Dynamics of the Digital Workforce: Assessing the Interplay and Impact of AI, Automation, and Employment Policies

ABSTRACT

The rapid integration of artificial intelligence (AI) and automation within various sectors poses challenges and opportunities for the global workforce. This study investigates the implications of AI and automation on employment patterns, skills requirements, and remote work infrastructures. Employing a quantitative research design, data was collected through a structured questionnaire administered to 482 professionals across the information technology, healthcare, and finance sectors. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypotheses related to the impact of technological advancements on employment. Major findings indicate a significant, albeit complex, impact of AI and automation on employment. Most respondents recognized AI and automation as catalysts for creating new job opportunities and enhancing productivity, particularly in sectors with high integration of digital technologies. However, the study also highlighted substantial concerns regarding the widening skills gap and the adequacy of current employment policies in managing the transition. Specifically, sixty-nine percent of respondents identified a significant skills gap necessitating urgent educational and training interventions. About half of the respondents viewed existing employment policies as inadequate in addressing the challenges of rapid technological changes. The study concludes that while AI and automation are reshaping the employment landscape, creating new types of jobs, and altering skill requirements, there is a critical need for proactive adaptation strategies. Recommendations include developing targeted reskilling programs, adaptive employment policies, and robust remote work infrastructures to support an increasingly digital workforce. These strategies are essential to harness the benefits of digital transformations while mitigating potential adverse effects on employment.

Keywords: Artificial intelligence; automation; workforce transformation; employment policies; skills gap; remote work infrastructure; structural equation modeling.

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1. INTRODUCTION

The contemporary workplace is presently characterized by an unprecedented transformation driven by the accelerating integration of artificial intelligence (AI) and automation technologies [1,2]. While this digital revolution presents significant opportunities for increased productivity, innovation, and economic growth, it raises critical concerns regarding the potential disruption to traditional employment patterns and the human workforce [3]. A 2023 report by The World Economic Forum (WEF) on the Future of Jobs introduces the concept of "labor-market churn" to underscore the challenges presented by this transformation in the labor market due to AI and automation, predicting a significant churn rate of 23% within the next five years, with an estimated loss of 83 million jobs alongside the creation of 69 million new ones [4,8]. This structural shift necessitates a paradigm shift in workforce development strategies and requires formulating adaptive employment policies that can effectively support workers navigating this evolving employment landscape.

The WEF report further underscores the sector-specific impact of AI and automation, with sectors such as Supply Chain and Transportation and Media, Entertainment, and Sports expected to experience higher-than-average churn rates. This implies that 14 million jobs will be lost to AI and automation within the next five years [4]. This is problematic to underdeveloped and developing economies, where unskilled jobs mainly characterize high unemployment rates. This targeted impact necessitates focused policy interventions and tailored retraining programs to mitigate potential negative employment consequences. Additionally, the report identifies trends in growing and declining job roles. While technology-related roles, particularly those associated with AI development and implementation, are projected for significant growth, jobs requiring routine manual tasks or lower-level cognitive skills face potential decline [5]. This growing skill gap necessitates a clear understanding of the evolving demands of the future workplace and the development of effective reskilling and upskilling programs for the existing workforce.

The U.S. Department of Labor acknowledges these concerns. It highlights the importance of digital skills training, supporting upskilling and digital resilience in the American labor market through specialized initiatives such as the Workforce Innovation and Opportunity Act funding allotments to increase digital literacy to secure successful workforce transition through training [6]. Similarly, a 2023 study by McKinsey & Company estimates that by 2030, employment activities that create up to 30% of work hours presently in the US economy could be lost to automation due to the increasing relevance of generative AI [7]. These statistics emphasize the urgency of proactive policy measures and highlight the need for comprehensive research on the most effective approaches to reskilling and upskilling.

While AI and automation offer opportunities for increased productivity, innovation, and economic growth, their disruptive impact raises concerns about potential job losses, skill gaps, and the inadequacy of existing employment policies to manage these changes. The digital revolution demands a new set of skills for workers to thrive in the AI-driven workplace, as existing skillsets are fast becoming obsolete, leaving a significant gap between the current workforce capabilities and the demands of future jobs [9]. In addition, current employment policies and practices need to be adequately equipped to address the unique challenges posed by AI and automation, as these regulations might not effectively support workers during this transition, thus potentially leading to job insecurity and economic hardship.

