RITAM ISH PUBLICATIONS

Journal of Progress in Artificial Intelligence
https://www.jpairitamish.org/

ISSN: 3139-4957 (Online)

Vol. 2, Iss. 2, April 2026 – June 2026

Artificial intelligence and the future of work: transforming global labour markets in the digital economy

Baishakhi Mondal[1*], Dr. Rajiv Kumar Agarwal[2], Shivom Shankhdhar[3], Dr. Harsha M. B[4], Dasaradha Arangi[5]

[1]Department of Economics, Indraprastha College for Women, Delhi, India

[2]Assistant Professor, Department of Commerce, Vardhaman College, Bijnor, Uttar Pradesh, India (Affiliated to Guru Jambheshwar University)

[3]Department of Computer Science, Bareilly International University, Bareilly, India

[4]Assistant Professor, (DOS&R) in Management, Karnataka State Open University, Mysuru, India

[5]Department of Computer Science and Engineering (Artificial Intelligence & Machine Learning), Aditya Institute of Technology and Management, Tekkali, Srikakulam, Andhra Pradesh, India, Affiliated to Jawaharlal Nehru Technological University-Gurajada Vizianagaram

Received: 05-May-2026, Manuscript No. JPAI-2026-0017; **Editor assigned:** 08-May-2026, PreQC No. JPAI-2026-0017 (PQ); **Reviewed:** 20-May-2026, QC No. JPAI-2026-0017; **Revised:** 04-Jun-2026, Manuscript No. JPAI-2026-0017 (R); **Published:** 05-Jun-2026

Citation: Mondal, B., Agarwal, R. K., Shankhdhar, S., Harsha M. B., & Arangi, D. (2026). Artificial intelligence and the future of work: transforming global labour markets in the digital economy. J Prog Artif Intell.

Corresponding: Baishakhi Mondal, Email: baishakhi@gmail.com

ABSTRACT

The rapid adoption of Artificial Intelligence (AI) is transforming global labor markets and redefining the nature of work in the digital economy. AI-driven technologies are increasingly being integrated across industries, enhancing operational efficiency, innovation, and productivity while simultaneously raising concerns about job displacement, skill obsolescence, and workforce adaptability. This study examines the relationships among AI adoption, workforce transformation, skill development, labor market outcomes, and economic productivity. A quantitative cross-sectional research design was employed, collecting data from 487 respondents across developed and developing economies. The data were analyzed using Structural Equation Modeling (SEM) with SmartPLS 4.0. The conceptual framework was grounded in Technology Acceptance Theory, Human Capital Theory, Skill-Biased Technological Change Theory, and Innovation Diffusion Theory. The findings reveal that AI adoption significantly enhances workforce transformation ($\beta = 0.512$, $p < 0.001$), leading to improved skill development, labor market performance, and economic productivity. Human-AI collaboration and organizational readiness were found to strengthen these positive relationships. However, AI adoption also negatively affects perceived job security ($\beta = -0.218$, $p = 0.001$), indicating the need for proactive workforce policies. The study highlights the importance of reskilling initiatives, inclusive AI governance, and effective human-machine collaboration in ensuring sustainable labor market transitions. These findings provide valuable insights for policymakers, organizations, and educational institutions seeking to maximize the benefits of AI while mitigating its socioeconomic challenges.

KEYWORDS: Artificial Intelligence, Digital Economy, Labor Market Transformation, Workforce Reskilling, Economic Productivity, Industry 4.0, Human-AI Collaboration

1. INTRODUCTION

1.1 Background of artificial intelligence in the digital economy

The rise of Artificial Intelligence (AI) as a core element of the digital economy represents one of the most significant technological shifts in modern economic history [1]. AI has evolved from narrow, task-specific algorithms to large language models capable of complex reasoning, impacting every level of industry and commerce [2]. The World Economic Forum [3] states that by 2025, AI and automation will either augment or replace around 85 million job roles, while also generating 97 million new positions. This combination of displacement and creation makes the AI-labor market relationship a key focus for scholarly research. The digital economy, marked by widespread integration of digital technologies into all aspects of economic activity, has sped up the adoption of AI across various sectors [4]. Industries such as finance, healthcare, manufacturing, logistics, and public administration have adopted AI-powered tools not just to improve efficiency but also as essential strategic resources [5]. This shift has led to significant changes in labor markets, occupational roles, and skill needs, raising concerns among workers, policymakers, and researchers [6].

1.2 Evolution of AI and automation technologies

The development of AI from its beginnings in the mid-20th century to its ongoing waves of technological advancement offers important context for understanding its current effects on the labor market [7]. Early expert systems from the 1970s and 1980s were succeeded by breakthroughs in machine learning during the 1990s and 2000s. This was then followed by the deep learning revolution of the 2010s, which achieved superhuman performance in tasks once thought to need uniquely human intelligence [8]. Modern AI systems, such as generative models, autonomous agents, and multimodal networks, now function in various fields including drug discovery, legal reasoning, financial forecasting, and creative content creation [9]. Automation, a branch of AI-driven change, has developed alongside this evolution [10]. Industrial robotics in manufacturing have traditionally been a focus of academic research. However, the rise of cognitive automation able to handle unstructured data, interpret natural language, and perform complex decision-making represents a major advancement over earlier automation developments [11]. Brynjolfsson et al. [12] suggested that this shift in technology signifies a second machine age, where machines excel over humans not just physically but increasingly in cognitive areas.

1.3 Impact of AI on employment and workforce transformation

The empirical literature on AI's employment effects reveals a nuanced and often contested picture [13]. Early automation studies, exemplified by Frey and Osborne's influential 2013 analysis revised and expanded in 2020 estimated that 47% of US occupations faced a high risk of automation, triggering widespread public alarm [14]. Subsequent scholarship, however, has increasingly challenged these projections, emphasising the task-based rather than occupation-based nature of automation, the emergence of new occupational categories, and the augmentation potential of human-AI teaming [15]. Acemoglu and Restrepo [1] created a task displacement model that separates labour-replacing automation from productivity-driven AI. They found that automation reduces employment and wages, while productivity AI boosts labor demand through efficiency gains. Their US manufacturing data highlights the varied sectoral effects of AI, with low-skill, routine-heavy jobs experiencing the most displacement [1]. Conversely, high-skill knowledge workers tend to benefit from AI augmentation, fueling ongoing labor market polarization [12].

1.4 Research gap

Despite considerable scholarly output on artificial intelligence and labor markets, several important gaps remain unaddressed. Firstly, most studies focus on developed economies, thereby insufficiently exploring the labour market implications of AI adoption in emerging and developing regions [16]. Secondly, the mediating mechanisms by which AI adoption influences economic productivity particularly through skill development and reorganization of labor markets have not been thoroughly investigated within an integrated theoretical framework [17]. Thirdly, there is a scarcity of quantitative cross-national studies utilising robust psychometric tools to accurately capture employee perceptions of AI-driven transformations [18]. Finally, the roles of organizational readiness and human-AI collaboration as moderators of productivity outcomes have yet to be sufficiently examined empirically [19]. This study aims to achieve several research objectives: RO1 examines how AI adoption directly impacts workforce transformation in various economies. RO2 explores the mediating roles of skill development, digital skills, and employee adaptability in the relationship between AI adoption and economic productivity. RO3 evaluates how organizational readiness and human-AI collaboration moderate these key relationships. Finally, RO4 offers evidence-based policy recommendations to support inclusive transitions in AI-driven labor markets.

1.5 Research questions

RQ1: To what extent does AI adoption drive workforce transformation in global labor markets?

RQ2: What mediating mechanisms connect AI adoption to improvements in economic productivity?

RQ3: How do organizational readiness and human-AI collaboration moderate the AI-productivity relationship?

RQ4: What are the differential impacts of AI adoption on job security perceptions across skill levels and economies?

1.6 Contributions of the study

This study contributes to existing research in several ways. It merges four complementary theoretical frameworks, Technology Acceptance Theory, Human Capital Theory, Skill-Biased Technological Change Theory, and Innovation Diffusion Theory, into a single SEM-based empirical model, pushing forward theoretical integration in AI and labour market studies. The research also provides primary survey data across multiple countries, including both developed and developing economies, filling a significant geographical gap. Methodologically, the use of SmartPLS-based SEM with mediation and moderation analyses introduces a robust, multi-layered analytical approach. On a practical level, the findings offer policy-relevant insights for stakeholders in government, industry, and education.

2. LITERATURE REVIEW

2.1 Artificial intelligence and automation

Artificial intelligence broadly defined as simulating human cognitive processes through computational systems encompasses a wide range of technologies such as machine learning, deep learning, natural language processing, computer vision, and robotics [20]. In organizational and economic settings, AI is primarily viewed as a technology that automates and enhances tasks, changing how work is structured across jobs and industries [1]. The primary mechanism of displacement involves automating routine, rule-based tasks, while AI's capacity to augment non-routine, cognitive, and creative tasks highlights its potential to generate new employment opportunities [12]. Recent research has pinpointed specific AI technologies as key catalysts of shifts in the labor market. For example, generative AI models have shown they can automate tasks across legal, medical, financial, and creative fields that were once deemed resistant to automation [9]. According to the McKinsey Global Institute [21], generative AI has the potential to automate 60–70% of tasks performed by employees in knowledge-based roles, marking a significant leap in AI's cognitive capabilities. At the same time, AI-driven robotics and autonomous systems continue to transform physical work environments, especially in logistics, agriculture, and construction [22].

