaniyi, O. J. Okunleye, and C. S. Adigwe, "Evolving Access Control Paradigms: A Comprehensive Multi-Dimensional Analysis of Security Risks and System Assurance in Cyber Engineering," *Asian Journal of Research in Computer Science*, vol. 17, no. 5, pp. 108–124, Mar. 2024, doi: https://doi.org/10.9734/ajrcos/2024/v17i5442.
[61] J. A. Hubbart, "Organizational Change: the Challenge of Change Aversion," *Administrative Sciences*, vol. 13, no. 7, pp. 162–162, Jul. 2023, doi: https://doi.org/10.3390/admsci13070162.
[62] H. Z. H. Alsharif, T. Shu, B. Obrenovic, D. Godinic, A. Alhujailli, and A. M. Abdullaev, "Impact of Entrepreneurial Leadership and Bricolage on Job Security and Sustainable Economic Performance: An Empirical Study of Croatian Companies during COVID-19 Pandemic," *Sustainability*, vol. 13, no. 21, p. 11958, Oct. 2021, doi: https://doi.org/10.3390/su132111958.
[63] O. O. Olateju, S. U. Okon, O. O. Olaniyi, A. D. Samuel-Okon, and C. U. Asonze, "Exploring the Concept of Explainable AI and Developing Information Governance Standards for Enhancing Trust and Transparency in Handling Customer Data," *Journal of Engineering Research and Reports*, vol. 26, no. 7, pp. 244–268, Jun. 2024, doi: https://doi.org/10.9734/jerr/2024/v26i71206
[64] S. McGuinness, K. Pouliakas, and P. Redmond, "Skills-displacing technological change and its impact on jobs: challenging technological alarmism?," *Economics of Innovation and New Technology*, vol. 32, no. 3, pp. 1–23, May 2021, doi: https://doi.org/10.1080/10438599.2021.1919517.
[65] M. Grégoire, G. Delalieux, and P. Fatien, "Alternative leadership and the pitfalls of hierarchy: When formalization enables power to be tamed," *Leadership*, vol. 18, no. 6, p. 174271502211283, Sep. 2022, doi: https://doi.org/10.1177/17427150221128358.
[66] A. D. Samuel-Okon, O. O. Olateju, S. U. Okon, O. O. Olaniyi, and U. T. I. Igwenagu, "Formulating Global Policies and Strategies for Combating Criminal Use and Abuse of Artificial Intelligence," *Archives of current research international*, vol. 24, no. 5, pp. 612–629, Jun. 2024, doi: https://doi.org/10.9734/acri/2024/v24i5735.
[67] X. Zhang, M. F. Antwi-Afari, Y. Zhang, and X. Xing, "The Impact of Artificial Intelligence on Organizational Justice and Project Performance: A Systematic Literature and Science Mapping

Review," *Buildings*, vol. 14, no. 1, p. 259, Jan. 2024, doi: https://doi.org/10.3390/buildings14010259.
[68] R. Van, B. Coetzee, and J. Bantjes, "Willing and unwilling digital cyborg assemblages: University students talk about mental health apps," *DIGITAL HEALTH*, vol. 9, Jan. 2023, doi: https://doi.org/10.1177/20552076231210658.
[69] T. O. Oladoyinbo, S. O. Olabanji, O. O. Olaniyi, O. O. Adebiyi, O. J. Okunleye, and A. I. Alao, "Exploring the Challenges of Artificial Intelligence in Data Integrity and its Influence on Social Dynamics," *Asian Journal of Advanced Research and Reports*, vol. 18, no. 2, pp. 1–23, Jan. 2024, doi: https://doi.org/10.9734/ajarr/2024/v18i2601.
[70] P. Tominc, D. Oreški, V. Čančer, and M. Rožman, "Statistically Significant Differences in AI Support Levels for Project Management between SMEs and Large Enterprises," *AI*, vol. 5, no. 1, pp. 136–157, Jan. 2024, doi: https://doi.org/10.3390/ai5010008.
[71] S. Y. Sung and J. N. Choi, "What drives firms to invest in training and developing employees? Time-dependent effects of firm internal and external contingencies," *The International Journal of Human Resource Management*, vol. 34, no. 2, pp. 1–30, Aug. 2021, doi: https://doi.org/10.1080/09585192.2021.1965007.
[72] A. A. Salami, U. T. I. Igwenagu, C. E. Mesode, O. O. Olaniyi, and O. B. Oladoyinbo, "Beyond Conventional Threat Defense: Implementing Advanced Threat Modeling Techniques, Risk Modeling Frameworks and Contingency Planning in the Healthcare Sector for Enhanced Data Security," *Journal of Engineering Research and Reports*, vol. 26, no. 5, pp. 304–323, Apr. 2024, doi: https://doi.org/10.9734/jerr/2024/v26i51156.
[73] N. Casemajor, G. Bellavance, and G. Sirois, "Cultural participation in digital environments: goals and stakes for Quebec cultural policies," *International Journal of Cultural Policy*, vol. 27, no. 5, pp. 1–17, Oct. 2020, doi: https://doi.org/10.1080/10286632.2020.1825403.