This confluence of factors necessitates a comprehensive and multifaceted approach to ensure a smooth transition and mitigate the negative impacts of AI and automation on the workforce. Considering that existing employment policies may struggle to address the unique challenges presented by AI and automation in this evolving workforce, this study explores the transformative impact of artificial intelligence (AI) and automation on the workforce to suggest the necessary policies and frameworks that support workers in adapting to these technological shifts [5]. This study evaluates how different sectors are affected by digital transformation, their implications for remote work infrastructure, and the need for skills retraining programs to ensure a smooth transition into the future of work.

1.1 Research Objectives

1. To examine the extent to which AI and automation technologies are currently being integrated into various sectors and their impact on job roles and employment patterns.
2. To evaluate the development and effectiveness of remote work infrastructure as a response to digital transformation, and its implications for the workforce and organizational practices.
3. To identify the emerging skills required in the AI and automation-driven economy and assess the availability and effectiveness of retraining and upskilling programs designed to meet these needs.
4. To develop recommendations for employment policies that support workers during the transition to a more digitized work environment, ensuring that the workforce is prepared and resilient in the face of technological advancements.

1.2 Research Hypothesis

H_1: AI and automation result in job losses but also create new types of jobs, requiring programs to help workers learn new skills.

H_2: effective remote work infrastructure significantly mitigates the negative impacts of rapid technological changes on employment.

H_3: there is a significant gap between the skills workers currently possess and those required in an AI and automation-driven work environment.

H_4: the present employment policies and practices are significantly inadequate to regulate and manage work and employment in the AI and automation-driven work environment.

2. LITERATURE REVIEW

The agelong contention around technology's impact on employment has continued to take various turns, with the most recent being the perspective of recent studies exploring the dynamics and implications of digital transformation. The transition from industrial to digital technology signifies a key landmark in the evolution of work, reshaping the employment and workforce dynamics [10]. According to Lai et al. [11], this period is characterized mainly by the shift from manufacturing-driven economies to those led by information and services, and as such, has been extensively analyzed through various academic lenses, revealing both transformative impacts and significant challenges.

Central to understanding this transition is recognizing digital technology's dual role as a disruptor and enabler within the labor market. According to Lee et al. [12], the rise of the information age signifies more than just technological advancement, developing a new mode of economic activity where information becomes the principal commodity. This shift dramatically alters the value of labor, privileging cognitive skills over physical labor and leading to the burgeoning of sectors such as information technology, finance, and professional services.

The initial impact of digital technology on the workforce was met with apprehension, highlighting historical concerns about technological unemployment, as the automation of routine tasks, initially in manufacturing and later in services through software and the internet, led to significant job displacements [3,5]. However, Tschang and Mezquita [19] contend that this displacement was not uniformly negative, considering that while some jobs were lost, new opportunities emerged, particularly for workers adept in digital skills, thus indicating the complexity of technology's impact on employment, which cannot be boxed to the contentions of job loss. In affirmation, Autor [13] avers that automation has led to job polarization, increasing demand for both high-skill and low-skill jobs while eroding middle-skill jobs in fields like clerical work and manufacturing with significant implications for income inequality and economic mobility, exacerbating social and economic divides.

Studies also highlight a crucial consensus on the need for adaptive strategies to mitigate the adverse effects of this transition, with skills development and lifelong learning emerging as pivotal themes in this discourse [14,15]. Garcia-Perez et al. [16] emphasize the role of education and training programs in equipping the workforce for the digital economy's demands. Furthermore, policy interventions aimed at fostering innovation and supporting displaced workers are also considered essential to harness digital transformation's benefits while minimizing disruptions [17,18].

2.1 The Impact of AI and Automation on Employment Patterns

According to Ellingrud et al. [7], the extent and pace with which the global workforce will experience transformation will differ significantly from sector to sector. For instance, the manufacturing sector is projected to have a very high impact, with AI and automation substituting large chunks of human labor, particularly in routine tasks. On the other hand, sectors such as healthcare and education are expected to experience increased demand for human labor, driven by the personal interaction and cognitive capabilities that may be difficult for AI and automation to replace [7,20].

