Analyzing The Impact Of AI-Driven Automation On Labor Markets In Sichuan Province Within The Context Of The Digital Economy

Qing Jiang

College of Economics and Manageme, Ya'an Polytechnic College, No. 659, Xuedao Street, Ya'an Economic and Technological Development Zone, Sichuan, China, Postal Code: 625100

Corresponding author. E-mail: Qing_Jiang76@outlook.com, Qing_Jiang76@outlook.com

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Focused on the fast-evolving Artificial Intelligence (AI)-driven automation and digital economy technologies, the research identifies a literature gap, as it ignores the provincial nature of Sichuan, particularly the issues of job displacement, skills imbalances, and inequality. A region-specific model was developed and tested using data from 500 respondents through Partial Least Squares Structural Equation Modeling (PLS-SEM). The growing role of Artificial Intelligence-driven Predictive technologies, where intelligent maintenance systems enhance operational efficiency while simultaneously influencing Workforce Adaptability and Labour Market Stability within the context of the Digital Economy. Results show that AAI negatively influences LMS ($\beta = -0.41$, $p < 0.001$), while DED positively influences LMS ($\beta = 0.696$, $p < 0.001$). DED also positively affects WA ($\beta = 0.515$, $p < 0.001$), which further contributes to LMS. The model demonstrates strong reliability and validity, with satisfactory Cronbach's alpha, AVE, HTMT, and SRMR values.

Keywords: Artificial Intelligence Automation Intensity, Digital Economy Development, Labour Market Stability, Workforce Adaptability, Partial Least Squares Structural Equation Modeling.

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1. Introduction

The acceleration of the rates of development of AI and automation technologies has become one of the features of the global digital [1]. This metamorphosis is pegged on several causes and factors. The Chinese government has specifically focused its strategic attention on the digital economy development [2]. The rising labour costs, demographic shifts, and the necessity to possess an industry that is globally competitive [3, 4]. Sichuan Province a strategically important region for examining the labour market implications of AI-driven automation and digital economy development. As one of China' s major inland provinces, Sichuan has experienced rapid growth in digital infrastructure, intelligent manufacturing, e-commerce platforms.

The model provides a more detailed perspective on the implications of automation by combining quantitative data with a local knowledge of the local industries [5]. The operational efficiency while simultaneously reshaping workforce skill requirements and labour market dynamics [6, 7]. Sichuan Sphere denotes a distinctive regional context within China' s digital economy because of its diversified economic structure, agriculture, and rapidly expanding digital industries. Unlike the highly developed coastal provinces, Sichuan is an inland province undergoing an accelerated digital transformation while maintaining a diverse industrial structure and workforce composition. These characteristics create unique labour market dynamics in which AI-driven automation, digital economy development, and workforce adaptability interact differently across sectors.

Research Questions

- **RQ1:** How does AAI influence LMS among workers in Sichuan Province?
- **RQ2:** What is the result of DED on Labour Market Stability?
- **RQ3:** Does WA mediate the relationship amongst DED and Labour Market Stability?
- **RQ4:** Does WA moderate the impact of AAI on Labour Market Stability?

Hypotheses Development

Hypothesis development refers to the process of developing statements or assumptions.

- **H1: AAI negatively affects Labour Market Stability.**
  - Empirical labour research often indicates automation increases the risk of job displacement and insecurity.
- **H2: DED positively affects Labour Market Stability.**
  - Digital Economy Development is expected to enhance Labour Market Stability by creating new employment opportunities, improving productivity, supporting business innovation, and facilitating workforce participation in emerging digital sectors.
- **H3: WA mediates the connection between DED and Labour Market Stability.**
  - Digital economy growth improves stability through improved adaptation skills among workers.
- **H4: WA positively moderates the relationship between AAI and Labour Market Stability.**
  - Workers with better adaptability may experience less negative impact from automation.

Paper Organization

The paper is organized into five sections:

- **Section 1:** Presents the background, research gap, research questions, and hypotheses.
- **Section 2:** Reviews the related literature and identifies research gaps.
- **Section 3:** Describes the methodology.
- **Section 4:** Presents the results.
- **Section 5:** Discusses the findings, concludes the study, and outlines limitations and future research directions.