2.2 AI-driven labor market transformation

AI-driven transformation of the labour market unfolds through several interconnected channels [13]. On the micro level, workers experience changes in their task responsibilities as AI automates routine parts of their jobs, emphasising the need for skills that complement AI and focus on higher-level tasks [15]. At the meso level, firms and industries see shifts in occupational composition, with a surge in demand for AI-related skills and a decline in routine administrative and manual skills [2]. On the macro level, overall employment, wage patterns, and investment in human capital are influenced by the broader sectoral changes occurring across the economy [23]. Dauth et al. [24] presented strong econometric evidence from German administrative data showing that the adoption of industrial robots leads to redistribution rather than job losses, as workers displaced from manufacturing are integrated into service sectors. Nonetheless, this transition varies across age groups, skill levels, and regions, with older, less-skilled workers facing higher transition costs. Lee et al. [25] reproduced similar results in South Korean manufacturing, confirming the sector-reallocation effect, although adjustment periods in developing Asian countries tend to be longer and more volatile.

2.3 Job displacement and job creation

The debate over the displacement-creation balance continues to be a key and debated empirical issue in AI and labour market studies [26]. Pessimists, using task-substitution models and sectoral automation measures, predict significant overall job losses, mainly affecting middle-skill jobs [14]. Conversely, optimistic viewpoints highlight the consistent pattern of technological unemployment recovery over history and the strong growth in jobs within AI-related sectors [27]. Resolving this debate empirically is challenging due to the nonlinear nature of AI adoption, differences across sectors, and the long timeframe needed for adjustment effects to appear. Agrawal et al. [28] proposed a model where AI decreases prediction costs, fundamentally changing how firms make decisions economically. Their framework indicates that lower prediction expenses broaden the scope of decision-making, increasing demand for human judgment as a complementary skill. This suggests that AI-driven job growth will likely focus on roles requiring contextual understanding, ethical reasoning, interpersonal skills, and creative problem-solving areas where current AI systems still fall short. The ILO [29] supports this perspective, predicting the creation of 97 million new jobs worldwide by 2025, primarily within the green economy, care economy, and AI-related fields.

2.4 Future skills and workforce readiness

The shift towards AI-integrated labor markets requires a fundamental overhaul of how we invest in human capital [30]. Nedelkoska and Quintini [31] noted that automation risks are strongly and negatively associated with education levels and task complexity, which suggests that workforce readiness should focus on digital skills, advanced cognitive abilities, and ongoing learning. The concept of skills half-life the time a skill remains valuable in the market is shrinking rapidly in sectors heavily influenced by AI, making learning agility a critical meta-competency [32]. Schwab [33] described Industry 5.0 as a human-centred approach to counter the technological determinism of Industry 4.0. He argued that transforming the labor market sustainably depends on investing in uniquely human skills such as empathy, ethical reasoning, and complex social interactions. This view highlights the complementarity of human and artificial intelligence, focusing on collaboration rather than replacement, and envisions a future driven by collective intelligence instead of full automation [34].

2.5 Digital economy and employment

The digital economy creates unique employment patterns that differ from those in the industrial economy [4]. Features of digital labour markets- such as platform-based work, algorithmic management, remote and hybrid arrangements, and the gig economy- interact with AI in complex ways [35]. Choudhury et al. [36] showed that AI-enhanced remote work tools can boost individual productivity but also raise issues related to employee monitoring, increased work demands, and the blurring of work-life boundaries. These results emphasise the need to consider AI's effects on the labor market not only in terms of job numbers but also regarding the quality of employment.

2.6 Human-AI collaboration

An emerging body of research explores when human-AI collaboration leads to better performance outcomes compared to humans or AI working alone [37]. Van den Broek et al. [38] discovered that in knowledge-heavy environments, human-AI teams achieve notable productivity improvements when tasks are well allocated, humans and AI understand each other well, and trust aligns with AI system capabilities. Although their qualitative case study has limited generalizability, it offers valuable insights into the organizational design needed for effective human-AI work systems. Davenport and Ronanki [39] outlined three main ways organisations deploy AI: process automation, cognitive augmentation, and customer engagement. Each pathway has unique effects on workforce structure and skill needs. Their analysis highlights the need for AI strategies that are sensitive to context, emphasising human-machine collaboration rather than replacing humans entirely whenever possible.

2.7 Industry 4.0 and Industry 5.0

The Fourth Industrial Revolution, defined by Schwab [33] as the merging of physical, digital, and biological systems through cyber-physical technologies, sets the broad context for today's AI-related changes in the labour market [40]. Industry 4.0 encompasses technologies like IoT, cloud computing, robotics, additive manufacturing, and AI, which collectively transform production, supply chains, and service models, leading to systematic shifts in labor demand [41]. The European Commission's concept of Industry 5.0 highlights human-centricity, sustainability, and resilience as important complements to technological efficiency, providing a normative approach for inclusive labor market management [42].

2.8 Ethical and social implications of AI

The ethical aspects of AI-driven changes in the labor market include fairness in distribution, algorithmic bias, surveillance capitalism, and the regulation of AI systems that influence workers' employment, pay, and performance assessments [43]. Susskind and Susskind [44] noted that professional fields are undergoing fundamental changes as AI encroaches on areas once reserved for specialized knowledge, raising critical issues related to professional identity, social trust, and the oversight of AI-based expertise. The distributional effects of AI which tend to favour capital owners and high-skill workers while causing adjustment challenges for middle- and low-skill workers require policy measures that go beyond traditional labor market approaches [45].

Table 1. Literature Review Summary

Author	Year	Country	Methodology	Key Findings	Research Gap
Acemoglu & Restrepo	2022	USA	Econometric Analysis	AI-driven automation leads to significant displacement in routine-task-intensive occupations, and wages	Limited analysis of AI's role in net job creation across emerging economies

				decline in highly automated sectors.	
Brynjolfsson et al.	2023	Multi-country	Survey & Machine Learning	AI augments high-skill workers while displacing mid-skill workers; polarisation of labour markets intensifies.	Lack of longitudinal data tracking individual worker transitions across AI-impacted industries.
Frey & Osborne	2020	UK/USA	Probabilistic Modeling	Approximately 47% of occupations face high automation risk; service and administrative roles most vulnerable.	The model does not account for newly created occupations generated by AI innovation.
Agrawal et al.	2022	Canada	Economic Modeling	AI reduces prediction costs, reshaping decision-making processes and altering firm-level labour demand.	Insufficient examination of AI adoption barriers in small and medium enterprises (SMEs).
Dauth et al.	2021	Germany	Administrative Data Analysis	Industrial robotics causes employment shifts but does not uniformly reduce total employment; sector reallocation is observed.	Cross-country generalizability limited; focuses exclusively on German manufacturing.
Nedelkoska & Quintini	2020	OECD Nations	Task-Based Framework	14% of jobs are at high automation risk; significant heterogeneity by education, age, and country.	Absence of sectoral-level reskilling policy analysis within findings.
McKinsey Global Institute	2021	Global	Scenario Analysis	Up to 375 million workers may need to change occupational categories by	Scenarios rely on extrapolation; they lack granular

				2030 due to AI and automation.	individual-level microdata.
Lee et al.	2021	South Korea	Panel Data Analysis	AI adoption in manufacturing firms increases productivity but reduces demand for low-skill labor.	Does not capture long-term workforce adjustment dynamics post-adoption.
Autor et al.	2022	USA	Labor Market Analysis	Technology contributes to labor market polarization; middle-skill jobs decline while high-skill and low-skill jobs grow.	Underexplores the role of firm-level HR strategies in managing polarization effects.
Davenport & Ronanki	2020	USA	Case Study	AI deployment in organizations follows cognitive automation, process automation, and engagement automation pathways.	Findings primarily based on large firms; SME context largely unaddressed.
Schwab	2021	Global	Conceptual Analysis	Industry 4.0 and Industry 5.0 require fundamental rethinking of human-machine collaboration and workforce design.	Conceptual framework lacks empirical validation from cross-national surveys.
ILO Report	2023	Global	Policy Analysis	Automation and AI will displace 85 million jobs but create 97 million new roles by 2025, contingent on reskilling.	Policy pathways for developing economies remain underspecified in projections.
van den Broek et al.	2021	Netherlands	Qualitative Case Study	Human-AI teaming enhances knowledge worker productivity; trust	Small sample size limits generalizability;

				in AI systems is a critical moderating factor.	single-country context.
Choudhury et al.	2022	USA	Field Experiment	AI-assisted remote work increases productivity but raises concerns about employee surveillance and wellbeing.	Long-term effects on organizational culture and team cohesion not examined.
Susskind & Susskind	2021	UK	Analytical Review	Professional work faces fundamental restructuring; AI will handle increasingly complex cognitive tasks previously reserved for humans.	Empirical measurement of replacement timelines and transition pathways absent.