[74] A. Imran, "Why addressing digital inequality should be a priority," *THE ELECTRONIC JOURNAL OF INFORMATION SYSTEMS IN DEVELOPING COUNTRIES*, vol. 89, no. 3, Nov. 2022, doi: https://doi.org/10.1002/isd2.12255.
[75] J. Semaan, J. Underwood, and J. Hyde, "An Investigation of Work-Based Education and Training Needs for Effective BIM Adoption and Implementation: An Organisational Upskilling Model," *Applied Sciences*, vol. 11, no. 18, p. 8646, Sep. 2021, doi: https://doi.org/10.3390/app11188646.
[76] O. O. Olateju, S. U. Okon, U. T. I. Igwenagu, A. A. Salami, T. O. Oladoyinbo, and O. O. Olaniyi, "Combating the Challenges of False Positives in AI-Driven Anomaly Detection Systems and Enhancing Data Security in the Cloud," *Asian Journal of Research in Computer Science*, vol. 17, no. 6, pp. 264–292, Jun. 2024, doi: https://doi.org/10.9734/ajrcos/2024/v17i6472.
[77] J. Colding, C. Nilsson, and S. Sjöberg, "Smart Cities for All? Bridging Digital Divides for Socially Sustainable and Inclusive Cities," *Smart Cities*, vol. 7, no. 3, pp. 1044–1059, Jun. 2024, doi: https://doi.org/10.3390/smartcities7030044.
[78] D. Grba, "Art Notions in the Age of (Mis)anthropic AI," *Arts*, vol. 13, no. 5, pp. 137–137, Aug. 2024, doi: https://doi.org/10.3390/arts13050137.
[79] M. L. Ruiu, G. Ruiu, M. Ragnedda, and F. Addeo, "Exploring Digital-Environment Habitus in Italy—How Digital Practices Reflect Users' Environmental Orientations?," *Sustainability*, vol. 16, no. 12, pp. 4880–4880, Jun. 2024, doi: https://doi.org/10.3390/su16124880.
[80] F. Matos, L. N. Potrich, P. M. Selig, and E. Giugliani, "Organisational Resilience in the Digital Age: Management Strategies and Practices," *Contributions to management science*, pp. 59–70, Jan. 2022, doi: https://doi.org/10.1007/978-3-030-85954-1_5.

[81] O. O. Olaniyi, “Ballots and Padlocks: Building Digital Trust and Security in Democracy through Information Governance Strategies and Blockchain Technologies,” *Asian Journal of Research in Computer Science*, vol. 17, no. 5, pp. 172–189, Mar. 2024, doi: https://doi.org/10.9734/ajrcos/2024/v17i5447.
[82] O. Popo-Olaniyan, O. O. James, C. A. Udeh, R. E. Daraojimba, and D. E. Ogedengbe, “FUTURE-PROOFING HUMAN RESOURCES IN THE U.S. WITH AI: A REVIEW OF TRENDS AND IMPLICATIONS,” *International Journal of Management & Entrepreneurship Research*, vol. 4, no. 12, pp. 641–658, Dec. 2022, doi: https://doi.org/10.51594/ijmer.v4i12.676.
[83] R. R. Taylor, B. O’Dell, and J. W. Murphy, “Human-centric AI: philosophical and community-centric considerations,” *AI & society*, May 2023, doi: https://doi.org/10.1007/s00146-023-01694-1.
[84] S. Badghish and Y. A. Soomro, “Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology–Organization–Environment Framework,” *Sustainability*, vol. 16, no. 5, pp. 1864–1864, Feb. 2024, doi: https://doi.org/10.3390/su16051864.
[85] K. Huang, A. Joshi, S. Dun, and N. Hamilton, “AI Regulations,” *Future of business and finance*, pp. 61–98, Jan. 2024, doi: https://doi.org/10.1007/978-3-031-54252-7_3.
[86] S. Bakare, N. Adekunle, C. U. Akpuokwe, and N. E. Eneh, “DATA PRIVACY LAWS AND COMPLIANCE: A COMPARATIVE REVIEW OF THE EU GDPR AND USA REGULATIONS,” *Computer science & IT research journal*, vol. 5, no. 3, pp. 528–543, Mar. 2024, doi: https://doi.org/10.51594/csitrj.v5i3.859.
[87] P. G. R. de Almeida, C. D. dos Santos, and J. S. Farias, “Artificial Intelligence Regulation: a Framework for Governance,” *Ethics and Information Technology*, vol. 23, no. 3, pp. 505–525, Apr. 2021, doi: https://doi.org/10.1007/s10676-021-09593-z.
[88] S. Chowdhury *et al.*, “Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability Framework,” *Human Resource Management Review*, vol. 33, no. 1, p. 100899, Mar. 2023, doi: https://doi.org/10.1016/j.hrmr.2022.100899.
[89] H. O. Khogali and S. Mekid, “The blended future of automation and AI: Examining some long-term societal and ethical impact features,” *Technology in Society*, vol. 73, no. 1, p. 102232, Mar. 2023, doi: https://doi.org/10.1016/j.techsoc.2023.102232.