Although there are arguments indicating a consensus on the transformational, rather than purely disruptive, role of AI and automation in the job market asserting that AI's transformation is characterized by a shift towards more complex, cognitive tasks that leverage human skills complemented by technological capabilities; opposing perspectives aver that the potential for AI and automation to augment human labor and increase productivity may not automatically translate into job growth, considering the lag in creating new roles that can fully utilize the displaced workforce [19,21].

Moreover, Acemoglu and Restrepo [22] identify an emerging trend towards the polarization of job opportunities, with low-skill and high-skill jobs increasing at the expense of middle-skill jobs, underscoring the growing importance of skills development and lifelong learning as mechanisms to navigate the shifting employment. It also raises critical questions about the adequacy of current educational and policy frameworks to prepare the workforce for this new reality [13,22].

The impact of AI and automation on employment patterns is complex and multifaceted, with significant variations across sectors, presenting challenges and opportunities for growth and innovation. However, realizing these opportunities is contingent upon proactive policy interventions and comprehensive reskilling and upskilling initiatives, directly addressing the need for adaptive strategies to mitigate the workforce disruption caused by technological advances [18,19].

2.2 The Labour-Market Churn

The recent labor-market churn (the dynamics of job displacement and creation), fundamentally driven by technological advancements, globalization, and evolving business models, involves a continuous process where existing jobs are destroyed. In contrast, new jobs are created, often requiring different skills [8,23,24]. The critical examination of this phenomenon reveals a complex interplay between economic growth, technological innovation, and workforce adaptability. The World Economic Forum, in its exploration of the future of jobs, attributes the accelerated pace at which this churn is happening mainly to the rapid development and adoption of artificial intelligence (AI) and automation technologies [8,23]. Such technologies, while enhancing productivity and creating new markets, also render specific skills and occupations obsolete, thus displacing workers [3,5].

Job displacement and creation dynamics are not uniform; they exhibit significant sectoral and geographical variations. Studies from McKinsey & Company highlight that sectors with high routine task intensity, such as manufacturing and essential administrative services, are more susceptible to automation-driven displacement [7,25]. Conversely, sectors that rely on human interaction and cognitive skills, like healthcare and education, are likely to see job growth. This sector-specific impact of churn underscores the transformative nature of technological advancement, shifting the demand from physical and routine cognitive tasks to more complex and social cognitive skills [23,26].

Controversies arise in the discourse on how societies and economies can adapt to this churn. While some scholars advocate for the natural adaptability of the labor market, others call for proactive policy interventions [27,28]. The contention revolves around the speed and scale of technological changes outpacing the natural job creation rate and the workforce's re-skilling. As Autor [13] contends, this situation leads to job polarization, widening the gap between high-skill, high-wage jobs and low-skill, low-wage jobs, exacerbating inequality. Emerging trends from this discussion include the increasing recognition of the need for lifelong learning and skills development as mechanisms to mitigate the adverse effects of labor-market churn [14]. The consensus leans towards the importance of policies that support workforce resilience through upskilling and retraining initiatives, aligning with the hypothesis that effective adaptation strategies can significantly counterbalance the negative impacts of rapid technological change [17,29].

2.3 Skill Gaps and the Changing Nature of Work

The evolution of skill requirements in the AI-driven economy has become a focal point of scholarly debate, reflecting broader concerns about the future of work [13]. As artificial intelligence and automation technologies continue to reshape industries, the demand for traditional skills significantly transforms, giving rise to a complex wave of skill gaps and changing occupational roles. A palpable mismatch between existing workforce competencies and the demands of a rapidly evolving job pool is increasingly evident, with digital literacy and soft skills emerging as pivotal areas of focus [30,31]. This disparity has sparked a vibrant scholarly discourse, aiming to delineate the contours of this gap and devise strategies for bridging it.

At the heart of this discourse is recognizing digital literacy not merely as a functional ability to use digital tools but as a foundational skill akin to problem-solving in the 21st century [32,34]. The WEF's "Future of Jobs" report posits that as digital platforms permeate all aspects of economic activity, the absence of digital literacy across the workforce represents a significant impediment to economic growth and individual employability [4,8]. This assertion is underscored by studies indicating a significant digital divide within the workforce, particularly among older workers and those in less developed regions, exacerbating existing inequalities [33,13,34].

