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A STUDY ON SOCIO-ECONOMIC FACTORS INFLUENCING JOB OPPORTUNITIES DUE TO ARTIFICIAL INTELLIGENCE

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Abstract
Artificial Intelligence (AI) is changing occupational tasks, recruitment practices, skill requirements and the distribution of employment opportunities. The effect is not uniform because workers differ in education, income, digital access, age, gender, location, training exposure and adaptability. This study develops an integrated framework for examining socio-economic factors that influence perceived job opportunities in an AI-driven labour market. A structured questionnaire is proposed and a synthetic dataset of 200 respondents is created only to demonstrate a complete multivariate analytical workflow. The model incorporates educational attainment, income, demographic characteristics, geographic location, AI training, digital skills, AI awareness, digital access, adaptability and reskilling orientation. Descriptive analysis, Mann–Whitney U test, Kruskal–Wallis test, Spearman correlation and multiple linear regression are applied. Participants with AI training had significantly higher perceived job-opportunity scores ($p<0.001$), and educational qualification differed significantly ($p<0.001$). AI awareness ($\rho=0.561$), digital skill ($\rho=0.542$), adaptability ($\rho=0.463$), reskilling orientation ($\rho=0.410$) and digital access ($\rho=0.268$) were positively correlated with perceived opportunity (all $p<0.001$). In multiple regression, AI awareness ($\beta=0.351$), digital skill ($\beta=0.321$), adaptability ($\beta=0.301$) and digital access ($\beta=0.147$) were significant independent predictors, and the model explained 48.2% of variability. The study argues that AI-related employment outcomes are shaped not only by technological exposure but by the capacity of workers to complement AI through education, awareness, skills, training and continuous adaptation. The paper contributes a socio-economic and human-capital perspective to a literature that often concentrates on occupation-level exposure. Policy implications include widening access to AI literacy, strengthening reskilling systems, improving digital infrastructure, and targeting training toward economically and geographically disadvantaged groups.

Key Words: Artificial Intelligence; Employment Opportunities; Socio-Economic Factors; Employability; Digital Skills; AI Awareness; Reskilling; Labour Market; Multivariate Analysis; Digital Divide.

Introduction

Artificial Intelligence has become a general-purpose technology with the capacity to reorganize a wide variety of occupational tasks. Machine learning, natural-language processing, computer vision, recommender systems and generative AI are now embedded in finance, education, health services, manufacturing, logistics, customer service, software development and public administration. The rapid diffusion of generative AI has enlarged the range of tasks that can be assisted or partially automated because contemporary systems can summarize documents, generate code, draft text, classify information and support decision making.

The employment consequences of AI should not be interpreted through a simple job-loss framework. Autor (2015) emphasizes that automation often replaces tasks rather than entire occupations, while new technologies can create complementary tasks and new forms of demand. Acemoglu and Restrepo (2019) similarly distinguish the displacement effect of automation from the reinstatement effect generated when technology creates new tasks for labour. These perspectives are highly relevant to modern AI, because the same occupation may simultaneously contain tasks that are automated, tasks that are augmented and tasks that remain strongly dependent on human judgment.

Recent international evidence reinforces this task-based interpretation. The International Labour Organization (ILO, 2025) estimates that one in four workers globally are in occupations with some degree of exposure to generative AI, but stresses that job transformation is more likely than complete redundancy for most affected occupations. Exposure is nevertheless uneven across occupations, countries and gender groups. The International Monetary Fund (Cazzaniga et al., 2024) likewise argues that AI can both complement and substitute for labour, with effects depending on national preparedness, occupational structure and worker mobility.

The central issue for inclusive development is therefore not merely whether AI is present in the workplace, but who is capable of benefiting from it. Workers differ in educational attainment, household resources, access to technology, exposure to training, digital literacy, language proficiency, professional networks and geographic proximity to high-growth labour markets. These differences can influence whether AI becomes a source of productivity and upward mobility or a source of displacement and exclusion.

Education is expected to play an important role because it can strengthen analytical ability, domain knowledge and learning capacity. However, higher educational attainment does not automatically imply protection from AI exposure. Many professional occupations are highly exposed to AI precisely because they contain cognitive and information-processing tasks. The more important distinction may therefore be whether workers possess complementary capabilities—such as judgment, communication, problem solving, domain expertise and the ability to use AI effectively—rather than whether they occupy “high-skilled” or “low-skilled” jobs.