2. Related works

Huang et al. [8] studied the returning migrant worker and its effect on land transfer-in behavior of the farmers in Sichuan Province through IV-Probit and IV-Tobit models. Although their results have illuminated the importance of risk tolerance. Du and Yang [9] changed their study to ethnic-minority counties, exploring the role of New-Quality Productivity (NQP) in promoting sustainability in the Economic-Social-Environmental System (ESES). Wu et al. [10] studied the industrial robot adoption in Chinese cities, and revealed that the penetration of robots lessens labour misallocation. Ma et al. [11] disaggregated the occupational changes among rural households. These occupational changes overlap with Liu et al. [12], who examined the topic of digital economy inequality and employment quality. Du et al. [13], who identified the effect of robot penetration on the labour income share as a way to address the distortive influence ignored by substitution-based studies and support the role of fair integration of technology. Similar to robotics, Lu et al. [14] explored the drive behind ICT advancement and construction labour productivity, and human resources and R&D were found to be the primary contributors, Liang et al. [15] evaluated the labour shortages due to the epidemic.

2.1. Conceptual Framework

The proposed conceptual framework integrates labour economics theory and the technological adaptation perspective to explain labour market transformation under AI-driven automation. Labour economics explains employment stability, job restructuring, and evolving skill requirements, while technological adaptation emphasizes workforce adaptability.

The digital economy influences labour market stability through interconnected pathways. Improvements in digital infrastructure, e-commerce, and data-driven technologies enhance productivity and efficiency. Digital transformation creates new employment opportunities while promoting skill acquisition, reskilling, and workforce adaptability.

As shown in Figure 1, the two key independent variables influencing Labour Market Stability (LMS) are AI and the Digital Economy (DED).

3. Methodology

3.1. Construct Operationalization and Measurement

Operationalization of the four constructs was done based on several items that used the five-point Likert scale of

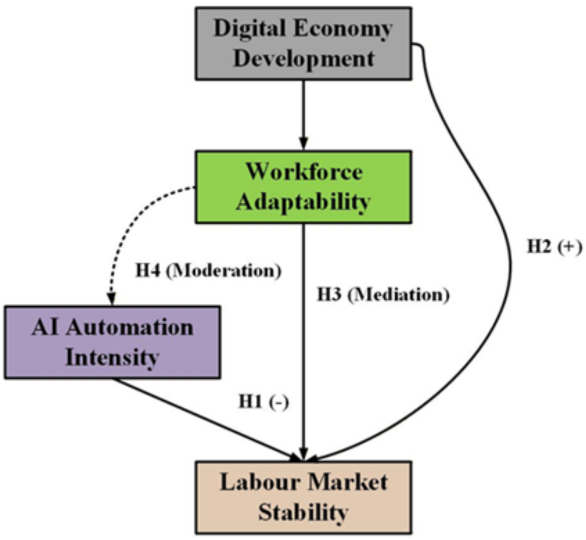

Fig. 1. Conceptual Framework

strongly disagree to strongly agree. The proposed framework also considers the relevance of AI Smart Manufacturing Systems, as intelligent maintenance technologies contribute to digital transformation, workforce adaptability, and sustainable labour market outcomes. The 35-item questionnaire underwent pilot testing to assess item clarity, relevance, and comprehensibility. The pilot participants were selected from groups representing the target population, and feedback was obtained regarding question wording, response interpretation, and overall survey structure. Based on the feedback received, minor revisions were made to improve clarity and reduce potential ambiguity.

Figure 2 above provides the general research design and methodological workflow. It commences with the quantitative survey. Google questionnaires with a five-point Likert scale are used to sample 500 respondents who work in the labour markets in Sichuan Province.