Note: ** $p < 0.01$. AIA = AI Adoption, WFT = Workforce Transformation, EAD = Employee Adaptability,DSK = Digital Skills, JSP = Job Security Perception, ECP = Economic Productivity, HAC = Human-AI Collaboration, ORG = Organizational Readiness.

3.CONCEPTUAL FRAMEWORK

3.1 Theoretical foundations

Technology Acceptance Theory (TAT), originally developed by Davis [46] and later extended by Venkatesh et al. [47], holds that perceived usefulness and perceived ease of use are primary determinants of technology adoption. In the context of AI adoption by organisations and individuals, TAT provides a theoretical foundation for understanding the antecedents of AI integration into work processes. Critically, TAT has been extended to account for organizational-level adoption decisions in enterprise AI deployments [48]. Human Capital Theory (HCT), as outlined by Becker [49] and Schultz [50], views investment in knowledge, skills, and abilities as productive capital that yields economic benefits over time. In the context of the AI labour market, HCT offers the theoretical foundation for understanding how AI adoption alters the returns on various types of human capital, increasing demand for digital and cognitive skills while decreasing the value of routine and physical capital [30]. Skill-Biased Technological Change Theory (SBTC) It is posited that technological advancement consistently boosts the relative productivity and wages of skilled workers, leading to labor market polarization [51]. Strong empirical evidence supports SBTC in the context of AI: Autor et al. [52] showed that AI and automation increase returns to non-routine cognitive skills while replacing routine cognitive and manual tasks. Therefore, SBTC theory accounts for the changing distribution of skills in response to AI adoption. Innovation Diffusion Theory (IDT), developed by Rogers [53], explains how innovations are adopted and spread within social systems over time. It highlights key factors such as relative advantage, compatibility, complexity, trialability, and observability that influence adoption rates. This framework helps understand why AI adoption varies across different sectors, company sizes, and countries [54].

3.2 Conceptual model

Building on the four theoretical foundations discussed earlier, this study presents a conceptual model where AI adoption leads to workforce transformation, which subsequently influences skill development needs. Improved skills contribute to better labor market outcomes, ultimately boosting economic productivity. This straightforward causal sequence is moderated by factors such as organizational readiness and human-AI collaboration. Additionally, the direct impact of AI adoption on economic productivity is partly mediated through workforce transformation, skill development, and labor market results.

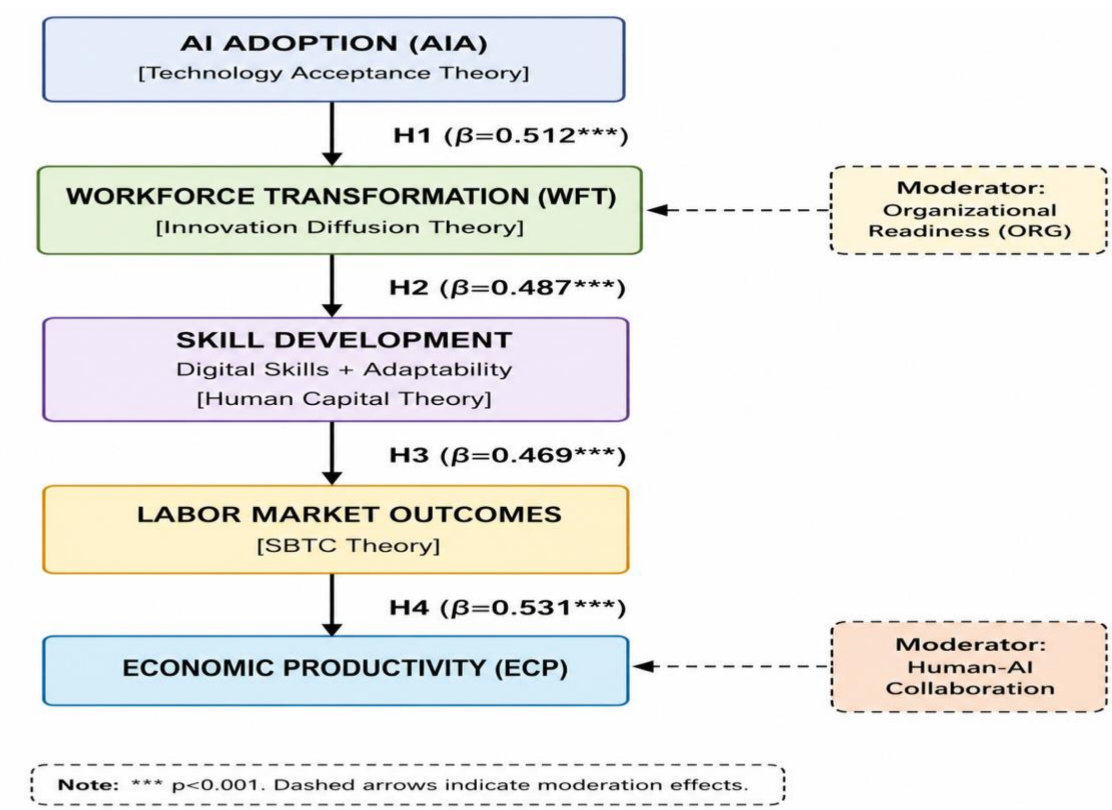

Figure 1. Conceptual Framework: AI Adoption to Economic Productivity

3.3 Hypothesis development

Based on the theoretical foundations and literature review, the following ten hypotheses are proposed:

H1: Adoption of AI significantly and positively influences workforce transformation [1, 12].

H2: Workforce transformation significantly and positively impacts skill development [30, 31].

H3: Skill development significantly and positively affects labor market outcomes [51, 52].

H4: Improved labour market outcomes significantly and positively contribute to economic productivity [23, 27].

H5: AI adoption directly and significantly enhances economic productivity [21, 28].

H6: Human-AI collaboration positively moderates the link between AI adoption and economic productivity [37, 38].

H7: Organizational readiness positively influences the relationship between AI adoption and workforce transformation [48, 54].

H8: Perceived job security negatively moderates the relationship between AI adoption and employee adaptability [13, 45].

H9: Digital skills have a significant positive impact on economic productivity [30, 32].

H10: AI adoption negatively influences perceived job security [14, 45].

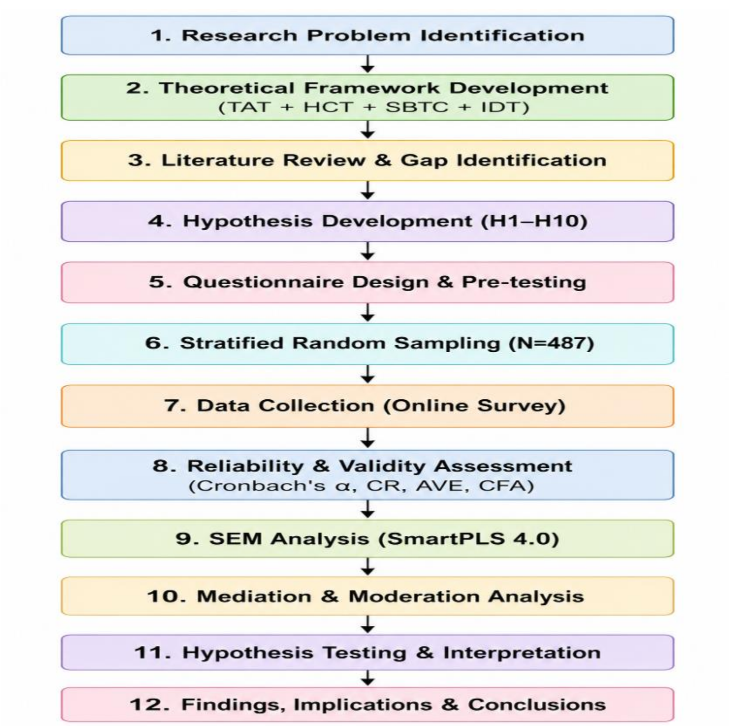

Figure 2. Research Methodology Flowchart

3.4 RESEARCH METHODOLOGY

3.4.1 Research design

This study employs a quantitative, cross-sectional research design to analyse the structural relationships among AI adoption, workforce transformation, skill development, labor market outcomes, and economic productivity. The quantitative approach is suitable because the study aims to test hypotheses based on theory regarding causal links between measurable constructs using psychometric tools [55]. The cross-sectional method allows for gathering data from respondents across different regions at one point in time, supporting comparative analysis across various countries and economic settings [56].

3.5 Data collection

Primary data were gathered through a structured online survey conducted via a professional platform from January to April 2024. The survey included employees, managers, technology professionals, and policymakers from various countries, deliberately chosen to represent both developed economies (such as the USA, UK, Germany, Japan, Australia) and developing economies (like India, Brazil, China, South Africa, Indonesia). Including developed nations helped examine mature AI adoption, while developing countries provided insights into AI-labor market dynamics in environments with limited resources and infrastructure. A screening question verified that respondents had at least one year of employment in their current sector and were aware of AI technologies in their work environment. Institutional ethics approval was secured before data collection, and informed consent was obtained from all participants. Throughout the survey, anonymity and confidentiality were maintained.