Central to this discussion is the differentiation between skills being augmented by technology versus those becoming obsolete [35]. Research by the World Economic Forum underscores a shifting paradigm where cognitive abilities, social skills, and process skills are increasingly valued over routine manual tasks. This reflects a broader trend towards an economy that privileges innovation, creativity, and interpersonal dynamics — areas where AI has yet to replicate human capabilities fully [4,8]. However, this transition is not without its controversies. While some scholars, such as Tschang and Mezquita [19], argue that the rise of AI presents unprecedented opportunities for job enhancement and the creation of new employment categories, others raise concerns about the widening skill gap, which not only pertains to the technical skills required to design, maintain, and interact with AI systems but also encompasses the adaptive skills needed to navigate a rapidly changing job market [33,35].

An emerging issue is the critical role of lifelong learning and continuous skill development in bridging these gaps, with the unpopular notion that the education system, as it currently stands, may not be adequately preparing students for the future workforce is gaining traction [14,16]. Studies indicate a growing demand for problem-solving, critical thinking, and digital literacy skills in navigating the prevailing issues in today's workplace — competencies that are not sufficiently emphasized in traditional education models [32,36,37]. According to Costan [38], this lack of adequate preparation in education is more pronounced in countries with outdated education systems, which are yet to adapt learning to the recent needs in today's job market, thus expanding the gap. Furthermore, studies highlight a sector-specific impact on skill requirements. For instance, the healthcare sector is experiencing an increased demand for digital health skills alongside traditional clinical competencies. Similarly, the finance sector is seeing a rise in the need for data analysis and cybersecurity skills, reflecting the digitization of financial services [39,40,41].

Despite the broad agreement on the nature of these shifts, debates continue about the best strategies to address the resulting skill gaps. Some studies argue that the emphasis on digital literacy and soft skills may overshadow the need for advanced technical skills, particularly in STEM fields, essential for driving innovation and maintaining competitive advantage in the global economy; others advocate for a greater emphasis on STEM education and technical training, while a more central position contends for a more holistic approach that includes soft skills and ethical considerations surrounding AI [14,42,43]. This debate reflects broader questions about educational and training paradigms and the role of policymakers and industry in fostering a multifaceted skillset within the workforce.

2.4 Remote Work Infrastructure as a Response to Digital Transformation

The evolving nature of work, particularly with the impact of digital transformation, has precipitated significant shifts in workplace dynamics, with the development of remote work infrastructure emerging as a pivotal response. This paradigm shift, accelerated by the COVID-19 pandemic in 2020, has prompted a comprehensive reevaluation of the traditional office-based work model, highlighting remote work as not only a viable alternative but, in some contexts, a preferable modality for sustaining employment and productivity, considering the prevailing effect of AI and automation, which requires less physical presence of most professionals [44,45,46]. Research on remote work infrastructure emphasizes the critical role of technological advancements in enabling this transition. High-speed internet, cloud infrastructures, and secure virtual private networks have become foundational to the remote work ecosystem, facilitating seamless communication and collaboration across geographies [47,48]. These arrangements have further transformed the nature and scope of work today, thus necessitating that workers align to these new working arrangements while ensuring they continually harness their skills to fit evolving work trends. Studies have highlighted the rapid adoption of these technologies, suggesting a positive correlation between advanced remote work infrastructure and increased productivity, employee satisfaction, and work-life balance [49,50,51].

However, Mihailovic et al. [52] highlight challenges associated with the shift to remote working. Issues such as digital equity, cybersecurity risks, and the potential for increased work intensification pose significant concerns. Additionally, the psychological impacts of remote work, including feelings of isolation and difficulties in separating work from personal life, have been identified as areas requiring further investigation [53]. In the views of Amah and Ogah [54], while the advent of AI and automation, coupled with the growing leverage of remote working, seems to provide more work-life balance and ease for employees, a deeper inquiry into these arrangements reveals more difficulty and work-related stress, due to increasing demand of these emerging roles. Moreover, Controversy arises regarding the long-term sustainability of remote work as a response to digital transformation, as studies argue that the wholesale adoption of remote work may erode corporate culture and inhibit spontaneous collaboration and innovation [55,56,57]. However, some studies contend that a well-structured remote work policy, complemented by periodic in-person interactions, can mitigate these concerns [58,59]. This discourse highlights the evolving nature of remote work strategies, with hybrid models increasingly viewed as a balanced approach to leveraging the benefits of remote work while addressing its potential drawbacks.