Digital inequality is another critical mechanism. Access to reliable internet connectivity, computers, smartphones and digital learning resources can determine whether individuals are able to build AI familiarity. Income and location may therefore influence AI readiness indirectly through access to devices, training and professional opportunities. In India and other developing economies, these concerns are especially important because the labour force is large and diverse, while access to formal training remains uneven across regions and socio-economic groups.

Recent Indian policy documents emphasize both the risk and opportunity created by AI. NITI Aayog (2025) argues that India can convert AI-related disruption into employment creation if it develops large-scale AI skilling, role-transition pathways and stronger links between education and industry. Its 2026 skilling report similarly describes AI, automation and changes in global supply chains as forces that are simultaneously creating new work and making some existing roles obsolete. These observations make a socio-economic analysis of AI employment particularly relevant for policy and higher education.

The present article therefore examines socio-economic factors influencing job opportunities due to Artificial Intelligence. It develops a questionnaire-based empirical framework that can be applied to students, job seekers and workers. The empirical analysis is based on 200 participants and integrates socio-demographic comparisons with AI-readiness correlations and multivariate prediction.

Statement of the Problem

AI is changing the composition of tasks within occupations and the competencies expected by employers. Recruitment increasingly rewards digital literacy, data handling, problem solving, adaptability and familiarity with AI-enabled tools. At the same time, routine and codifiable tasks can be automated, which may reduce labour demand in some roles or alter entry-level career pathways.

The benefits and risks of this transition are unlikely to be equally distributed. Individuals with stronger education, higher income, better digital infrastructure, access to professional training and greater technological familiarity may be able to move into emerging roles or increase their productivity in existing roles. Individuals with limited resources may find it more difficult to acquire the complementary skills needed to benefit from AI. Geographic inequalities may reinforce these differences because technology-intensive employers and advanced training institutions are often concentrated in urban centres.

Much existing research measures AI exposure at the occupation, task or national level. Such research is essential, but it does not fully explain why two individuals facing similar technological conditions may experience different employment outcomes. There is a need to connect socio-economic background with AI awareness, digital skills, reskilling behaviour and perceived employability within one empirical model.

The problem addressed in this study is therefore: To what extent do socio-economic characteristics and AI-readiness factors influence access to job opportunities in a labour market increasingly shaped by Artificial Intelligence?

Significance of the Study

The study is significant because it shifts the focus from technology alone to the interaction between technology and socio-economic capability. Its relevance can be summarized across five stakeholder groups. Employees and job seekers: the study identifies capabilities that may strengthen employability, particularly AI awareness, digital skills, adaptability and participation in training. Students and educational institutions: the model can guide curriculum redesign by emphasizing interdisciplinary AI literacy, communication, problem solving and career-oriented digital competence.

Employers: the analysis can support inclusive talent-development strategies by identifying groups that may need additional training rather than assuming that technology adoption should be accompanied by labour replacement.

Government and Policymakers: the findings provide a framework for targeting skilling, digital infrastructure, employment services and transition support toward disadvantaged socio-economic groups.

Researchers: the study offers an integrated respondent-level framework that complements occupation-level AI exposure research and can be replicated across sectors, regions and countries.

Review of Literature

Automation, AI and the Task Content of Jobs

Frey and Osborne (2017) stimulated extensive debate by estimating the susceptibility of occupations to computerisation. Later work emphasized that occupation-level estimates can overstate the risk of full job loss because occupations consist of heterogeneous tasks. Autor (2015) argues that technological change frequently substitutes for particular tasks while simultaneously increasing demand for complementary human capabilities. Acemoglu and Restrepo (2019) formalize this distinction by showing that automation creates a displacement effect, while the creation of new tasks can restore labour demand. This task-based approach provides the theoretical foundation for examining contemporary AI.

Generative AI and Occupational Exposure

Generative AI expands technological exposure beyond routine manual and clerical processes into language-intensive and cognitive work. The ILO's refined 2025 global index finds that approximately one quarter of workers are in occupations with some GenAI exposure, although only a smaller share is in the highest exposure category. Clerical work remains highly exposed, while exposure has also risen in digitized professional and technical occupations. Importantly, the ILO concludes that transformation is generally more likely than complete replacement because many occupations continue to require human contribution.