3.2. Research Design

A cross-sectional research design was adopted because the study aims to examine the relationships among AI Automation Intensity, Digital Economy Development, Workforce Adaptability, and Labour Market Stability at a specific point in time. This approach is appropriate for capturing current perceptions of employees, employers, and policymakers regarding ongoing technological and economic changes in Sichuan Province. Compared with longitudinal designs, which require repeated observations over extended periods to assess changes over time, the cross-sectional approach provides a practical and efficient means of evaluating the proposed relationships within the available timeframe and resources.

Sichuan Province encompasses diverse geographical environments that include both highly urbanized cities and extensive mountainous regions, creating differences in workforce development conditions across the province. Variations in transportation networks, digital infrastructure, educational resources, and vocational training opportunities contribute to unequal access to skill development and technology-oriented learning. These regional characteristics influence employees' capacity to acquire new competencies and adapt to changing technological requirements, particularly in AI-enabled work environments.

3.3. Sampling Structure

The labour market stakeholders across Sichuan Province, including employees, employers, and policymakers. The survey was distributed electronically through professional networks, organizational contacts, industry associations, and government-related communication channels to reach participants with relevant experience in labour market and digital transformation issues. The overall size of the sample was 500 respondents, 40% of whom were employees, 32% employers and 28% policymakers. The demographic characteristics of the respondents reflect the regional economic environment of Sichuan Province, where Chengdu serves as the primary centre for digital transformation and technological innovation. Rapid growth in AI applications, smart manufacturing, and digital infrastructure has increased employees' exposure to digitally enabled workplaces, shaping perceptions of automation, adaptability, and labour market stability across sectors.

3.4. Study Variables

This study examines the direct effects of AAI and DED on Labour Market Stability (LMS), the mediating role of Workforce Adaptability (WA) in the relationship between DED.

3.5. Statistical Design

The statistical design of the study is a response of 500 participants that will be processed in SmartPLS to test the proposed labour market model. The potential influence of common method bias and response bias, several procedural remedies were implemented during data collection. The questionnaire employed clear and neutral wording, and construct items were organized into separate sections to minimize response pattern tendencies. During data analysis, collinearity statistics were examined, and all VIF values remained below the recommended threshold, suggesting