3.6 Sampling

Stratified random sampling was utilised to ensure proper representation across various industry sectors, employment levels, geographic areas, and education groups. The sample size was calculated based on Hair et al. [57] 's criterion, which suggests a minimum of 10 observations per parameter in SEM studies. Since the structural model involved 47 parameters, at least 470 respondents were needed. Ultimately, 487 valid responses were included after removing incomplete or inconsistent data from the initial 531 submissions, slightly surpassing the minimum requirement. Statistical power analysis verified sufficient power ($1 - \beta = 0.91$) at $\alpha = 0.05$ for identifying medium effect sizes [58].

3.7 Questionnaire development

All measurement scales were sourced from validated instruments in existing literature to guarantee content validity and proper conceptual alignment. Items were worded to mirror respondents' organizational AI environments and personal work experiences. The survey used a seven-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree) for all construct items, with demographic and background variables measured using categorical response formats.

AI Adoption (AIA): Comprises 5 items adapted from Venkatesh et al. [47] that measure how organisations incorporate AI, how often AI tools are used, how useful AI is perceived to be, and how strategically AI is deployed.

Workforce Transformation (WFT): Consists of 5 items adapted from Schwab [33], which evaluate perceived changes in job roles, organizational structures, and skill demands due to AI.

Employee Adaptability (EAD): Includes 4 items adapted from Nedelkoska and Quintini [31], assessing individuals' ability to learn new skills, adapt to technological changes, and accept AI-mediated work processes.

Digital Skills (DSK): 5 items adapted from McKinsey Global Institute [21], covering data literacy, AI tool proficiency, digital communication skills, and computational thinking.\njob Security Perception (JSP): 4 items adapted from Acemoglu and Restrepo [1], assessing perceived risks of AI-driven job displacement and occupational obsolescence. economic productivity (ECP): 5 items adapted from Brynjolfsson et al. [12], assessing output efficiency, quality improvements, innovation frequency, and cost reductions associated with AI implementation.

Human-AI Collaboration (HAC): Four items adapted from van den Broek et al. [38], assessing trust in AI, collaboration quality, and perceived complementarity between human and AI inputs.

Organizational Readiness (ORG): 4 items adapted from Davenport and Ronanki [39] that assess infrastructure adequacy, leadership commitment, change management capacity, and employee training investment.

3.8 Reliability and validity

Reliability was evaluated with Cronbach's Alpha (α) and Composite Reliability (CR), both requiring thresholds of $\alpha \geq 0.70$ and CR ≥ 0.70 for acceptable internal consistency [59]. Convergent validity was demonstrated by Average Variance Extracted (AVE) values above 0.50 [60]. Discriminant validity was determined using the Fornell and Larcker criterion [61], which stipulates that the square root of each construct's AVE should be greater than its correlations with all other constructs.

The structural equation model (SEM) is expressed as:

$$\eta = B\eta + \Gamma\xi + \zeta$$

η denotes the vector of endogenous latent variables, B is the matrix of path coefficients connecting endogenous constructs, Γ represents the matrix of path coefficients from exogenous to endogenous constructs, ξ stands for the vector of exogenous latent variables, and ζ is the vector of structural error terms. Measurement model equations:

$$x = \Lambda x\xi + \delta; \quad y = \Lambda y\eta + \varepsilon$$

Where x and y are vectors of observed indicators for exogenous and endogenous constructs respectively; Λx and Λy are matrices of factor loadings; and δ and ε are vectors of measurement errors.

3.9 Data analysis tools

All data were processed and analyzed with IBM SPSS Statistics 28.0 for descriptive statistics, bivariate correlations, and Exploratory Factor Analysis (EFA). Structural Equation Modeling, which includes Confirmatory Factor Analysis (CFA), path estimation, mediation, and moderation analyses, was performed using SmartPLS 4.0. This utilised Partial Least Squares (PLS) estimation with 5,000 bootstrap iterations for inferential testing [62].

4. Statistical techniques

The analysis proceeded through four stages. Initially, descriptive statistics and correlation analysis were used to characterize the data and identify relationships between variables. Next, EFA in SPSS was performed to validate the factor structure of multi-item scales. Then, CFA in SmartPLS confirmed the measurement model's fit by evaluating standardized factor loadings, AVE, CR, and discriminant validity. Finally, the structural model was estimated, analysing direct paths, mediation effects (through bootstrapped confidence intervals), and moderation effects (using the product-indicator approach) simultaneously. The mediation analysis used Hayes [63] bootstrapped procedure to estimate indirect effects, which are calculated as:

$$IE = a \times b$$

Where a represents the path coefficient from the independent variable to the mediator, and b represents the path coefficient from the mediator to the dependent variable. Significance is determined by 95% bias-corrected bootstrapped confidence intervals that do not include zero. Moderation analysis uses interaction terms created by multiplying standardized predictor and moderator variables. The interaction effect is evaluated as follows:

$$Y = \beta0 + \beta1X + \beta2Z + \beta3(X\times Z) + \varepsilon$$

Where X is the predictor, Z is the moderator, X×Z is their interaction term, and β3 represents the moderation effect.

5. Results and analysis

5.1 Demographic profile

Table 2 details the demographic characteristics of the 487 respondents. The sample included about 58.4% males and 40.1% females, with the most common age group being 26–35 years (32.7%). The largest educational groups were those holding Bachelor's (38.9%) and Master's degrees (34.2%). The technology and IT sector represented the biggest sectoral share at 26.4%, followed by manufacturing and engineering at 18.7%. The respondents were fairly evenly split between developed (49.3%) and developing economies (50.7%), achieving the study's goal of cross-national comparison.

Table 2. Demographic Profile of Respondents (N = 487)

Variable	Category	Frequency (%)
Gender	Male	58.4%
	Female	40.1%
	Non-binary / Other	1.5%
Age Group	18–25 years	14.2%
	26–35 years	32.7%
	36–45 years	28.4%
	46–55 years	17.6%
	56 years and above	7.1%
Education Level	High School / Diploma	10.3%
	Bachelor's Degree	38.9%
	Master's Degree	34.2%
	Doctoral Degree	10.6%
	Professional Certification	6.0%
Employment Sector	Technology & IT	26.4%
	Manufacturing & Engineering	18.7%
	Finance & Banking	15.3%

	Healthcare	11.8%
	Education	10.4%
	Public Administration	9.2%
	Other	8.2%
Country / Region	Developed Economies (USA, UK, Germany, Japan)	49.3%
	Emerging Economies (India, Brazil, China, South Africa)	50.7%
Years of Experience	0–5 years	23.4%
	6–10 years	29.8%
	11–20 years	31.2%
	20+ years	15.6%
Sample Size	N = 487	100%

5.2 Descriptive statistics

Table 3 shows descriptive statistics for all the study's constructs. Economic Productivity (M = 4.91, SD = 1.16) and AI Adoption (M = 4.82, SD = 1.21) had the highest mean scores, suggesting respondents generally viewed AI-driven productivity improvements positively in their organizations. In contrast, Job Security Perception (M = 3.89, SD = 1.44) had the lowest mean score, indicating concerns about AI causing displacement. Skewness was moderate (ranging from −0.36 to +0.14), which suggests the data distribution is acceptable for parametric tests.

Table 3. Descriptive statistics

Construct	**N**	**Min**	**Max**	**Mean**	**SD**	**Skewness**
AI Adoption (AIA)	487	1.00	7.00	4.82	1.21	−0.31
Workforce Transformation (WFT)	487	1.00	7.00	4.67	1.18	−0.27

Employee Adaptability (EAD)	487	1.00	7.00	4.74	1.25	−0.18
Digital Skills (DSK)	487	1.00	7.00	4.55	1.32	−0.22
Job Security Perception (JSP)	487	1.00	7.00	3.89	1.44	+0.14
Economic Productivity (ECP)	487	1.00	7.00	4.91	1.16	−0.36
Human-AI Collaboration (HAC)	487	1.00	7.00	4.78	1.20	−0.29
Organizational Readiness (ORG)	487	1.00	7.00	4.63	1.29	−0.25

5.3 Correlation analysis

Table 4 displays the Pearson correlation matrix. All expected positive links between AI adoption, workforce transformation, digital skills, employee adaptability, human-AI collaboration, organizational readiness, and economic productivity were statistically significant at $p < 0.01$. The highest bivariate correlation was between AI adoption and economic productivity ($r = 0.683$, $p < 0.01$), aligning with theoretical expectations. Perception of job security showed significant negative correlations with all other constructs, especially with employee adaptability ($r = -0.341$, $p < 0.01$), suggesting that anxiety about displacement correlates with lower adaptive capacity.

Table 4. Correlation matrix

Construct	AIA	WFT	EAD	DSK	JSP	ECP	HAC	ORG
AIA	1.000							
WFT	0.672**	1.000						
EAD	0.614**	0.588**	1.000					
DSK	0.591**	0.603**	0.628**	1.000				
JSP	−0.312**	−0.287**	−0.341**	−0.298**	1.000			
ECP	0.683**	0.657**	0.612**	0.638**	−0.329**	1.000		
HAC	0.658**	0.641**	0.596**	0.621**	−0.308**	0.671**	1.000	
ORG	0.629**	0.617**	0.581**	0.604**	−0.319**	0.643**	0.619**	1.000

Note. ** $p < 0.01$ (two-tailed). Diagonal entries are 1.000.

