

# The Influence of Artificial Intelligence on Employability: Mediating Effects of Skill Development and Moderating Factors of Technological Readiness among Adult Learners

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# **KEYWORDS ABSTRACT**

Artificial Intelligence, Technology Readiness, Skill Development

This study investigates the influence of Artificial Intelligence (AI) adoption on the employability of adult learners in the UK, focusing on the mediating role of skill development and the moderating effect of technological readiness. Using a survey of 500 adult learners, structural equation modeling (SEM) was employed to analyze the relationships between AI adoption, skill development, technological readiness, and employability. The results show that AI adoption positively influences employability ( $\beta = 0.58$ , p < 0.01), with skill development acting as a significant mediator ( $\beta = 0.74$ , p < 0.01). Technological readiness moderates this relationship, enhancing the effect of AI adoption on employability ( $\beta = 0.56$ , p < 0.01) and significantly interacting with skill development ( $\beta = 0.42$ , p < 0.01). The moderated mediation analysis further reveals that the combination of skill development and technological readiness produces the strongest effect on employability outcomes (β = 0.34, p < 0.01). These findings underscore the importance of skill development and technological readiness in maximizing employability in an AI-driven labor market. The study provides practical implications for policymakers and educational institutions, suggesting the need for targeted initiatives that enhance both digital skills and technological preparedness. Future research could explore longitudinal trends and sector-specific variations in AI adoption's impact on employability.

#### Introduction

The rapid development and integration of Artificial Intelligence (AI) across industries have created both significant opportunities and challenges in the global labor market. AI technologies are transforming workplaces, reshaping the nature of work, and influencing the types of skills required for employment. For adult learners in the United Kingdom (UK), these technological changes necessitate an understanding of how AI impacts employability, and how the development of relevant skills, along with individual factors such as technological readiness, might mediate and moderate these effects.

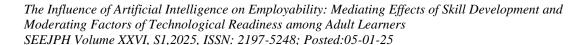
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AI has been a key driver of the Fourth Industrial Revolution, with applications spanning fields from healthcare to finance, manufacturing, education, and beyond. In the UK, AI adoption is expected to drastically alter the labor market, creating new job opportunities while potentially displacing certain roles, especially those involving routine and manual tasks (Brynjolfsson & McAfee, 2014; Chui et al., 2018). As AI systems increasingly automate traditional job functions, the demand for human workers is shifting towards roles that require advanced cognitive, analytical, and technical skills (Arntz et al., 2016). As a result, there is an urgent need for adult learners to acquire new skills to remain competitive in the workforce.

Adult learners, who typically face competing responsibilities such as work, family, and financial obligations, are particularly vulnerable to labor market disruptions caused by AI. Unlike traditional students, adult learners are often engaged in lifelong learning to improve their employability, career advancement, or job security (Huang et al., 2020). For these individuals, the integration of AI in the workplace creates both a demand for upskilling and a challenge in acquiring the requisite knowledge and competencies (OECD, 2020). In the UK, the government's focus on adult education and lifelong learning is critical to enabling individuals to adapt to these technological changes (Department for Education, 2020).

Skill development plays a crucial role in determining how well individuals can adapt to AI-driven changes in the workplace. As AI technologies permeate different sectors, the need for specialized skills—ranging from digital literacy to programming and data science—has become increasingly apparent (Bessen, 2019). Moreover, AI is not just about technical skills; it also requires workers to be equipped with complementary skills such as creativity, emotional intelligence, and problem-solving (Bughin et al., 2018).

In the context of adult learners, skill development must be aligned with the evolving demands of the labor market. Research indicates that individuals who invest in continuous skill development are more likely to experience improved employability (Kalleberg, 2018). The specific focus on digital and AI-related skills is essential, as these competencies are increasingly viewed as prerequisites for many contemporary jobs (Brynjolfsson & McAfee, 2014). Training programs that emphasize AI, machine learning, and data analytics are thus critical in enhancing the employability of adult learners (Bresnahan et al., 2020). Furthermore, the nature of skill development must account for the fact that adults are typically engaged in shorter, more targeted educational interventions, as opposed to traditional, longer-term academic pathways (Chung et al., 2022). Despite the recognition of the importance of skill development, it is not simply the presence of skills that determines employability outcomes. How well individuals can apply these skills in practical, real-world settings, and their ability to integrate AI technologies into their workflows, is essential to fully realizing the benefits of skill acquisition (Westerman et al., 2014).