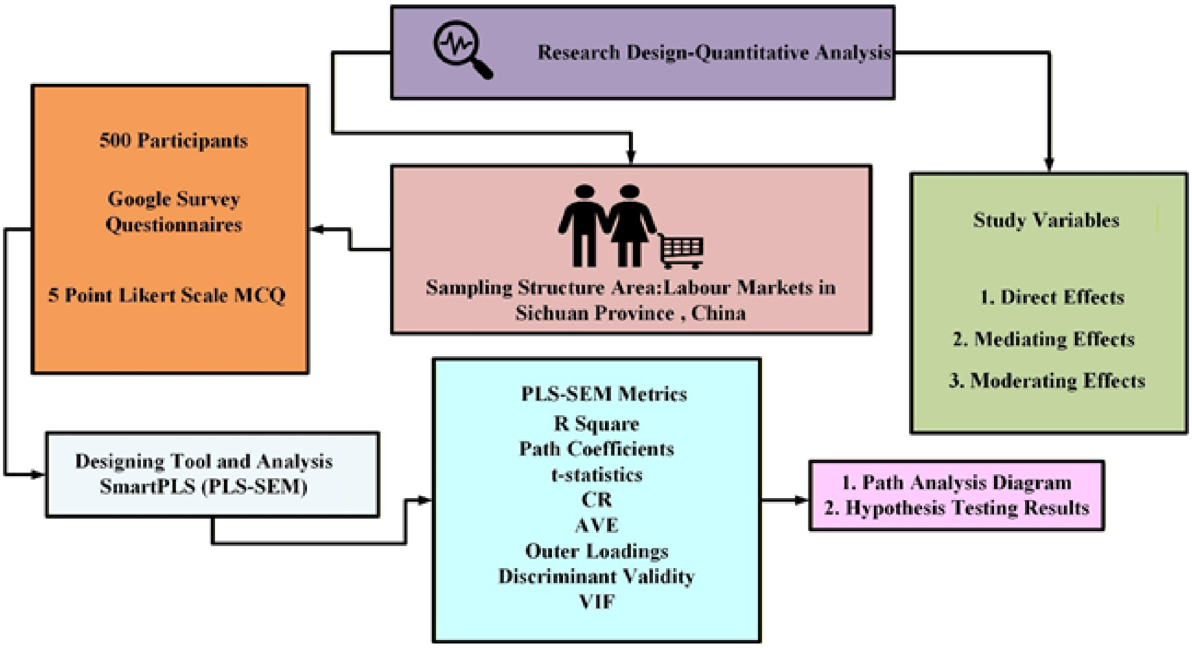

Fig. 2. Research Design and Methodology Flow

that common method bias was unlikely to pose a serious threat to the validity of the findings.

4. Results

The analysis of the results will commence with the demographical data of the respondents in the results section and the summary of the results will be in form of the descriptive statistics.

4.1. Descriptive Statistics

This section provides a general description of respondents. The following Table 1 descriptive statistics of the four constructs used in the research, i.e.: AAI, DED, WA, and LMS.

4.2. Measurement Model Assessment

The Q6 (0.649), Q12 (0.652), and Q17 (0.59) exhibited lower outer loadings than the remaining indicators, these values remained within the acceptable range for exploratory research. Furthermore, the removal of these items did not result in substantial improvements in composite reliability or average variance extracted. The discriminant of the measurement model was confirmed using both the Fornell–Larcker criterion and the HTMT ratio. The Fornell–Larcker that the square root of the AVE for each construct is greater than its correlations with the remaining constructs, demonstrating satisfactory discriminant validity.

Table 2 shows AAI, DED, WA, and LMS measurement system reliability together with internal validity assessment.

4.3. Structural Model Assessment

The positive moderating effect of AAI_WA on Labour Market Stability indicates that workforce adaptability reduces the adverse consequences of AI-driven automation. Employees who possess stronger adaptive capabilities, continuous learning orientation.

4.4. Model Fit Indices

The goodness of fit of the proposed structural model was using multiple model fit indicators. The SRMR values of 0.077 for the saturated model and 0.084 for the estimated model indicate an acceptable level of model fit, as they close to the recommended threshold of 0.08.

The NFI values of 0.704 and 0.700 suggest a moderate level of model fit when compared with the commonly accepted benchmark of 0.90. SRMR, d_ULS, d_G, and Chi-square values in Table 3.

4.5. Hypothesis Testing

As it is observed in Table 4, AAI influences LMS negatively ($b = -0.41$, $t = 6.875$, $p < 0.001$).

Table 1. Descriptive Statistics and Normality Assessment

Variable	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
AAI	500	1.63	3.88	2.7835	0.45405	-0.214	-0.382
DED	500	1.78	4.44	3.0202	0.41653	0.186	-0.295
WA	500	1.44	4.67	3.0071	0.55922	0.092	-0.417
LMS	500	1	4.89	3.3789	0.61087	-0.356	0.241

Table 2. Outer Loadings for AAI, DED, WA and LMS

Indicator Path	Outer Loadings
AAI_WA ← AAI_WA	1.000
Q10 ← AAI	0.762
Q11 ← AAI	0.722
Q12 ← AAI	0.652
Q13 ← AAI	0.761
Q14 ← DED	0.759
Q15 ← DED	0.776
Q16 ← DED	0.751
Q17 ← DED	0.590
Q18 ← DED	0.761
Q19 ← DED	0.730
Q20 ← DED	0.740
Q21 ← WA	0.782
Q22 ← WA	0.768
Q23 ← WA	0.723
Q24 ← WA	0.707
Q25 ← WA	0.679
Q26 ← WA	0.711
Q27 ← WA	0.790
Q28 ← LMS	0.844
Q29 ← LMS	0.839
Q30 ← LMS	0.767
Q31 ← LMS	0.783
Q32 ← LMS	0.783
Q33 ← LMS	0.753
Q34 ← LMS	0.812
Q35 ← LMS	0.820
Q6 ← AAI	0.649
Q7 ← AAI	0.778
Q8 ← AAI	0.778
Q9 ← AAI	0.670

Table 3. Model Fit

Fit Measure	Saturated Model	Estimated Model
SRMR	0.077	0.084
d_{ULS}	2.974	3.465
d_G	1.202	1.210
Chi-square	575.678	583.441
NFI	0.704	0.700

4.6. Path Analysis

Path Analysis illustrates the direct, indirect and moderating interactions among AAI, DED, WA and LMS.