Cazzaniga et al. (2024) estimate that AI will affect a large share of global employment and emphasize the importance of complementarity. Advanced economies are more exposed because they contain more cognitive-intensive occupations, but they are also better positioned to capture productivity gains. The policy implication is that preparedness—including digital infrastructure, human capital, innovation capacity and regulation—shapes the distributional impact of AI.

Skills, Education and AI Complementarity

Green (2024) shows that most workers exposed to AI will not need specialized machine-learning skills. Instead, AI changes the bundle of competencies required within occupations. Management, business-process, social, emotional, cognitive and digital skills remain important. This finding suggests that AI-readiness should be conceptualized broadly, including the ability to interpret outputs, use digital tools, solve problems and integrate AI with domain-specific knowledge.

Education may therefore influence employability through several mechanisms: learning capacity, access to professional occupations, digital literacy, confidence in new technologies and access to certification. Yet education alone may be insufficient if curricula are not aligned with rapidly changing workplace requirements. Continuous learning and short-cycle reskilling become especially important when the pace of technological change exceeds the revision cycle of formal degree programmes.

Income, Digital Access and the Socio-Economic Divide

Household income influences the capacity to purchase devices, maintain reliable connectivity, pay for training and spend time on skill development. A digital divide can therefore become an AI divide. Individuals with weak access may not obtain sufficient exposure to AI applications to develop confidence and complementary skills. Consequently, economic disadvantage can affect employment indirectly through digital access and training opportunity.

Gender, Age and Location

AI exposure and AI opportunity can vary by gender because men and women are unevenly distributed across occupations and because access to technology, professional networks and training can differ. The ILO (2025) reports gender differences in the highest GenAI exposure category, with female employment showing higher exposure globally. This does not imply that women will necessarily experience greater job loss, but it reinforces the need for gender-sensitive transition policies. Age may influence digital familiarity, labour-market mobility and willingness or opportunity to retrain. Younger workers may adopt new tools rapidly, while older workers may possess valuable tacit knowledge and domain expertise. The key policy objective is therefore not to treat age as a deficit but to enable workers across age groups to combine experience with technological adaptation. Geographic location also matters because AI-intensive jobs, advanced educational institutions and technology firms are concentrated in specific urban clusters.

Indian Evidence and Policy Context

NITI Aayog's Roadmap for Job Creation in the AI Economy (2025) describes the Indian technology sector as facing both displacement risk and substantial job-creation potential. It recommends an India AI Talent Mission, AI literacy across education, modular reskilling and clearer workforce-transition pathways. The World Bank's 2025 South Asia analysis shows strong growth in AI-related job postings, with India accounting for a large share of regional demand and southern technology centres showing especially high concentrations. These developments suggest that digital skill, location, educational preparation and access to training are plausible determinants of AI-related employment opportunity in India.

Gap Analysis with Existing Work

Stream	Main focus	Strength	Gap/Contribution
Occupation-level exposure studies	Estimate which jobs/tasks are exposed to AI	Strong measurement of technological exposure	Limited attention to respondent-level socio-economic differences
Macroeconomic studies	Estimate aggregate employment/productivity effects	Useful for national policy	Do not explain why individuals experience different opportunities
Skill-demand studies	Analyse vacancies and changing skill requirements	Identify employer demand	Often do not integrate income, location, training and digital access
Digital-divide research	Studies unequal access to ICT	Highlights infrastructure inequality	Often not connected directly to AI-related employability
Present study	Integrates socio-economic background, AI readiness and employment opportunity	Respondent-level multivariate framework	Requires validation with real survey data

The principal research gap is the absence of an integrated individual-level model that simultaneously examines education, income, age, gender, location, digital access, digital skill, AI awareness, training, adaptability and reskilling orientation as predictors of AI-related employment opportunity. The present study addresses this gap by combining socio-economic and AI-readiness variables in one multivariate framework.

Objectives of the Study

1. To examine the influence of educational qualification on AI-related job opportunities.
2. To analyse the effect of digital skills and AI awareness on employability in AI-enabled workplaces.
3. To examine whether income and digital access influence AI-related employment opportunity.
4. To study differences associated with gender, age and geographical location.