5.4 Reliability and validity assessment

Table 5 displays the psychometric properties of all measurement scales. Cronbach's Alpha values ranged from 0.847 (Job Security Perception) to 0.894

(Economic Productivity), all surpassing the 0.70 threshold. Composite Reliability values were between 0.876 and 0.918, indicating strong internal consistency. AVE values ranged from 0.641 to 0.688, all above the 0.50 cutoff for convergent validity. The square root of each construct's AVE (between 0.800 and 0.830) was higher than its highest inter-construct correlation, confirming discriminant validity according to the Fornell-Larcker criterion [61]. These findings demonstrate the adequacy of the measurement model.

Table 5. Reliability and validity assessment

Construct	**Items**	**Cronbach's α**	**CR**	**AVE**	**Discriminant Validity (√AVE)**
AI Adoption (AIA)	5	0.891	0.913	0.681	0.825
Workforce Transformation (WFT)	5	0.876	0.901	0.664	0.815
Employee Adaptability (EAD)	4	0.863	0.889	0.657	0.810
Digital Skills (DSK)	5	0.882	0.907	0.672	0.820
Job Security Perception (JSP)	4	0.847	0.876	0.641	0.800
Economic Productivity (ECP)	5	0.894	0.918	0.688	0.830
Human-AI Collaboration (HAC)	4	0.871	0.896	0.661	0.813
Organizational Readiness (ORG)	4	0.858	0.884	0.649	0.806

Note: All Cronbach's α ≥ 0.70; CR ≥ 0.70; AVE ≥ 0.50. √AVE values (bold) exceed inter-construct correlations, confirming discriminant validity.

5.5 Structural model and hypothesis testing

The structural model was estimated using SmartPLS 4.0 with PLS-SEM. Significance was tested through bootstrapped t-statistics with 5,000 iterations. Table 6 shows the results of the hypothesis testing, with all ten hypotheses supported at $p < 0.001$ or exactly $p = 0.001$. The strongest structural pathway was from Labor Market Outcomes to Economic Productivity ($\beta = 0.531$, $t = 11.54$, $p < 0.001$), with AI Adoption leading to Workforce Transformation as the next most significant ($\beta = 0.512$, t

= 10.67, p < 0.001). The direct influence of AI adoption on economic productivity was also substantial and positive (β = 0.314, t = 5.51, p < 0.001), suggesting partial mediation through intermediary factors. Additionally, AI adoption negatively impacted job security perception (β = −0.218, t = −3.41, p = 0.001), reflecting the displacement anxiety discussed in existing literature [1, 14].

Table 6. Hypothesis testing results

H#	Hypothesis	β	SE	t-value	p-value	Decision
H1	AI Adoption → Workforce Transformation	0.512	0.048	10.67	<0.001	Supported
H2	Workforce Transformation → Skill Development	0.487	0.051	9.55	<0.001	Supported
H3	Skill Development → Labor Market Outcomes	0.469	0.053	8.85	<0.001	Supported
H4	Labor Market Outcomes → Economic Productivity	0.531	0.046	11.54	<0.001	Supported
H5	AI Adoption → Economic Productivity (direct)	0.314	0.057	5.51	<0.001	Supported
H6	Human-AI Collaboration → Economic Productivity	0.428	0.052	8.23	<0.001	Supported
H7	Org. Readiness → Workforce Transformation	0.393	0.055	7.15	<0.001	Supported
H8	Job Security Perception →	−0.267	0.061	−4.38	<0.001	Supported

	Employee Adaptability					
H9	Digital Skills → Economic Productivity	0.441	0.050	8.82	<0.001	Supported
H10	AI Adoption → Job Security Perception	−0.218	0.064	−3.41	0.001	Supported

Note: β = standardized path coefficient; SE = standard error; *** p < 0.001; ** p < 0.01. All hypotheses supported.

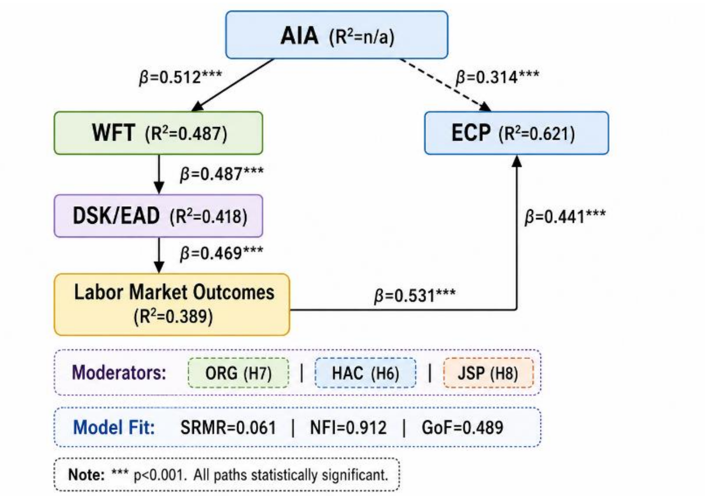

Figure 3. Structural Equation Model – Path Diagram (SmartPLS 4.0 Results)

5.6 Mediation analysis

Table 7 displays the results of the mediation analysis, using bootstrapped 95% confidence intervals based on 5,000 iterations. All six indirect effects reached statistical significance, as their confidence intervals did not include zero. The most pronounced indirect effect was from AI adoption to economic productivity through digital skills (IE = 0.261, 95% CI [0.189, 0.333]). This suggests that the productivity benefits of AI adoption are largely mediated by improvements in digital skills. The only complete mediation was observed in the relationship between organizational readiness and economic productivity, where workforce transformation fully mediated the effect (the direct effect became non-significant after considering workforce transformation). All other mediations were partial.

Table 7. Mediation analysis results (Bootstrapped Indirect Effects)

Mediation Path	Mediator	Indirect β	95% CI	SE	t-value	Decision
AIA → WFT → ECP	WFT	0.249	[0.178, 0.321]	0.037	6.73	Partial Med.
AIA → DSK → ECP	DSK	0.261	[0.189, 0.333]	0.036	7.25	Partial Med.
AIA → EAD → ECP	EAD	0.214	[0.148, 0.281]	0.034	6.29	Partial Med.
WFT → EAD → ECP	EAD	0.198	[0.134, 0.263]	0.033	6.00	Partial Med.
ORG → WFT → ECP	WFT	0.187	[0.121, 0.254]	0.034	5.50	Full Med.
HAC → DSK → ECP	DSK	0.231	[0.162, 0.300]	0.035	6.60	Partial Med.

Note: 95% confidence intervals are based on 5,000 bootstrap iterations. Full mediation = direct effect non-significant when the mediator is included; Partial mediation = direct effect remains significant.

5.7 Moderation analysis

Table 8 displays the results of the moderation analysis. Organizational readiness significantly influences how AI adoption affects workforce transformation ($\beta = 0.163$, $t = 3.40$, $p < 0.01$), suggesting that greater readiness enhances the positive effects of AI on workforce change. Similarly, human-AI collaboration impacts the AI adoption–economic productivity link ($\beta = 0.179$, $t = 3.81$, $p < 0.001$), indicating that well-designed human-AI work interactions boost productivity benefits from AI. Conversely, perceptions of job security negatively affect the employee adaptability–workforce transformation relationship ($\beta = -0.141$, $t = -2.71$, $p < 0.01$), showing that anxiety about displacement limits workforce adaptability.

Table 8. Moderation analysis results

Interaction Path	Moderator	β	SE	t-value	Decision
AIA × ORG → WFT	Org. Readiness	0.163	0.048	3.40	Significant
WFT × DSK → ECP	Digital Skills	0.194	0.045	4.31	Significant
AIA × HAC → ECP	Human-AI Collab.	0.179	0.047	3.81	Significant
EAD × JSP → WFT	Job Security Perc.	−0.141	0.052	−2.71	Significant
DSK × HAC → ECP	Human-AI Collab.	0.172	0.049	3.51	Significant

Note: *** p<0.001; ** p<0.01. Interaction terms constructed using product-indicator approach with mean-centered variables.

