Saudi Vision 2030: Government Investment in Ai and Its Impact on Job Creation

Sultan Mohammed M Alqahtani, Songsong Li[*], Qaiser Mohi Ud Din

School of Management, Harbin Institute of Technology, Harbin, China

*lisongsong@hit.edu.cn

Abstract. The present study analyzes the effect of governmental investment in AI technology on creating jobs in Saudi Arabia, framed within the scope of Vision 2030. The study employs Structural Equation Modeling (SEM) to examine the mediating effect of training and upskilling initiatives and the moderating impact of AI technology adoption rates. Vision 2030 underscores economic diversification and innovation, identifying AI as pivotal in reshaping the labor market. The results demonstrate that governmental investment in AI substantially increases employment creation directly and indirectly via improved training and upskilling initiatives. Increased AI adoption rates further reinforce this relationship, underscoring the necessity for a conducive environment for technological integration. The research presents empirical information regarding the relationship among policy-driven AI investments, workforce development, and technology uptake, delivering practical recommendations for policymakers. These findings highlight the strategic significance of customized investment and training frameworks to optimize AI's employment potential, enhancing the literature on AI-driven employment ecosystems by incorporating mediation and moderation effects.

Keywords: Saudi Vision 2030, Artificial Intelligence, Job Creation, Government Investment

1 Introduction

Artificial Intelligence (AI) is a revolutionary technology instigating substantial changes in global economies, especially employment. AI has become a pivotal priority in alignment with Saudi Arabia's Vision 2030, a strategic framework designed to diversify the economy and diminish reliance on oil [1]. Government investment in AI technologies is anticipated to stimulate innovation, generate new sectors, and transform worker dynamics. The current literature highlights AI's capacity to generate employment in new industries while simultaneously eliminating positions in conventional ones [2]. The degree to which these technologies can produce net beneficial employment results is contingent mainly upon intermediary factors, including training and upskilling initiatives [3]. Furthermore, the rate of AI technology adoption serves as a significant moderating

rates associated with more extensive employment effects [4]. This study employs a conceptual framework to analyze the mediating effect of training programs and the moderating influence of AI technology adoption on the link between government investment and employment creation in AI-related sectors. The central research inquiry is: How do training programs and the adoption rates of AI technology affect the efficacy of government investments in job creation under Saudi Vision 2030? This article seeks to enhance the discussion on AI-driven employment dynamics by including these factors in a Structural Equation Modeling (SEM) framework, providing strategic insights for policymakers and stakeholders in emerging economies. The results are anticipated to offer a detailed comprehension of how governmental investments in AI might facilitate sustainable job creation, thus advancing the overarching objectives of economic diversification and innovation outlined in Vision 2030.

2   Hypotheses

H1: Government investment in AI technology substantially enhances employment creation in AI-related sectors.

*Investments in AI foster innovation, entrepreneurship, and the emergence of new job positions, following Saudi Vision 2030's economic diversification objectives.

H2: Training and upskilling programs facilitate the connection between government investment in AI and job creation.

*Robust training programs enable the workforce to obtain the requisite skills for AI-driven industries, enhancing the efficacy of government investments.

H3: The adoption rate of AI technologies influences the correlation between government investment in AI and job creation, whereby increased adoption rates enhance this relationship.

*Regions with accelerated AI adoption are more prone to experience significant job creation as incorporating AI into industries becomes easier.

H4: Training and upskilling initiatives directly increase job creation in AI-related areas.

*Well-structured training efforts, independent of government investments, provide individuals with the technical skills necessary for AI positions, increasing employment opportunities.

H5: The efficacy of training and upskilling initiatives is contingent upon the adoption rate of AI technologies, with elevated adoption rates amplifying their influence.

*The prevalence of high AI adoption rates escalates the demand for skilled labor, thereby rendering training programs more effective in fostering job creation.

H6: Government investment in AI technology indirectly influences employment creation through training programs and the adoption rate of AI technologies.

*Investments alone are inadequate; their efficacy depends on supplementary elements such as workforce preparedness and the pragmatic execution of AI solutions.

3　　Methodology and Data Analysis

This quantitative analysis examines government AI technology investment, employment creation, training and upskilling programs, and AI adoption. A structured study of Saudi AI-related and traditional firms test the conceptual framework. The ability of quantitative tools like SEM to analyze complex interactions between numerous variables is well-known [5]. The target audience includes Saudi managers, HR professionals, and technology officers from technology, manufacturing, healthcare, and services firms. This supports prior research on multi-stakeholder perspectives in technology adoption and workforce transformation [6]. Stratified random sampling ensures sector representation, which improves generalizability [7]. The sample size of 156 participants (136 valid responses) is set using power analysis to provide statistical reliability for SEM analysis [8].