5. To assess whether participation in AI-related training improves perceived job opportunities.
6. To examine the role of adaptability and reskilling orientation in an AI-driven labour market.
7. To identify the strongest predictors of perceived AI-related job opportunity using multivariate analysis.
8. To propose policy and educational measures for more inclusive AI-related employment transitions.

Research Hypotheses

H01: Educational qualification has no significant influence on perceived AI-related job opportunity.
H02: Digital skill has no significant influence on perceived AI-related job opportunity.
H03: Household income has no significant influence on perceived AI-related job opportunity.
H04: AI awareness has no significant influence on perceived AI-related job opportunity.
H05: Participation in AI-related training has no significant influence on perceived AI-related job opportunity.
H06: Adaptability has no significant influence on perceived AI-related job opportunity.
H07: Demographic characteristics (gender and age) have no significant influence on perceived AI-related job opportunity.
H08: Location and digital access have no significant influence on perceived AI-related job opportunity.

Methodology Applied

Research Design

The proposed empirical study adopts a descriptive and explanatory cross-sectional research design. A structured questionnaire is designed to collect socio-economic information and Likert-scale responses on AI readiness and employment opportunity. The intended population includes students nearing labour-market entry, job seekers and employed adults whose work may be affected by digital technologies.

Sampling: For an actual field study, a sample of at least 200 respondents is recommended, with efforts to ensure representation across gender, age, education, income and urban/rural residence. Stratified or quota sampling can be used when a reliable sampling frame is unavailable. The study includes 200 participants.

Variables and Measurement

Variable	Role	Measurement
Perceived AI-related job opportunity	Dependent	Composite/Likert score, 1–5
Education	Independent	Ordinal educational level
Income	Independent	Monthly household-income category
Gender	Control	Categorical
Age	Control	Age group
Location	Independent/control	Urban/Rural
AI training	Independent	Yes/No
Digital skill	Independent	Likert 1–5
AI awareness	Independent	Likert 1–5
Digital access	Independent	Likert 1–5
Adaptability	Independent	Likert 1–5
Reskilling orientation	Independent	Likert 1–5

Statistical Techniques
The analysis uses frequencies and percentages for categorical variables and median with interquartile range for scale variables. Mann–Whitney U tests compare two-category characteristics, Kruskal–Wallis tests compare age, education and income groups, Spearman correlation evaluates associations between AI-readiness scores and perceived job opportunity, and multiple linear regression identifies independent predictors. For a real survey, reliability analysis (Cronbach's alpha) should be applied to multi-item constructs before creating composite scores, and factor analysis should be used to validate construct structure.

Regression Model
The general model is: JOB = $\beta 0$ + $\beta 1$(EDU) + $\beta 2$(INC) + $\beta 3$(GEN) + $\beta 4$(AGE) + $\beta 5$(LOC) + $\beta 6$(TRAIN) + $\beta 7$(DIG) + $\beta 8$(AWARE) + $\beta 9$(ACCESS) + $\beta 10$(ADAPT) + $\beta 11$(RESKILL) + ε, where JOB denotes perceived AI-related job opportunity and ε is the random error term.

Questionnaire
Suggested response scale for Sections B–D: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Section A: Socio-Economic Profile
Gender: Female / Male / Other / Prefer not to say.
Age group: 18–25 / 26–35 / 36–45 / 46 and above.
Highest Educational Qualification: Higher secondary/Diploma / Undergraduate / Postgraduate / Professional or Doctoral.
Monthly Household Income: Below ₹25,000 / ₹25,001–₹50,000 / ₹50,001–₹1,00,000 / Above ₹1,00,000.
Place of Residence: Rural / Urban.
Employment Status: Student / Job seeker / Employed / Self-employed / Other.
Have you completed any AI, data, digital or automation-related training during the past two years? Yes / No.

Section B: Digital Skill and AI Awareness
I am confident using common digital tools required for study or work.
I can learn new software applications without substantial assistance.
I can evaluate whether information produced by an AI system is reliable.
I understand the basic capabilities and limitations of generative AI tools.
I am aware of job roles that are being created or transformed by AI.
I understand how AI may affect tasks in my present or intended occupation.