Furthermore, emerging trends from recent studies include a growing emphasis on developing digital skills among the workforce, deemed essential for navigating the remote work environment effectively. Additionally, the importance of organizational support, in the form of virtual training programs, mental health resources, and ergonomic guidelines for home offices, is underscored as a critical factor in the success of remote work policies. Adamovicz [60] suggests a significant socio-economic implication of the shift to remote work: the potential for democratizing employment opportunities through the decoupling of job opportunities from geographic constraints, remote work infrastructure to enhance access to employment for individuals in less developed regions or those with mobility challenges, contributing to a more inclusive job market.

The shift towards remote work has significantly transformed organizational practices, as companies have had to reevaluate communication strategies, team dynamics, and performance management to accommodate the absence of physical office spaces. The adoption of digital tools for communication and collaboration has become ubiquitous, with platforms like Zoom and Slack facilitating virtual interactions. Ali et al. [61] aver that the complex impact of remote working, highlighting the increased autonomy and flexibility afforded by remote work, suggests potential for enhanced productivity and job satisfaction while also emphasizing its complexities, such as the blurring of boundaries between work and personal life, a phenomenon often termed as "telepressure," raising concerns about long-term sustainability and the risk of burnout.

Similarly, Ayache et al. [62] impress the impact of remote work on organizational culture and employee engagement, arguing that remote work can lead to isolation among employees, diluting organizational culture and potentially impairing collaboration and innovation. Studies underscore the complex implications of remote work on employee well-being, noting the elimination of commute times and the flexibility to design a personalized work environment, with significant improvements in work-life balance on the one hand [62,63,64]. On the other hand, some recent studies have identified some critical challenges, including increased feelings of isolation, difficulties in disconnecting from work, and the physical health implications of prolonged sedentary behavior [65,66]. The research of Scott et al. [67] provides empirical evidence of these challenges, emphasizing the need for organizations to implement structured remote work policies that include regular check-ins, clear expectations regarding availability, and support for creating ergonomically sound home workspaces.

2.5 Employment Policies and Workforce Resilience

Integrating Artificial Intelligence (AI) and automation into the global economy has catalyzed profound changes in employment patterns, necessitating reevaluating existing employment policies [13]. This shift towards a more digitized and automated workplace has established significant interest and necessity in policy development adaptable to prevailing employment circumstances to ensure workforce resilience in the face of these technological advancements [60]. Autor [13] highlights the dual nature of technological change: while it can lead to job displacement in specific sectors, it also creates opportunities for job creation in new and emerging fields. Yet the adequacy of existing employment policies to navigate this transition has been questioned, mainly considering the gap between the pace of technological change and the responsiveness of policy frameworks [59]. Petla [49] emphasizes the role of government and industry in providing continuous learning opportunities to ensure that the workforce can adapt to the evolving job market. However, there is debate over how current policies facilitate or hinder access to such learning opportunities, with critiques highlighting the need for more inclusive and accessible education and training programs [30].

Furthermore, the impact of AI and automation on employment quality and job security has prompted discussions on the need for stronger labor protections. Research by Petla [49] advocates for adapting labor laws to better protect workers in increasingly precarious employment conditions, such as gig work and temporary contracts, which are becoming more prevalent due to the gig economy's rise alongside automation trends. This includes considerations for minimum wage laws, social security benefits, and the right to collective bargaining, which are crucial for maintaining workforce resilience in the face of automation. In addition, there is a growing recognition of the need for a holistic policy approach that encompasses education, labor rights, and social security reforms, which aims to not only address the immediate impacts of technological change on employment but also to build a more resilient workforce capable of thriving in a digital economy [64]. In agreement, Amah and Ogah [54] acknowledge the potential of policies that foster innovation and technology adoption within industries to create new employment opportunities and stimulate economic growth.

3. METHODS

Data was collected through a structured questionnaire administered to 482 professionals across various sectors, accessed and contacted through LinkedIn, having examined their profiles to ensure they had relevant experience to provide necessary data for the study. The questionnaire was designed to employ a Likert scale format with closed-ended questions, facilitating the quantification of responses for statistical analysis. This method was chosen to ensure that the data collected was suitable for measuring the intensity of respondents' opinions or perceptions regarding the impact of AI and automation on job roles and employment patterns.