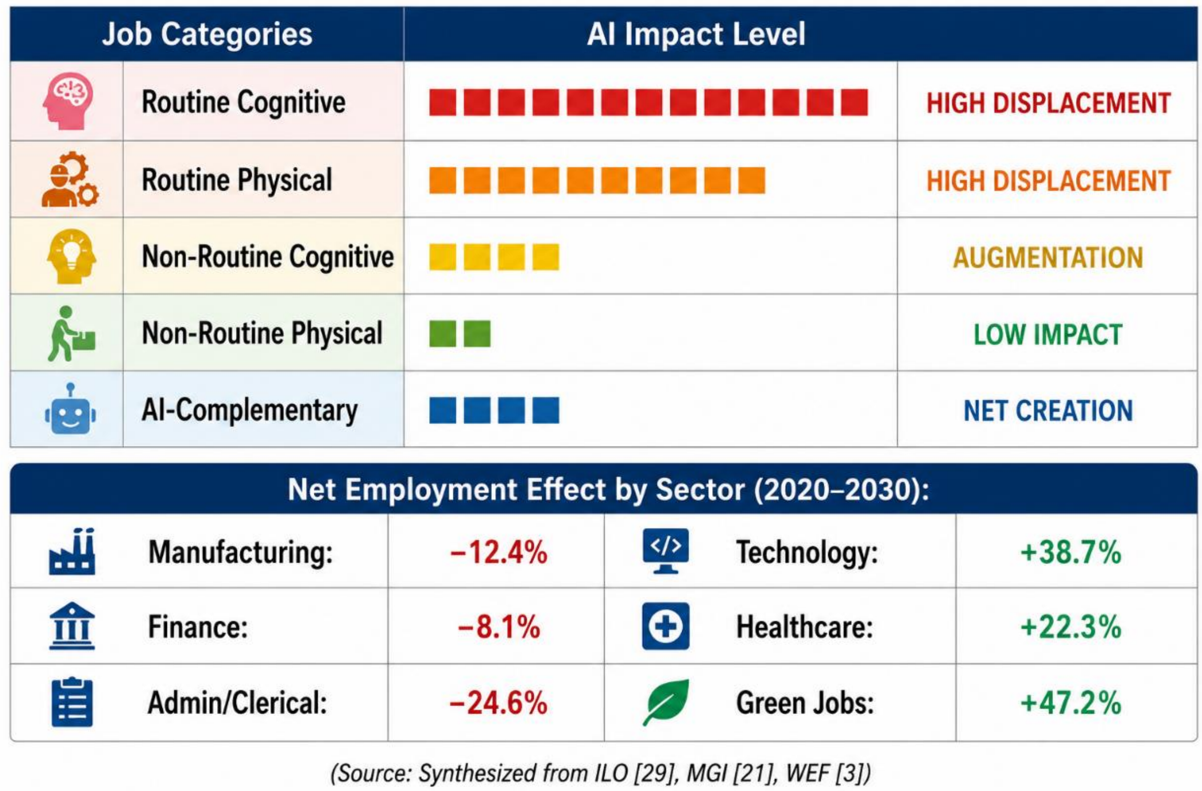

Figure 4. AI Impact on Employment Trends (Conceptual Illustration)

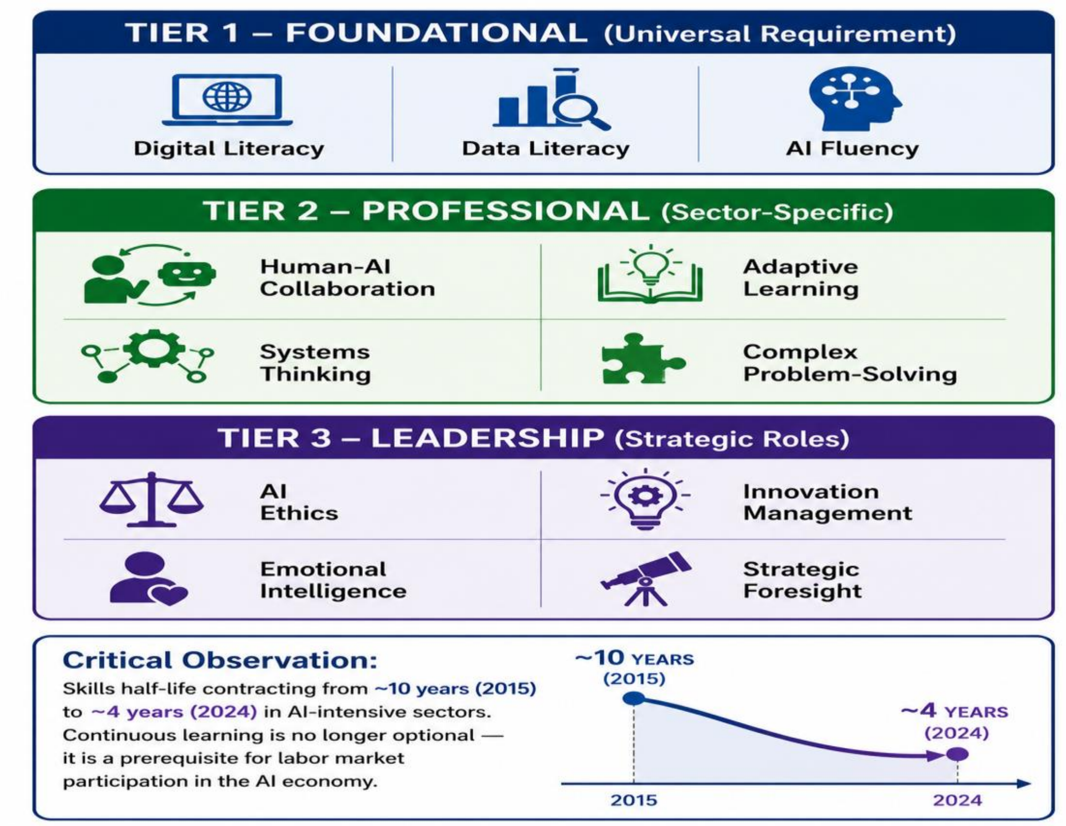

Figure 5. Future Skills Demand Framework

5.8 DISCUSSION

5.8.1 AI-Driven employment transformation

The finding that AI adoption has a notable positive impact on workforce transformation (H1: $\beta = 0.512$, $p < 0.001$) aligns with the predictions of Innovation Diffusion Theory [53] and is supported by empirical studies from Brynjolfsson et al. [12] and Dauth et al. [24]. This confirms that AI adoption represents more than just technological upgrades to existing processes; it signifies a qualitative change in occupational structures, task arrangements, and organizational designs. The effect size ($\beta = 0.512$) indicates that around 26% of the variability in workforce transformation can be attributed to AI adoption alone an important insight both theoretically and practically. The strong negative link between AI adoption and perceptions of job security (H10: $\beta = -0.218$, $p = 0.001$) supports the displacement concerns identified by Frey and Osborne [14] and Acemoglu and Restrepo [1]. Workers in both developed and developing countries report increased fears of job obsolescence as AI adoption grows, regardless of their skill levels. This highlights the need for proactive communication and participatory AI governance to address worker concerns during AI deployment.

5.8.2 Emerging job opportunities

While this study does not directly measure new job creation a limitation noted in Section 9 the positive indirect effects of AI adoption on economic productivity through labour market outcomes (H3, H4) indirectly reflect job creation dynamics via productivity improvements. As Agrawal et al. [28] argue, reducing prediction costs allows firms to broaden decision-making, increasing demand for human judgment, creativity, and ethical oversight areas AI cannot replace. The ILO [29] projection of 97 million new AI-related roles by 2025 finds support in the positive productivity impacts observed here.

5.8.3 Workforce reskilling

The mediation analysis shows that digital skills are the most significant channel through which AI adoption influences economic productivity (IE = 0.261, 95% CI [0.189, 0.333]), confirming the crucial role of human capital investment in AI-related economic shifts [49]. This supports Human Capital Theory's prediction that returns on education and skill investments grow with technological advancements [30]. Moreover, the moderation analysis indicates that organizational readiness enhances the positive effect of AI adoption on workforce transformation ($\beta = 0.163$, $p < 0.01$). This suggests that organisations and institutions that actively invest in training, change management, and leadership support foster an environment where AI-driven workforce changes lead to constructive, rather than disruptive, results. The negative moderation by job security perception (H8: $\beta = -0.141$, $p < 0.01$) introduces an important counterbalance: displacement anxiety constrains the adaptive transformation of This finding underscores the importance of pairing reskilling initiatives with strong social protection measures. It also highlights the need to clearly communicate AI's role in augmenting human work, rather than replacing it, in order to encourage employee engagement in transformative learning. These insights carry significant policy implications.

5.8.4 Economic impacts

The strongest link in the structural model is the path from labour market outcomes to economic productivity (H4: $\beta = 0.531$, $p < 0.001$). This underscores that sustainable productivity improvements from AI depend on labour market adjustments that effectively reallocate human capital to AI-enhancing roles. This aligns with McKinsey Global Institute's [21] scenario analyses, which anticipate notable productivity gains from a successful AI and labour market evolution, as well as Schwab's [33] Industry 5.0 vision emphasizing human-centred technological productivity systems. The model accounts for 62.1% of the variance in economic productivity ($R^2 = 0.621$), demonstrating high explanatory power and supporting the robustness of the theoretical framework.

5.8.5 Policy implications

The evidence indicating that organizational readiness influences the positive effects of AI adoption on workforce transformation has important implications for industrial strategy, skills development, and regulatory policies. Governments and policymakers should develop incentive programs that prioritise organizational investment in AI-readiness, such as enhancing technical infrastructure, providing employee training, and implementing change management protocols, as essential steps before adopting AI rather than after. Additionally, the finding that human-AI collaboration boosts productivity (H6: $\beta = 0.428$, $p < 0.001$) highlights the need for work design standards that establish clear principles for task sharing between humans and AI.