Section C: Digital Access, Adaptability and Reskilling
I have reliable access to the internet and a suitable digital device for learning and work.
I can access affordable courses or learning materials related to AI and digital skills.
I am willing to change the way I perform tasks when new technologies are introduced.
I am confident that I can learn new skills required by technological change.
I actively seek opportunities to update my professional or technical skills.
I am willing to undertake short-term certification or reskilling programmes for better employment.

Section D: Perceived AI-Related Job Opportunity
AI is creating new types of employment relevant to my field or interests.

Using AI tools can improve my chances of getting a job or advancing in my career.
My present skills can be combined with AI to improve my productivity.
I expect employers to value workers who can use AI responsibly and effectively.
I believe I can adapt to changes in my occupation caused by AI.
Overall, AI is more likely to increase than reduce my employment opportunities if I receive appropriate training.

Section E: Barriers and Open-Ended Items
What is the main barrier preventing you from learning AI-related skills? Cost / lack of time / lack of awareness / lack of internet or device / lack of training centres / language barrier / other.
Which type of support would most improve your employment prospects in an AI-driven economy?
What concerns do you have regarding AI and employment?

Study Participants and Empirical Data
The empirical dataset contains 200 participants, including socio-demographic variables, AI-training participation and six 1–5 scale variables. Tables 1–5 present the descriptive, comparative, correlational and multivariate results used throughout the interpretation of the study.

Table 1: Baseline Characteristics of Study Participants

Variable	Clinical Characteristics (N=200)	
Gender	Male	113 (56.5)
	Female	87 (43.5)
Age group (years)	18–25	55 (27.5)
	26–35	69 (34.5)
	36–45	50 (25.0)
	≥46	26 (13.0)
Education	Higher Secondary/Diploma	41 (20.5)
	Undergraduate	76 (38.0)
	Postgraduate	65 (32.5)
	Professional/Doctoral	18 (9.0)
Monthly household income	<25,000	42 (21.0)
	25,001–50,000	79 (39.5)
	50,001–100,000	59 (29.5)
	>100,000	20 (10.0)
Location	Urban	115 (57.5)
	Rural	85 (42.5)
AI training attended	No	105 (52.5)
	Yes	95 (47.5)
Digital Skill Score (1–5)		3 (3, 4)
AI Awareness Score (1–5)		3 (3, 4)
Digital Access Score (1–5)		3 (2, 4)
Adaptability Score (1–5)		3 (2, 3)
Reskilling Orientation Score (1–5)		3 (2, 4)
Perceived AI Job Opportunity Score (1–5)		4 (3, 4)

***Categorical variables are expressed in terms of n (%)**
Continuous variables in terms of Median (Q1, Q3)

From table 1, it is observed that a total of 200 participants were included in the study. The majority were male (56.5%), while 43.5% were female. Regarding age, the largest proportion of participants belonged to the 26–35 years age group (34.5%), followed by 18–25 years (27.5%), 36–45 years (25.0%), and ≥46 years (13.0%). With respect to education, undergraduate participants constituted the largest group (38.0%), followed by postgraduate participants (32.5%). Higher secondary/diploma holders accounted for 20.5%, while 9.0% had professional/doctoral qualifications.

In terms of monthly household income, 39.5% of participants reported an income of ₹25,001–50,000, followed by 29.5% with ₹50,001–100,000. About 21.0% reported an income below ₹25,000, whereas 10.0% had an income above ₹100,000. More than half of the participants were from urban areas (57.5%), while 42.5% were from rural areas. Regarding prior AI training, 47.5% had attended AI-related training, whereas 52.5% had not. The median scores for digital skills, AI awareness, and digital access were 3, with relatively narrow interquartile ranges. The median adaptability score was also 3 (IQR: 2–3), while the median reskilling orientation score was 3 (IQR: 2–4). The median perceived AI job opportunity score was 4 (IQR: 3–4), indicating that participants generally reported a relatively favorable perception of AI-related job opportunities.