An online and paper-based survey collects data on government investment in AI technology, training and upskilling initiatives, AI adoption rate, and employment development. The questionnaire uses a 5-point Likert scale to quantify respondents' agreement or experience with these characteristics, a standard quantitative research method [9]. A 20-person pilot group tests the survey instrument for clarity, reliability, and validity. Cronbach's alpha measures internal consistency for each construct, revealing government investment in AI technology (0.85), training and upskilling programs (0.82), AI adoption rate (0.87), and employment creation (0.84). These results surpass the 0.7 internal consistency requirement, ensuring reliability [9]. The survey is sent to 200 participants, with 136 valid responses for the main study and 20 for the pilot test. This sample size matches SEM-based studies that propose 100–200 samples for robust analysis [10]. Respondent demographics provide a complete sample overview. The respondents work in technology (35%), manufacturing (25%), healthcare (20%), and services (20%). Managers make up 40%, HR professionals 30%, and technology officers 30%. Company sizes are small (1–50 personnel, 25%), medium (51–200, 35%), and large (201+, 40%). 20% have less than 5 years of experience, 30% have 5–10 years, 35% have 11–20 years, and 15% have more than 20 years. A robust and representative sample across industries, job functions, and firm sizes improves the study's validity and reliability [9]. This methodology is ideal for testing hypotheses and answering research problems.

The measuring approach is designed to evaluate the validity and reliability of the examined dimensions, encompassing government investment in AI technology, training, upskilling initiatives, the adoption rate of AI technologies, and job creation. Each concept is assessed by several indicators obtained from the survey, with items evaluated on a 5-point Likert scale from "strongly disagree" to "strongly agree." The model undergoes Confirmatory Factor Analysis (CFA) evaluation to ascertain construct validity, encompassing both convergent and discriminant validity. Convergent validity is determined by evaluating factor loadings (all >0.70), average variance extracted (AVE > 0.55), and composite reliability (all > 0.80), following suggested benchmarks [10]. Discriminant validity is evaluated by the Fornell-Larcker criterion, which requires that each construct's square root of the Average Variance Extracted (AVE) exceeds its correlations with other constructs. Cronbach's alpha values, between 0.82

and 0.86, affirm internal consistency dependability, surpassing the suggested criterion of 0.7 [10]. Conventional fit indices assess the model's fitness: Chi-square/df ratio (2.35), Comparative Fit Index (CFI = 0.92), Tucker-Lewis Index (TLI = 0.91), and Root Mean Square Error of Approximation (RMSEA = 0.06), all suggesting a well-fitting model [8]. These findings validate the robustness and appropriateness of the measurement model, affirming its usefulness for Structural Equation Modeling (SEM) research.

The hypothesis testing utilized a Structural Model to evaluate the components' direct, indirect, and moderating links. All hypotheses were validated, with statistically significant outcomes demonstrating the resilience of the conceptual model. **H1:** The findings validated a substantial positive correlation between governmental investment in AI and employment generation (β = 0.45, t = 5.12, p < 0.01, 95% CI [0.33, 0.57]). The standard deviation of the construct was 0.14, with a mean score of 4.1. This finding underscores the essential function of government investment in stimulating employment development by establishing AI-intensive positions. These findings correspond with previous studies indicating that investments in emerging technologies foster economic diversification and innovation [1]. **H2:** The training programs had a significant mediating impact (indirect effect = 0.28, t = 4.37, p < 0.01, 95% CI [0.17, 0.39]). The standard deviation for training and upskilling programs was 0.16, with a mean score of 4.0. This outcome underscores the necessity for focused upskilling to reconcile the disparity between emerging technological requirements and workforce competencies in alignment with the conclusions of [4]. **H3:** The moderating influence of AI adoption rates was substantial (β = 0.30, t = 3.85, p < 0.01, 95% CI [0.20, 0.40]). The standard deviation for AI adoption rates was 0.12, with a mean score of 3.9. This outcome indicates that increased adoption rates enhance the beneficial effect of government investments on employment generation. Organizations with enhanced AI integration are more prone to provide employment possibilities owing to the increased need for skilled labor. **H4:** A direct correlation between training programs and job creation was established (β = 0.40, t = 4.96, p < 0.01, 95% CI [0.29, 0.51]). The standard deviation for creating jobs was 0.13, with a mean score of 4.2. The finding highlights the significance of training programs in preparing the workforce for emerging AI-driven positions, irrespective of governmental funding. The outcome supports previous research promoting workforce preparedness in the AI era [6]. **H5:** The correlation between training programs and AI adoption rates was substantial (β = 0.35, t = 4.15, p < 0.01, 95% CI [0.24, 0.46]). The standard deviation for this interaction was 0.15, with a mean score of 3.8. The finding underscores the necessity for staff development to be synchronized with technological preparedness to optimize effectiveness. **H6:** The overall indirect impacts of training programs and AI adoption rates were substantial (total indirect effect = 0.32, t = 4.52, p < 0.01, 95% CI [0.22, 0.42]). The cumulative standard deviation for the indirect effects was 0.14, with a mean score 4.0. This shows that government investments alone are inadequate; their efficacy is influenced and tempered by worker readiness and technological assimilation factors.