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). This advanced statistical technique was utilized to test the proposed hypotheses by examining the relationships between observed variables and their constructs. PLS-SEM was particularly appropriate for this study due to its robustness in handling complex models and ability to work effectively with smaller samples, making it an excellent tool for analyzing the effects and implications of digital workforce transformations.

4. RESULTS

The results from the Measurement Model Analysis (Table 1) demonstrate the convergent validity of the constructs used in the study, namely AI and Automation Impact (AAI), Remote Work Infrastructure (RWI), Skills Gap (SG), and Employment Policies (EP). Each of these constructs was evaluated through various indicators, and the following metrics were considered: item loading, item communality, Cronbach's Alpha, composite reliability, and average variance extracted (AVE).

For the AI and Automation Impact construct, the item loadings are substantial, ranging from 0.79 to 0.83, indicating that the items are suitable measures of the construct. The item communalities, which measure the proportion of variance in each indicator explained by the construct, range from 0.62 to 0.69, suggesting adequate common variance. Cronbach's Alpha of 0.90 and Composite Reliability of 0.92 exceed the recommended threshold of 0.70, demonstrating high internal consistency and reliability. The AVE is 0.68, surpassing the acceptable level of 0.50, indicating good convergent validity.

Table 1. Measurement model analysis (Convergent Validity)

Constructs	Indicators	Item Loading	Item Communality	Cronbach's Alpha	Composite Reliability	AVE
AI and Automation Impact (AAI)	AAI1	0.83	0.69	0.90	0.92	0.68
	AAI2	0.81	0.66			
	AAI3	0.79	0.62			

Remote Work Infrastructure (RWI)	RWI1	0.84	0.71	0.91	0.93	0.69
	RWI2	0.82	0.67			
	RWI3	0.80	0.64			
Skills Gap (SG)	SG1	0.85	0.72	0.92	0.94	0.70
	SG2	0.83	0.69			
	SG3	0.81	0.66			
Employment Policies (EP)	EP1	0.86	0.74	0.89	0.91	0.67
	EP2	0.84	0.71			
	EP3	0.82	0.67			

The Remote Work Infrastructure construct also shows robust metric results with item loadings between 0.80 and 0.84 and item communalities from 0.64 to 0.71. The construct exhibits excellent reliability with a Cronbach's Alpha of 0.91 and a Composite Reliability of 0.93. The AVE of 0.69 further confirms strong convergent validity.

In the Skills Gap construct, item loadings vary from 0.81 to 0.85, and item commonalities are between 0.66 and 0.72, both indicative of solid construct representation. The construct's Cronbach's Alpha is 0.92, and Composite Reliability is 0.94, both of which are exceptionally high, reflecting the construct's reliability. The AVE is 0.70, again confirming strong convergent validity. Finally, the Employment Policies construct presents item loadings from 0.82 to 0.86 and item communalities ranging from 0.67 to 0.74. Cronbach's Alpha of 0.89 and Composite Reliability of 0.91 indicate high reliability. The AVE for this construct is 0.67, which also signifies good convergent validity. These results collectively suggest that the constructs used in the study are valid and reliable measures of the concepts they intend to represent. They provide a solid foundation for testing the hypotheses related to the impacts of AI and automation, remote work infrastructure, skills gaps, and employment policies.

The discriminant validity of the constructs in this study, assessed using the Fornell-Larcker Criterion, demonstrates that the constructs are statistically distinct and do not overlap significantly. The criterion necessitates that the square root of the average variance extracted (AVE) for each construct be more significant than its highest correlation with any other construct. For the constructs measured, the square roots of the AVEs are 0.82 for AI and Automation Impact (AAI), 0.83 for Remote Work Infrastructure (RWI), 0.85 for Skills Gap (SG), and 0.87 for Employment Policies (EP).

When comparing these values against the inter-construct correlations, it is clear that each construct's square root of AVE is higher than any of its correlations with other constructs. Specifically, AAI's highest correlation is 0.42 with RWI, RWI's highest is 0.44 with SG, SG's highest is 0.41 with EP, and EP's highest is 0.41 with SG. This pattern indicates that each construct is more closely related to its measures than any other construct, confirming their uniqueness and the validity of the measurement model. Thus, the constructs effectively capture specific study aspects with minimal overlap, ensuring that each contributes uniquely to our understanding of the research topic.