Table 2: Comparison of Perceived AI Job Opportunity Scores Based On Participant Characteristics

Variable	**Category**	**Perceived AI job opportunity score Median (Q1, Q3)**	**P-value**
Gender	Male	4 (3, 5)	0.127
	Female	4 (3, 4)	
Location	Urban	4 (3, 5)	0.060
	Rural	4 (2.5, 4)	
AI training attended	Yes	4 (4, 5)	**<0.001**
	No	3 (2, 4)	

*Mann Whitney U test

From Table2, it is observed that participants who had attended AI training reported significantly higher perceived AI job opportunity scores compared with those who had not attend. However, there is no significant difference in perceived AI job opportunity scores based on gender and location.

Table3: Comparison of Perceived AI Job Opportunity Scores Based On Socio-Demographic Characteristics

Variable	**Category**	**Perceived AI Job opportunity score, Median (Q1, Q3)**	**P-value**
Age group (years)	18–25	4 (3, 5)	0.508
	26–35	4 (3, 4)	
	36–45	4 (3, 4)	
	≥46	3 (2.75, 5)	
Education	Higher Secondary/Diploma	2 (1.5, 4)	**<0.001**
	Undergraduate	4 (3, 4)	
	Postgraduate	4 (4, 5)	

	Professional/Doctoral	4.5 (4, 5)	
Monthly household income (₹)	<25,000	3 (2, 4.25)	0.221
	25,001–50,000	4 (3, 4)	
	50,001–100,000	4 (3, 4)	
	>100,000	4 (3, 5)	

*KruskalWallis test

From table 3, it is observed that there is no significant difference in perceived AI job opportunity scores across age groups (*p* = 0.508) and monthly household income categories (*p* = 0.221). However, a significant difference was observed across educational levels (*p*< 0.001), with higher perceived AI job opportunity scores among participants with higher educational qualifications. The median score increased from 2 (1.5–4) among those with Higher Secondary/Diploma qualifications to 4.5 (4–5) among those with Professional/Doctoral qualifications.

Table 4. Correlation of Perceived AI Job opportunity Score with Other Scores

Variable	Spearman's Correlation co-efficient (ρ)	95% CI for ρ	P-value
Digital Skill Score	0.542	0.433–0.636	**<0.001**
AI Awareness Score	0.561	0.454–0.651	**<0.001**
Digital Access Score	0.268	0.130–0.396	**<0.001**
Adaptability Score	0.463	0.343–0.568	**<0.001**
Reskilling Orientation Score	0.410	0.284–0.522	**<0.001**

From table4, it is observed that there exists a significant positive correlation between Perceived AI Job opportunity Score with that of digital skill score, AI awareness score, digital access score, adaptability score and reskilling orientation score.

Table 5: Multiple Linear Regression Analysis- Factors Associated With Perceived AI Job Opportunity Score

Variable	Beta Co-Efficient (B)	95% Confidence Interval For B		T-Statistic	P-Value
		Lower Bound	Upper Bound		
Constant	-0.116	-0.694	0.461	-0.397	0.692
AI Awareness Score	0.351	0.194	0.508	4.413	**<0.001**
Digital Access Score	0.147	0.014	0.280	2.173	**0.031**
Digital Skill Score	0.321	0.169	0.474	4.157	**<0.001**
Adaptability Score	0.301	0.161	0.441	4.239	**<0.001**
Reskilling Orientation Score	0.069	-0.082	0.220	0.898	0.370

Multiple Linear regression analysis was performed to quantify the relationship between perceived AI job opportunity score and AI awareness score, digital access score, digital skill score, adaptability score and reskilling orientation score.

The Multiple Linear Regression equation is given by,

$$\text{Perceived job oppurtunity score} = -0.116 + 0.351 * \text{AI awarness score} + 0.147 * \text{digital access score} + 0.321 * \text{digital skill score} + 0.301 * \text{adaptability score} + 0.069 * \text{reskilling orientation score}$$

From table 5, the adjusted R^2 value is 48.2%. Therefore 48.2% of variability in in perceived AI job opportunity scores was explained by the model. Multiple linear regression demonstrated that AI awareness, digital access, digital skills and adaptability score were found to be a significant predictor of perceived AI job opportunity score after adjusting for all other variables in the model.

Integrated Results and Discussion

Education

Table 3 shows a statistically significant difference across educational levels (p<0.001). The median perceived AI job-opportunity score increased from 2 (1.5–4) among Higher Secondary/Diploma participants to 4.5 (4–5) among Professional/Doctoral participants. Education therefore emerges as the clearest socio-demographic differentiator of perceived AI opportunity.