The structural equation model is represented in Figure 3 above, graphically, such that the relationship between AAI, DED, WA, and LMS and the moderating variable AAI-WA.

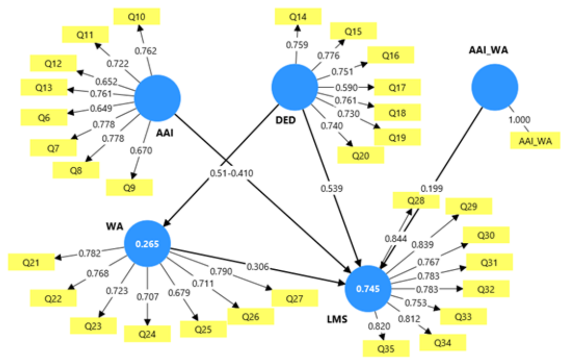

Fig. 3. SEM Path Diagram

4.7. Discussion

AI-driven automation extends earlier automation by combining task mechanization with intelligent decision-making and adaptive processes. While traditional automation main routine manual work, AI increasingly transforms cognitive and analytical jobs.

The negative effect of AI Automation Intensity on labour market stability reflects Sichuan Province's heterogeneous industrial development. While digitally advanced sectors benefit from AI adoption, traditional and labour-intensive industries. The workforce adaptability can be strengthened through targeted training programmes and supportive education policies focused on digital skill development. Continuous reskilling and upskilling initiatives in areas such as AI applications, data analytics, digital platforms, and emerging technologies can improve employees' capacity by expanding digital literacy programmes and technology-oriented training opportunities.

Table 4. Hypothesis Testing

Hypothesis	Relationship	Path Coefficient (β)	T-value	P-value	Decision
H1	AAI $\rightarrow$ LMS	-0.410	6.875	< 0.001	Supported
H2	DED $\rightarrow$ LMS	0.696	15.063	< 0.001	Supported
H3	DED $\rightarrow$ WA	0.515	6.978	< 0.001	Supported
H4	WA $\rightarrow$ LMS	0.306	5.239	< 0.001	Supported

5. Conclusion and future work

Finally, it can be stated that this paper proves the fact that the impact of AI-based automation is a threat to the LMS in the Sichuan Province, while the growth of the digital economy and the adaptability of the labour force are the factors that can mitigate the shocks. By applying a specific scheme for the area and using the SmartPLS (PLS-SEM) tool for the content analysis of the survey from 500 participants. These findings also have practical implications for Smart Manufacturing Systems, to workforce adaptability, the effective adoption of intelligent maintenance technologies and enhancing organizational resilience during digital transformation. Future research may extend the present study by conducting comparative analyses across different sectors, including manufacturing, agriculture, services, and digital industries, to identify variations in labour market responses to AI-driven automation. Additional investigation of urban-rural employment differences would provide a deeper understanding of how technological transformation affects workforce adaptation across diverse regional contexts.

Declarations

Data availability

Click here to open the Google Form

Conflicts of interest

The author declares there are no conflicts of interest regarding the publication of this paper.

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Author contributions

Qing Jiang conceptualized the study, designed the methodology, conducted data collection and analysis, and wrote and revised the manuscript.

Ethical approval

All procedures performed in this study involving human participants were conducted in accordance with ethical standards. Ethical approval was obtained from the relevant institutional review body of Ya'an Polytechnic College.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

Consent to publication

The author confirms that all participants provided consent for anonymized data to be used for research and publication purposes.

Competing interests

The author declares that there are no competing interests.

Code availability

The analytical code used in this study is available from the corresponding author upon reasonable request.

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