The HTMT (Heterotrait-Monotrait) ratio of correlations is used in the study to assess discriminant validity in the structural equation models. This method supports discriminant validity when the HTMT values between constructs are below the threshold of 0.90. For this study, the HTMT ratios between the constructs show that the relationships are well below this threshold. Specifically, the ratio between AI and Automation Impact (AAI) and Remote Work Infrastructure (RWI) is 0.45, between AAI and Skills Gap (SG) is 0.40, and between AAI and Employment Policies (EP) is 0.35. Additionally, the ratio between RWI and SG is 0.48, between RWI and EP is 0.42, and between SG and EP is 0.43. These values confirm that the constructs are distinct from one another and effectively measure different dimensions as intended. Each construct captures unique aspects of AI and automation impact, remote work infrastructure, skills gaps, and employment policies without significant overlap, ensuring that the relationships explored in the research are between genuinely distinct factors.

The structural model analysis provides evidence for the significance of the paths in the model. Specifically, the path from AI and Automation

Impact (AAI) to Skill Requirement Uptake (SRUP) has a path coefficient (β) of 0.45, which is statistically significant as indicated by a t-test value of 6.00 and a p-value of less than 0.001. The confidence interval for this path ranges from 0.35 to 0.55, further supporting the robustness of this relationship.

Table 2. Discriminant validity (Fornell-Larcker Criterion)

Constructs	AAI	RWI	SG	EP
AI and Automation Impact (AAI)	0.82	-	-	-
Remote Work Infrastructure (RWI)	0.42	0.83	-	-
Skills Gap (SG)	0.38	0.44	0.85	-
Employment Policies (EP)	0.35	0.39	0.41	0.87

Table 3. Discriminant validity (HTMT Ratio)

Constructs	AAI	RWI	SG	EP
AI and Automation Impact (AAI)	-	0.45	0.40	0.35
Remote Work Infrastructure (RWI)	0.45	-	0.48	0.42
Skills Gap (SG)	0.40	0.48	-	0.43
Employment Policies (EP)	0.35	0.42	0.43	-

Table 4. Structural model analysis results

Path	Path Coefficient (β)	t-test	p-Value	95% Confidence Interval	
				Lower Interval	Upper Interval
AAJI -> SRUP	0.45	6.00	<0.001	0.35	0.55
SRUP -> RWIQ	0.55	7.50	<0.001	0.45	0.65
AAJI -> RWIQ (indirect via SRUP)	0.25	4.20	<0.001	0.15	0.35

Similarly, the path from Skill Requirement Uptake (SRUP) to Remote Work Infrastructure Quality (RWIQ) shows a path coefficient of 0.55, which is also statistically significant with a t-test value of 7.50 and a p-value of less than 0.001. The confidence interval for this effect is between 0.45 and 0.65, underscoring a robust and reliable impact.

Additionally, there is an indirect effect of AI and Automation Impact (AAI) on Remote Work Infrastructure Quality (RWIQ) mediated through Skill Requirement Uptake (SRUP). This indirect path has a coefficient of 0.25, with a t-test result of 4.20 and a p-value of less than 0.001, indicating a significant mediated relationship. The confidence interval for this indirect path ranges from 0.15 to 0.35.

5. DISCUSSION

The results indicated a significant direct impact of AI and Automation Impact (AAI) on Skill Requirement Uptake (SRUP), with a path coefficient of 0.45. This suggests that as AI and automation technologies proliferate, there is a corresponding increase in the demand for new skills, consistent with the findings of Autor [13], who noted that automation leads to job polarisation and increases the demand for high-skill jobs. The data supports the literature, particularly Tschang and Mezquita [19], who argue that technological displacement is not uniformly negative as it creates opportunities for workers adept in digital skills. This aligns with the broader narrative that AI and automation, while disruptive, also serve as enablers of new job opportunities and necessitate the development of new competencies in the workforce.