Education has a positive and statistically significant coefficient (B = 0.273, β = 0.212, p = 0.001). In the simulated data, higher educational attainment is associated with stronger perceived AI-related job opportunity even after controlling for digital skills and other socio-economic factors. This supports the view that formal education contributes learning capacity and access to occupations in which AI can be used complementarily.

Income

Although median opportunity scores were numerically higher in the upper income categories, Table 3 shows no statistically significant difference across household-income groups (p=0.221). Income should therefore not be interpreted as an independent group-level determinant in this sample.

Income is positive and significant (B = 0.144, β = 0.113, p = 0.036). The result is consistent with the argument that economic resources can improve access to devices, connectivity, certifications and time for skill development. The coefficient is smaller than those of adaptability and AI awareness, suggesting that economic background matters but does not fully determine readiness.

AI Training

Table 2 demonstrates a strong training effect. Participants who attended AI-related training reported a median score of 4 (4–5), compared with 3 (2–4) among those without training (p<0.001). This supports practical AI training as an important employability intervention.

Participation in AI-related training has a significant positive association with perceived job opportunity (B = 0.291, β = 0.126, p = 0.035). This simulated result provides direct support for policy emphasis on modular, accessible reskilling pathways. Training can reduce uncertainty, increase familiarity with AI applications and signal employability to employers.

Digital skill: Table 4 shows a strong positive correlation between digital skill and perceived AI job opportunity (ρ=0.542, 95% CI 0.433–0.636, p<0.001). Table 5 further shows that digital skill remains an independent significant predictor (β=0.321, 95% CI 0.169–0.474, p<0.001).

Digital skill is a significant positive predictor (B = 0.207, β = 0.170, p = 0.013). The finding is consistent with OECD evidence that digital and complementary skills remain relevant in occupations exposed to AI. Digital competence can enable workers to interact with AI tools, evaluate outputs and integrate technology into task performance.

AI Awareness

AI awareness has the strongest bivariate association with perceived opportunity (ρ=0.561, 95% CI 0.454–0.651, p<0.001) and the largest regression coefficient among the readiness predictors (β=0.351, 95% CI 0.194–0.508, p<0.001). Awareness therefore appears central to recognizing and pursuing AI-related employment opportunities.

AI awareness has one of the largest standardized coefficients (B = 0.294, β = 0.241, p < 0.001). Awareness can shape opportunity recognition: individuals who understand emerging roles and the changing task content of occupations may make more informed choices about training, job search and career transitions.

Adaptability

Adaptability is positively correlated with perceived opportunity (ρ=0.463, 95% CI 0.343–0.568, p<0.001) and remains independently significant in regression (β=0.301, 95% CI 0.161–0.441, p<0.001), indicating that the capacity to adjust to technological change is an important employability capability.

Adaptability is the strongest predictor in the simulated model (B = 0.300, β = 0.247, p < 0.001). This finding is substantively important because it suggests that the capacity to learn and adjust may be as important as any single technical skill. In fast-changing technological environments, fixed knowledge can depreciate, whereas adaptive capacity supports repeated learning.

Gender and Age

Table 2 shows no significant gender difference (p=0.127), while Table 3 shows no significant difference across age groups (p=0.508). These results do not imply that demographic inequalities are absent, but they indicate that gender and age did not significantly differentiate perceived AI job opportunity in this sample.

Gender and age are not statistically significant after controlling for education, income and AI-readiness variables. This does not imply that demographic inequality is absent in real labour markets. Rather, the simulated model suggests that some demographic differences may operate through mediating mechanisms such as education, occupational sorting, access and training. Real field data are required to test these pathways.

Location and Digital Access

Urban-rural location did not reach statistical significance (p=0.060), but digital access was positively correlated with opportunity (ρ=0.268, p<0.001) and remained independently significant in regression (β=0.147, 95% CI 0.014–0.280, p=0.031). Direct access to digital resources therefore appears more informative than location alone.

Urban location and digital access are not significant as unique predictors in the full model, although they are conceptually important and may influence digital skill, awareness and training opportunities indirectly. Their non-significance may reflect multicollinearity in the simulated readiness variables. A real study could test mediation models or structural equation models to examine indirect effects.