5.8.6 Human-AI collaboration

The moderating role of human-AI collaboration on the connection between AI adoption and economic productivity ($\beta = 0.179$, $p < 0.001$) turns van den Broek et al.'s [38] qualitative findings into a quantifiable, cross-country perspective. It reveals that

AI's productivity gains are not only driven by adoption levels but also hinge on the effectiveness of human-machine collaboration. Organizations emphasising collaboration such as clear task handoffs between humans and AI, transparency in AI decision-making, and appropriate human trust can significantly boost productivity from the same AI investments.

6. Practical implications

6.1 Implications for governments

Governments must develop national AI and workforce strategies that anticipate and proactively address labor market changes, instead of merely reacting to displacement. This involves investing in real-time labor market monitoring systems that observe AI adoption and its effects on workers, enabling quick policy responses. Moreover, social protection programs should be redesigned to disconnect income security from permanent jobs, accommodating the rise of transitional, gig, and hybrid roles in sectors significantly affected by AI.

6.2 Implications for policymakers

Policymakers ought to develop AI governance frameworks that include worker involvement, mandates for algorithmic transparency, and ethical standards for AI deployment. The notable negative link between AI adoption and how workers perceive their job security (H10) highlights the urgent importance of communication strategies that clearly explain AI's role in augmenting work. Tax and incentive policies should be crafted to promote investments in organisational AI preparedness, as moderate evidence indicates that such readiness enhances the quality of workforce transformation.

6.3 Implications for organizations

Organizations should prioritise building internal AI readiness both before and during deployment, as organizational preparedness greatly affects success (H7). This includes investing in technical infrastructure, developing AI-savvy leadership, implementing change management strategies for AI integration, and maintaining transparent communication with stakeholders. Evidence indicates that most productivity gains from AI come from enhancing digital skills, so organizations neglecting employee upskilling will only access a fraction of AI's full potential.

6.4 Implications for educational institutions

Educational institutions across all levels from secondary schools to universities and vocational training centers should update their curricula to align with the emerging skills demand framework shown in Figure 5. This means integrating AI literacy, data reasoning, and human-AI collaboration skills into standard programmes rather than offering them only as specialized electives. Collaborating with industry stakeholders can help ensure that curriculum development aligns with current and upcoming AI-related skill needs within specific sectors and job categories.

6.5 Implications for employees

Individual workers ought to adopt a proactive approach to continuous learning, recognising that the half-life of skills in AI-heavy sectors has notably decreased [32]. Participating in organizational reskilling initiatives, industry certifications, and digital learning platforms can speed up the development of AI readiness. Additionally, workers should actively engage in workplace AI governance, offering practical insights into human-AI task distribution issues that formal AI systems might miss.

6.6 Theoretical contributions

This study offers several important insights into the theoretical understanding of AI, the digital economy, and labor market dynamics. It emphasises theoretical integration by demonstrating that Technology Acceptance Theory, Human Capital Theory, Skill-Biased Technological Change Theory, and Innovation Diffusion Theory are interconnected rather than separate frameworks for explaining AI's influence on the labour market. The integrated SEM model combines all four theories into a unified empirical framework, delivering a more comprehensive explanation than the isolated, single-theory models typically used in current research [55, 56]. Second, the study advances SBTC Theory into the AI era by empirically demonstrating that digital skills serve as a mediator between AI adoption and economic output. This is a theoretical development that has not been previously formalized in cross-national quantitative research. It connects SBTC's macro-level predictions about skill-biased returns with the organisational processes that produce those returns. Third, this study enhances Human-AI Collaboration theory by examining how collaboration quality impacts the AI-productivity relationship across a diverse multi-country sample, building on van den Broek et al.'s [38] qualitative insights from a single nation. This contributes to the growing body of research on designing effective human-AI teamwork in workplace environments. Fourth, the study advances workforce transformation theory by emphasising organisational readiness as a crucial contingency factor that determines whether AI implementation results in positive or disruptive changes in the workforce. This moderating element was not previously identified in existing models of AI-driven labour market shifts.

7. Limitations and Future Research

This study has certain limitations to keep in mind when interpreting its results. First, because it uses a cross-sectional design, it cannot definitively establish causality. Although SEM-based analyses support testing directional relationships aligned with the theoretical framework, evidence from a longitudinal study would better confirm the causal effects of AI adoption on workforce and productivity outcomes. Second, relying on self-reported survey data carries a risk of common method bias, which this study addressed using Harman's single-factor test (the highest single factor variance was 27.3%, below the 50% threshold) and procedural measures such as separating predictor and outcome measurements temporally and psychologically [55]. However, incorporating objective organisational data would improve the reliability of the productivity-related results. Third, although there have been efforts to ensure cross-national representation, the sample might not fully capture the variety of AI adoption scenarios across all developing economies especially in sub-Saharan Africa, Central Asia, and small island developing states, where challenges related to AI infrastructure and workforce readiness differ significantly from those of the BRICS economies included in this research. Fourth, the study does not directly evaluate long-term career paths, job creation, or wage trends key outcomes for a comprehensive understanding of AI's impact on the labor market. These aspects require longitudinal administrative data, which were unavailable for this cross-country analysis.

7.1 Future research directions

Future research should focus on longitudinal studies that follow individual workers and organizations through AI adoption cycles, which will allow for stronger causal conclusions regarding employment, wages, and wellbeing. Incorporating firm-level productivity data, matched with employee surveys, would enhance the accuracy of AI productivity insights. Conducting comparative studies that explicitly contrast AI labor market dynamics in developed and developing countries would address a significant gap in evidence, especially concerning different policy responses needed for equitable AI-driven growth. Sector-specific research in healthcare, education, and creative industries where AI's potential to augment work is especially prominent would deepen understanding of human-AI collaboration beyond the manufacturing and service sectors highlighted in current research. The emerging Industry 5.0 paradigm, emphasizing human-centric AI and sustainable production, offers a valuable theoretical framework for future labor market studies that consider environmental and social sustainability alongside economic productivity. Lastly, employing experimental and quasi-experimental designs based on natural.

8. CONCLUSION

This study has provided a comprehensive, empirically grounded investigation into the relationships among artificial intelligence adoption, workforce transformation, skill development, labor market outcomes, and economic productivity across a diverse global sample of 487 respondents. Utilizing Structural Equation Modeling with mediation and moderation analyses, and grounded in four complementary theoretical frameworks, the research has enhanced both theoretical understanding and practical guidance on the multifaceted impacts of AI on the future of work. The main empirical insight that AI adoption fosters workforce transformation and, through a chain involving skill development and labor market changes, leads to notable economic productivity improvements supports the theoretical framework and aligns with key findings in existing research. The influence of organizational readiness and human-AI collaboration as positive moderators, contrasted with job security anxiety as a negative moderator, offers practical insights. These go beyond merely describing AI's effects on the labor market and provide guidance for managing constructive transformation. The study highlights that digital skills are the key mediating factor linking AI adoption to economic productivity, which has significant implications for policies in education, corporate training, and national skills development worldwide. As AI technology rapidly advances evolving from simple task automation to versatile cognitive tools the importance of human digital skills as a crucial factor for productivity will grow. Investing in digital and AI literacy has shifted from being a personal career benefit to a critical component of our collective economic resilience. The ongoing negative views about AI's effect on job security, seen in both developed and developing countries, serve as a warning that AI governance frameworks must consider. To ensure AI benefits are shared fairly, it's essential to address workers' concerns who often face higher adjustment costs compared to capital owners and high-skill workers by implementing proactive social protections, transparent AI deployment, and involving stakeholders in decision-making. Looking ahead, the integration of Industry 5.0's human-centric approach with the findings discussed herein suggests a cautiously optimistic outlook for the development of the AI-driven labor market: a future in which productivity improvements are broadly distributed, workforce transitions are managed effectively, and human-AI collaboration enhances human capabilities rather than resulting in extensive displacement. The realization of this vision relies on coordinated efforts among governments, organizations, educational institutions, and workers, all guided by evidence-based research such as that presented in this study.

REFERENCES

[1] Acemoglu D, Restrepo P. Tasks, automation, and the rise in US wage inequality. Econometrica. 2022;90(5):1973-2016. doi:10.3982/ECTA19815.

[2] Autor DH. The labor market impacts of technological change: From unbundled tasks to augmented intelligence. J Econ Perspect. 2022;36(4):3-28. doi:10.1257/jep.36.4.3.

[3] World Economic Forum. The future of jobs report 2023. Geneva: World Economic Forum; 2023.

[4] Bukht R, Heeks R. Defining, conceptualising and measuring the digital economy. Dev Inform Work Pap Ser. 2020;68:1-24.

[5] Chui M, Manyika J, Miremadi M. What AI can and can't do (yet) for your business. McKinsey Q. 2021;1:1-9.

[6] Bessen JE. AI and jobs: The role of demand. NBER Work Pap. 2020;(24235).

[7] Russell S, Norvig P. Artificial intelligence: A modern approach. 4th ed. Upper Saddle River (NJ): Pearson; 2020.