4   Conclusion

This paper offers a fundamental examination of the correlation between governmental investment in AI technology and job creation, emphasizing the objectives of Saudi Vision 2030 on economic diversification and workforce change. The research utilizes a conceptual framework and Structural Equation Modeling (SEM) to elucidate critical dynamics, including the mediating influence of training and upskilling programs and the moderating impact of AI technology adoption rates. The findings highlight that government investment is a crucial catalyst for employment growth in AI-related sectors, and its efficacy is enhanced when combined with comprehensive training programs and a high rate of AI adoption across industries. This research could examine how government investment and AI adoption rates affect different industries in addition to AI's general impact. Healthcare, industry, and finance have distinct AI adoption rates, affecting employment growth and displacement. Some businesses profit from AI by generating new roles, while others, especially manual labor, lose jobs to automation. These sector-specific dynamics would inform targeted policy measures. The results are significant for policymakers, industry leaders, and educational institutions, as they offer practical suggestions for linking AI investments with workforce preparation to facilitate sustained job development.

Notwithstanding its contributions, this research has limits that offer additional research opportunities. The research depends on survey data that reflects opinions and self-reported experiences, although it lacks real-time or longitudinal information regarding AI's influence on job markets. Since self-reported data is subjective, it cannot reflect real-time or longitudinal labor market developments. Future studies could include longitudinal or real-time data to understand further how AI investments affect employment creation. This would help track AI's effects on job markets as implementation continues. In addition to quantitative analysis, qualitative research approaches like interviews, focus groups, and case studies can reveal sector-specific AI adoption hurdles and enablers. These methodologies can reveal employee and employer experiences, workforce attitudes, AI technology cultural acceptability, and workforce upskilling problems. This qualitative data would enhance the comprehension of how various stakeholder groups perceive and react to government-led AI efforts.

A further direction for future study involves investigating the impact of particular AI applications, including automation, robotics, natural language processing, and machine learning, on job outcomes. AI technologies like robotics, automation, natural language processing (NLP), and machine learning affect employment positions across industries; therefore, understanding their effects is crucial. Automation and robotics replace physical work, while machine learning and NLP provide data analysis and customer service jobs. Considering these technologies by sector would provide a more nuanced understanding of AI's contribution to employment development. This will enable researchers to analyze the intricate effects of several AI technologies on various job categories, differentiating between occupations enhanced by AI and those at risk of displacement. Moreover, examining the interaction between AI adoption and additional factors, including cultural readiness, organizational leadership, and global technical trends, would yield a more thorough understanding of the variables influ-

encing AI-driven job creation. The effects of AI on societal and geographical inequities in employment prospects require additional investigation. Future studies should examine how AI adoption influences employment inequalities based on geography and society. Due to infrastructure constraints, rural places may struggle to adopt AI, whereas urban areas may gain. AI adoption may also worsen gender and socioeconomic inequality in tech jobs. Understanding how demographics, including vulnerable communities, are affected will help policymakers make more inclusive and equitable decisions. Future research may investigate the impact of AI adoption on job dynamics in rural and urban settings, gender parity in technology-driven positions, and prospects for marginalized demographics. Comprehending these differences would empower policymakers to formulate more inclusive and equitable tactics for utilizing AI to assist all societal segments.

Declaration of AI and AI-assisted technologies in the writing process: During the preparation of this work, the author used ChatGPT to refine the idea and language of the article. After using this tool, the author reviewed and edited the content as needed and took full responsibility for the publication's content.

References

1. B. Cheng, H. Lin, and Y. Kong, "Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting," J. Bus. Res., vol. 164, p. 113987, 2023, doi: 10.1016/j.jbusres.2023.113987.
2. R. Madan and M. Ashok, "AI adoption and diffusion in public administration: A systematic literature review and future research agenda," Gov. Inf. Q., vol. 40, no. 1, p. 101774, 2023.
3. Q. Mohi Ud Din and L. Zhang, "Unveiling the Mechanisms through Which Leader Integrity Shapes Ethical Leadership Behavior: Theory of Planned Behavior Perspective," Behav. Sci. (Basel)., vol. 13, no. 11, p. 928, 2023, doi: 10.3390/bs13110928.
4. J. Zeng et al., "Linking ethical leadership to employee voice: The role of trust," Soc. Behav. Pers., vol. 48, no. 8, pp. 653–663, Jan. 2020, doi: 10.2224/sbp.9200.
5. M. D. C. Tongco, "Purposive sampling as a tool for informant selection," Ethnobot. Res. Appl., vol. 5, pp. 147–158, 2007, doi: 10.17348/era.5.0.147-158.
6. V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," Decis. Sci., vol. 39, no. 2, pp. 273–315, 2008.
7. J. W. Creswell and J. D. Creswell, Research design: Qualitative, quantitative, and mixed methods approaches. Sage Publications, 2017.
8. R. B. Kline, Principles and practice of structural equation modeling. Guilford Publications, 2023.
9. A. Leguina, "A primer on partial least squares structural equation modeling (PLS-SEM)," Int. J. Res. Method Educ., vol. 38, no. 2, pp. 220–221, 2015, doi: 10.1080/1743727x.2015.1005806.
10. J. F. Hair, G. T. M. Hult, C. M. Ringle, M. Sarstedt, and K. O. Thiele, "Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods," J. Acad. Mark. Sci., vol. 45, pp. 616–632, 2017.