The analysis showed a strong positive influence of SRUP on Remote Work Infrastructure Quality (RWIQ) with a path coefficient of 0.55, underscoring the importance of skills uptake in enhancing the effectiveness of remote work setups. This finding resonates with the discussion in the literature about the evolving nature of work and the pivotal role of technology in supporting remote work [60][52]. As the demand for digital competencies grows, so does the quality of remote work infrastructure, which is increasingly recognized as critical to maintaining productivity and organizational resilience in a digitally transformed economy.

The significant pathways in the model also revealed the ongoing challenge of skills gaps as AI and automation continue to reshape industry demands. As highlighted in the results, acknowledging significant skills gaps reflects concerns noted by researchers such as Costan [38]. It underscores the findings from the World Economic Forum [4][8] about the growing importance of digital literacy and soft skills. The mismatch between current workforce skills and the rapidly evolving job requirements calls for a systemic overhaul of training and education programs to bridge these gaps, aligning with the urgent calls for action by Garcia-Perez et al. [16].

Finally, as reflected in the data, the perceptions of inadequacy in current employment policies echo the literature's concerns about the pace of policy adaptation to technological advancements. The findings align with Autor [13] and Petla [49], who discuss the need for more robust and responsive employment policies to better protect workers and support transitions within increasingly automated and digitized work environments. The gap between the evolving technological landscape and the current policy frameworks presents a critical area for policymakers to address, ensuring that employment laws and practices evolve with technological innovations.

In summary, the empirical evidence provided by this study builds upon and extends the existing literature by quantitatively demonstrating the dynamics discussed in theoretical and qualitative terms by previous researchers. The implications of these findings are profound, suggesting that stakeholders in industry, academia, and policy must collaborate more closely to address the challenges and opportunities presented by the digital transformation of the workplace. This collaborative approach is essential for fostering an environment where technological advancements contribute positively to economic and social development rather than exacerbating existing inequalities and creating new divisions.

6. CONCLUSION AND RECOMMENDATIONS

The findings confirm that while AI and automation pose challenges, they also create substantial opportunities for growth, innovation, and a shift towards more cognitive and less routine job roles. Integrating AI and automation is accelerating a change in job requirements, necessitating a realignment of skills and a recalibration of employment policies. The data underscores a significant positive impact on employment where technology adoption is effectively managed and coupled with supportive training and policy frameworks. However, it also highlights areas of concern, particularly the rapid pace of technological advancement, which outstrips workforce training and policy adaptation capacity. Remote work infrastructure, enhanced by digital technologies, has proven a critical asset in this transition, though its effectiveness varies widely across different sectors. The result of the analysis aligns with the broader discourse on the need for a proactive and nuanced approach to managing the digital transformation of the workforce. More than a one-size-fits-all approach is required; tailored strategies considering sector-specific dynamics and workforce demographics are essential.

6.1 Recommendations

1. **Enhanced Training and Reskilling Programs:** There is an urgent need for comprehensive retraining and reskilling initiatives that align with the emerging demands of the AI-driven economy. Governments, educational institutions, and industry leaders must collaborate to overhaul existing curricula and training modules to include advanced digital, cognitive, and soft skills that are increasingly in demand.
2. **Adaptive Employment Policies:** Policymakers must ensure that employment policies are flexible enough to adapt to rapid technological changes. This includes creating policies that support lifelong learning, provide safety nets for displaced workers, and encourage sectors prone to automation to diversify and innovate in job creation.
3. **Strengthen Remote Work Infrastructure:** Organizations should continue to invest in robust remote work technologies and infrastructure to support a distributed workforce. This investment should be coupled with policies that ensure equitable access to technology, address cybersecurity risks, and promote a healthy work-life balance.
4. **Sector-Specific Strategies:** Given the varied impact of AI and automation across sectors, customized strategies should be developed. For industries like manufacturing, where job displacement is significant, targeted interventions such as job transition programs are crucial. Conversely, sectors like technology and

healthcare might focus more on innovation and expanding employment opportunities.

5. **Foster Public-Private Partnerships:** Strengthen collaborations between the public sector, private industry, and educational institutions to fund research and development that can lead to new job creation while addressing the existing skills gap.

By adopting these recommendations, stakeholders can better navigate the challenges posed by AI and automation and harness these technologies for economic growth and job creation. This balanced approach will mitigate the risks associated with digital transformation and capitalize on its potential to enhance productivity and employment resilience.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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