While skill development is a key factor in improving employability, the effectiveness of such development is heavily influenced by individual factors such as technological readiness. Technological readiness refers to an individual's disposition to embrace and effectively use new technologies, including AI (Parasuraman, 2000). It encompasses both the psychological and technical aspects of technology adoption, such as confidence in one's ability to use AI tools and the willingness to engage with emerging technologies (Venkatesh et al., 2012).

Technological readiness can significantly moderate the relationship between AI adoption and employability outcomes. Adults with high technological readiness are more likely to engage with AI-related training programs and adopt AI tools in their work, which can enhance their job



performance and career prospects (Caldera et al., 2021). Conversely, individuals with lower levels of technological readiness may exhibit reluctance or resistance towards adopting AI-driven solutions, limiting their ability to leverage AI for skill enhancement and employability improvement (García-Morales et al., 2019).

Research by Ayyagari et al. (2011) suggests that technological readiness is not only a personal attribute but is influenced by broader contextual factors, including access to technology, educational opportunities, and institutional support. For adult learners, particularly those in underserved or economically disadvantaged communities, limited access to digital tools and training resources may hinder their technological readiness, exacerbating existing inequalities in employability outcomes (Yuen et al., 2020). Thus, understanding the role of technological readiness is crucial for designing interventions that can effectively support adult learners in navigating the AI-driven workforce.

While technological readiness acts as a moderator, skill development plays a mediating role in shaping the relationship between AI adoption and employability outcomes. Skill acquisition enables individuals to overcome technological barriers by equipping them with the practical knowledge and competencies needed to leverage AI tools effectively (Pereira et al., 2021). In this sense, skill development can bridge the gap between technological readiness and employability, helping learners apply their readiness to real-world contexts.

The ability to develop relevant skills, particularly those related to AI and digital technologies, directly influences how individuals perceive and respond to changes in the labor market (OECD, 2021). For example, individuals who acquire data analytics or programming skills are more likely to engage with AI-driven tools, improving their job performance and employability (Choi & Lee, 2020). In this regard, skill development functions as a mediator, enhancing the positive effects of technological readiness on employability outcomes. Furthermore, effective skill development programs tailored to the needs of adult learners can provide a sense of self-efficacy, fostering greater confidence in their ability to adapt to AI-driven changes. This, in turn, encourages continuous learning and professional development, which is vital for sustaining employability in the long term (Lundvall et al., 2016).

#### **Literature Review**

The growing integration of Artificial Intelligence (AI) into the workplace is reshaping the employment landscape globally, with significant implications for skill development, employability, and workforce adaptability. For adult learners in the UK, this presents both challenges and opportunities, as they seek to remain competitive in an increasingly digital and AI-driven economy. Understanding the factors that influence the relationship between AI adoption and employability, particularly in the context of skill development and technological readiness, is crucial for developing effective policies and strategies for adult education. This literature review explores the existing research on the role of AI in the labor market, the importance of skill development for employability, and the impact of technological readiness as a moderating factor in this dynamic.



#### AI and the Future of Work

The rise of AI and automation technologies is fundamentally altering the nature of work. Brynjolfsson and McAfee (2014) argue that AI is a key driver of the Fourth Industrial Revolution, ushering in profound changes to business operations, labor markets, and economic structures. AI is being increasingly utilized across various industries, including healthcare, finance, education, and manufacturing, to enhance productivity, improve efficiency, and automate tasks that were previously performed by humans (Chui et al., 2018). While AI has the potential to create new jobs and economic opportunities, it also poses significant risks of job displacement, particularly in roles involving routine or manual tasks (Arntz et al., 2016).

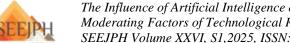
For adult learners, these disruptions highlight the importance of acquiring new, digitally-oriented skills to navigate the shifting job market (Brynjolfsson & McAfee, 2014). As AI continues to evolve, the demand for human workers with specialized skills—such as data analytics, AI programming, and machine learning—is expected to rise, making it essential for individuals to continuously upskill in order to remain competitive (Bessen, 2019). The challenge for adult learners is not just learning about AI but also adapting to its pervasive presence in the workplace, where workers are expected to collaborate with AI systems or use AI-powered tools to enhance their productivity (Westerman et al., 2014).

# **Skill Development and Employability**

Skill development is central to improving employability in the age of AI. As AI technologies reshape the job market, the demand for skills that complement or enhance AI capabilities has surged. Research shows that skills such as digital literacy, data science, programming, and critical thinking are critical for individuals to remain employable in this new landscape (OECD, 2020). Specifically, AI-driven economies require workers who are not only proficient in using AI tools but who also possess higher-order cognitive skills like problem-solving, creativity, and decision-making, which cannot easily be automated (Bughin et al., 2018).