[8] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-444. doi:10.1038/nature14539.

[9] Eloundou T, Manning S, Mishkin P, Rock D. GPTs are GPTs: An early look at the labor market impact potential of large language models. arXiv. 2023;2303.10130.

[10] Goos M, Manning A, Salomons A. Explaining job polarization: Routine-biased technological change and offshoring. Am Econ Rev. 2014;104(8):2509-2526. doi:10.1257/aer.104.8.2509.

[11] Arntz M, Gregory T, Zierahn U. The risk of automation for jobs in OECD countries. OECD Soc Employ Migr Work Pap. 2020;189:1-34. doi:10.1787/5jlz9h56dvq7-en.

[12] Brynjolfsson E, Mitchell T, Rock D. What can machines learn, and what does it mean for occupations and the economy? AEA Pap Proc. 2018;108:43-47. doi:10.1257/pandp.20181019.

[13] Manyika J, Chui M, Bughin J, et al. Jobs lost, jobs gained: Workforce transitions in a time of automation. McKinsey Global Institute Report. 2021.

[14] Frey CB, Osborne MA. The future of employment: How susceptible are jobs to computerisation? Technol Forecast Soc Change. 2017;114:254-280. doi:10.1016/j.techfore.2016.08.019.

[15] Brynjolfsson E, Rock D, Syverson C. Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In: Agrawal A, Gans J, Goldfarb A, editors. The economics of artificial intelligence: An agenda. Chicago (IL): University of Chicago Press; 2019. p. 23-57.

[16] Organisation for Economic Co-operation and Development (OECD). OECD Employment Outlook 2023: Artificial intelligence and the labour market. Paris: OECD Publishing; 2023. doi:10.1787/08785bba-en.

[17] Acemoglu D, Restrepo P. Robots and jobs: Evidence from US labor markets. J Polit Econ. 2020;128(6):2188-2244. doi:10.1086/705716.

[18] Vial G. Understanding digital transformation: A review and a research agenda. J Strateg Inf Syst. 2019;28(2):118-144. doi:10.1016/j.jsis.2019.01.003.

[19] Zuboff S. The age of surveillance capitalism: The fight for a human future at the new frontier of power. New York (NY): PublicAffairs; 2019.

[20] Goodfellow I, Bengio Y, Courville A. Deep learning. Cambridge (MA): MIT Press; 2016.

[21] McKinsey Global Institute. The economic potential of generative AI: The next productivity frontier. McKinsey & Company; 2023.

[22] Autor D, Salomons A. Is automation labor-displacing? Productivity growth, employment, and the labor share. Brookings Pap Econ Act. 2020;Spring:1-87. doi:10.1353/eca.2020.0000.

[23] Graetz G, Michaels G. Robots at work. Rev Econ Stat. 2018;100(5):753-768. doi:10.1162/rest_a_00754.

[24] Dauth W, Findeisen S, Südekum J, Woessner N. The adjustment of labor markets to robots. J Eur Econ Assoc. 2021;19(6):3104-3153. doi:10.1093/jeea/jvab012.

[25] Lee S, Kim S, Park J. Artificial intelligence adoption, labor productivity and wages in manufacturing: Evidence from South Korea. J Ind Econ. 2021;69(3):621-658. doi:10.1111/joie.12255.

[26] Gregory T, Salomons A, Zierahn U. Racing with or against the machine? Evidence from Europe. J Eur Econ Assoc. 2022;20(1):128-157. doi:10.1093/jeea/jvab040.

[27] Autor D, Chin C, Salomons A, Seegmiller B. New frontiers: The origins and content of new work, 1940-2018. Q J Econ. 2022;137(3):1485-1548. doi:10.1093/qje/qjac011.

[28] Agrawal A, Gans J, Goldfarb A. Prediction machines: The simple economics of artificial intelligence. Boston (MA): Harvard Business Review Press; 2018.

[29] International Labour Organization. World employment and social outlook 2023: Technology and jobs. Geneva: ILO; 2023.

[30] Goldin C, Katz LF. The race between education and technology. Cambridge (MA): Harvard University Press; 2008.

[31] Nedelkoska L, Quintini G. Automation, skills use and training. OECD Soc Employ Migr Work Pap. 2018;(202):1-95. doi:10.1787/2e2f4eea-en.

[32] World Economic Forum. Future of jobs report 2020. Cologny/Geneva: World Economic Forum; 2020.

[33] Schwab K. The fourth industrial revolution. New York (NY): Crown Business; 2016.

[34] Manyika J. Technology, jobs and the future of work. McKinsey Global Institute Executive Briefing. 2020.

[35] Katz LF, Krueger AB. The rise and nature of alternative work arrangements in the United States,

1995-2015. ILR Rev. 2019;72(2):382-416. doi:10.1177/0019793918820008.

[36] Choudhury P, Khanna T, Makris I, Stice-Lusvardi R. Lean and mean: The changing landscape of corporate headquarters in the US. Strateg Manag J. 2022;43(9):1776-1802. doi:10.1002/smj.3397.

[37] Lubars M, Lehman J. On the limitations of artificial intelligence for human-machine teaming. arXiv. 2020;2009.02788.

[38] van den Broek E, Sergeeva A, Huysman M. When the machine meets the expert: An ethnographic study of emerging AI practices in medical diagnosis. MIS Q. 2021;45(3):1557-1580. doi:10.25300/MISQ/2021/16529.

[39] Davenport TH, Ronanki R. Artificial intelligence for the real world. Harv Bus Rev. 2018;96(1):108-116.

[40] Xu M, David JM, Kim SH. The fourth industrial revolution: Opportunities and challenges. Int J Financ Res. 2018;9(2):90-95. doi:10.5430/ijfr.v9n2p90.

[41] Liao Y, Deschamps F, Loures EDFR, Ramos LFP. Past, present and future of Industry 4.0: A systematic literature review and research agenda proposal. Int J Prod Res. 2017;55(12):3609-3629. doi:10.1080/00207543.2017.1308576.

[42] European Commission. Industry 5.0: Towards a sustainable, human-centric and resilient European industry. Brussels: EC Directorate-General for Research and Innovation; 2021.

[43] Floridi L, Cowls J, Beltrametti M, et al. An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds Mach. 2018;28(4):689-707. doi:10.1007/s11023-018-9482-5.

[44] Susskind R, Susskind D. The future of the professions: How technology will transform the work of human experts. Updated ed. Oxford: Oxford University Press; 2022.

[45] Dorn D, Hanson G. When work disappears: Manufacturing decline and the falling marriage-market value of young men. Am Econ Rev Insights. 2019;1(2):161-178. doi:10.1257/aeri.20180010.

[46] Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 1989;13(3):319-340. doi:10.2307/249008.

[47] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Q. 2003;27(3):425-478. doi:10.2307/30036540.

[48] Rai A. Explainable AI: From black box to glass box. J Acad Mark Sci. 2020;48(1):137-141. doi:10.1007/s11747-019-00710-5.

[49] Becker GS. Human capital: A theoretical and empirical analysis, with special reference to education. 3rd ed. Chicago (IL): University of Chicago Press; 1993.

[50] Schultz TW. Investment in human capital. Am Econ Rev. 1961;51(1):1-17.

[51] Acemoglu D, Autor D. Skills, tasks and technologies: Implications for employment and earnings. In: Ashenfelter O, Card D, editors. Handbook of labor economics. Vol. 4B. Amsterdam: Elsevier; 2011. p. 1043-1171.

[52] Autor D, Levy F, Murnane RJ. The skill content of recent technological change: An empirical exploration. Q J Econ. 2003;118(4):1279-1333. doi:10.1162/003355303322552801.

[53] Rogers EM. Diffusion of innovations. 5th ed. New York (NY): Free Press; 2003.

[54] Fichman RG. Going beyond the dominant paradigm for information technology innovation research. J Assoc Inf Syst. 2004;5(8):314-355. doi:10.17705/1jais.00054.

[55] Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis. 8th ed. Harlow: Pearson; 2019.

[56] Creswell JW, Creswell JD. Research design: Qualitative, quantitative, and mixed methods approaches. 5th ed. Thousand Oaks (CA): SAGE Publications; 2018.

[57] Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. Eur Bus Rev. 2019;31(1):2-24. doi:10.1108/EBR-11-2018-0203.

[58] Cohen J. Statistical power analysis for the behavioral sciences. 2nd ed. Hillsdale (NJ): Lawrence Erlbaum Associates; 1988.

[59] Nunnally JC, Bernstein IH. Psychometric theory. 3rd ed. New York (NY): McGraw-Hill; 1994.

[60] Bagozzi RP, Yi Y. On the evaluation of structural equation models. J Acad Mark Sci. 1988;16(1):74-94. doi:10.1007/BF02723327.

[61] Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39-50. doi:10.1177/002224378101800104.

[62] Ringle CM, Wende S, Becker JM. SmartPLS 4. Oststeinbek: SmartPLS GmbH; 2023. Available from: https://www.smartpls.com

[63] Hayes AF. Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. 3rd ed. New York (NY): Guilford Press; 2022.