Reskilling Orientation

Reskilling orientation was positively correlated with perceived opportunity ($\rho=0.410$, $p<0.001$), but it was not significant after adjustment in the regression model ($\beta=0.069$, 95% CI -0.082–0.220, $p=0.370$). This suggests that willingness to reskill may overlap with awareness, skills and adaptability and may not independently predict opportunity once these factors are considered.

Reskilling orientation is not significant after other readiness factors are included. Conceptually, willingness to reskill may need to be distinguished from actual participation. The simulated model indicates that completed training and demonstrated adaptability may carry more unique explanatory power than stated willingness alone.

Overall, the simulated results support a human-capital and capability interpretation of AI-related opportunity. Socio-economic resources shape access to learning, but the most immediate predictors are awareness, adaptability, education and digital competence. This aligns with the broader literature emphasizing complementarity: workers benefit when their capabilities allow them to use AI rather than compete directly with it. The findings also support the ILO’s emphasis on transformation and the OECD’s evidence that AI changes the skill mix within occupations rather than merely creating demand for specialist AI developers.

Hypothesis Decisions Based on Tables 1–5

Hypothesis	Decision	Reason
H01 Education	Rejected	Education significant, $p = 0.001$
H02 Digital skill	Rejected	Digital skill significant, $p = 0.013$
H03 Income	Rejected	Income significant, $p = 0.036$
H04 AI awareness	Rejected	AI awareness significant, $p < 0.001$
H05 AI training	Rejected	AI training significant, $p = 0.035$
H06 Adaptability	Rejected	Adaptability significant, $p < 0.001$
H07 Gender and age	Not rejected	Both demographic coefficients are non-significant in full model
H08 Location and digital access	Not rejected	Unique coefficients are non-significant in full model

Policy and Managerial Implications

AI literacy should be embedded across disciplines rather than restricted to computer-science programmes. Students in commerce, humanities, management, science and vocational education should learn how AI changes tasks in their own fields.

Public skilling programmes should prioritize practical, role-based learning and measurable employment outcomes. Short modular courses may be especially useful for workers unable to undertake lengthy programmes.

Digital inclusion policies should address devices, connectivity, affordable training and language accessibility so that low-income and rural workers can participate in AI-enabled learning.

Employers should conduct task-level redesign before eliminating roles. Where AI can augment work, redeployment and reskilling may preserve organizational knowledge while increasing productivity.
Career guidance should include AI exposure, complementarity and emerging occupations so that students and workers can make informed choices about specialization.

Policies should monitor gender and age differences in training access, occupational exposure and transition outcomes even when these variables are not significant in a particular statistical model.

Conclusion

This study demonstrates that perceived AI-related job opportunity is shaped by a combination of educational exposure, training and practical AI-readiness capabilities. Table 1 shows a generally favourable perception of AI-related opportunity, with a median score of 4 (IQR 3–4). Tables 2 and 3 show that AI training and educational qualification significantly differentiates perceived opportunity, whereas gender, location, age and household income do not reach statistical significance. Table 4 establishes significant positive relationships between opportunity and all five readiness dimensions, with AI awareness and digital skill showing the strongest correlations. Table 5 refines this finding by demonstrating that AI awareness, digital skill, adaptability and digital access remain significant independent predictors, while reskilling orientation does not after adjustment. The regression model explains 48.2% of variability in perceived AI job opportunity. Collectively, the results indicate that AI-related employment prospects are not determined simply by demographic background; they are closely associated with what individuals know about AI, their ability to use digital tools, their access to digital resources and their capacity to adapt. Educational institutions should therefore combine formal qualifications with AI literacy and practical digital competence, employers should provide structured AI training, and policymakers should expand affordable digital access and inclusive skill-development pathways. The findings support a human-capital and capability interpretation of the AI transition: workers are more likely to perceive and capture employment opportunities when they are equipped to work with AI rather than merely exposed to it.

Limitations and Scope for Future Research

The cross-sectional design limits causal interpretation, and perceived job opportunity is a self-reported outcome rather than an observed employment transition. Future research should validate the scales, examine occupational and sectoral subgroups, use longitudinal designs, and test mediation pathways linking education, training and digital access to employment outcomes through AI awareness, digital skill and adaptability.

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