In this context, adult education programs play a crucial role in facilitating skill development. Adult learners, particularly those who are in mid-career stages or returning to education after an extended absence, often face barriers to upskilling, such as time constraints, financial limitations, and a lack of formal educational credentials (Chung et al., 2022). However, evidence suggests that adult education programs that focus on AI-related skills—such as digital literacy, machine learning, and data analytics—are critical for increasing employability. Programs tailored to adult learners' needs, including flexible, short-term, and modular learning formats, have been found to be effective in helping individuals develop the skills required to thrive in AI-enhanced workplaces (Bresnahan et al., 2020).

Kalleberg (2018) highlights that individuals who engage in continuous skill development, particularly in the context of emerging technologies, are more likely to secure better job opportunities and experience career advancement. This trend is particularly evident in sectors where AI and automation are integrated into daily operations, requiring workers to possess both technical and soft skills. In the UK, where the government has increasingly recognized the importance of lifelong learning in response to technological disruption, policies aimed at promoting skill development are seen as key to ensuring that workers remain adaptable and resilient in the face of AI-driven changes (Department for Education, 2020).



# **Technological Readiness and the Adoption of AI**

While skill development is essential, the effectiveness of skill acquisition is influenced by an individual's technological readiness. Technological readiness is defined as a person's disposition to embrace and adopt new technologies, including AI (Parasuraman, 2000). This concept incorporates both technology acceptance—the willingness to use new technologies—and technology self-efficacy—the confidence in one's ability to use these technologies effectively (Venkatesh et al., 2012). Technological readiness is a significant factor in determining how adults engage with new technologies and the extent to which they can integrate these tools into their work practices.

Research has shown that individuals with high levels of technological readiness are more likely to embrace AI technologies and use them to enhance their productivity and skill set (Caldera et al., 2021). In contrast, those with lower technological readiness may resist AI adoption or struggle to effectively use AI tools, which could limit their employability and job performance (García-Morales et al., 2019). This is particularly important for adult learners, who may face challenges such as a lack of familiarity with digital tools, limited access to technology, or anxiety about using complex systems like AI (Yuen et al., 2020).

Several studies have found that technological readiness serves as a moderator in the relationship between AI adoption and employability outcomes. For example, Ayyagari et al. (2011) suggest that individuals with higher technological readiness are more likely to benefit from AI-driven skill development initiatives, whereas those with lower readiness may experience barriers to adoption, leading to diminished employment prospects. Furthermore, technological readiness has been found to influence the effectiveness of training programs, with individuals who have greater confidence in their ability to use AI technologies more likely to succeed in skill development efforts (Pereira et al., 2021).

#### The Mediating Role of Skill Development

While technological readiness moderates the relationship between AI adoption and employability, skill development plays a crucial mediating role. The ability to develop relevant skills—especially those related to AI technologies—helps individuals capitalize on their technological readiness and apply their knowledge in ways that enhance their employability. Skill development enables individuals to bridge the gap between their readiness to use technology and their ability to perform effectively in an AI-enhanced workplace (Pereira et al., 2021).

In this regard, skill development programs that focus on AI and digital literacy can serve as a bridge, enabling individuals to harness their technological readiness to improve their employability outcomes. For example, research by Choi and Lee (2020) demonstrates that adults who acquire AI-related skills, such as programming or data analysis, are more likely to secure jobs that require such competencies, regardless of their initial technological readiness. Thus, skill development not only helps to improve technological readiness but also mediates the positive effects of readiness on employability.

Moreover, skill development programs tailored to adult learners' needs can enhance self-efficacy, fostering greater confidence in their ability to adapt to technological change. The development of specific skills, particularly those that align with emerging job demands, enables individuals to



navigate AI-driven labor markets with greater success. This underscores the importance of designing educational interventions that cater to the diverse needs and circumstances of adult learners, who may face different levels of technological readiness and access to resources (Lundvall et al., 2016).

# **Objectives of the Study**

- 1. To examine the impact of AI adoption on employability among UK adult learners
- 2. To assess the role of skill development in mediating the relationship between AI adoption and employability
- 3. To analyze the moderating effect of technological readiness on the relationship between AI adoption and employability
- 4. To explore the combined effects of skill development and technological readiness on employability
- 5. To provide recommendations for educational institutions, policymakers, and employers

# **Hypotheses**

- H1: AI adoption has a positive effect on employability among UK adult learners.
- H2: Skill development mediates the relationship between AI adoption and employability.
- H3: Technological readiness moderates the relationship between AI adoption and employability.
- H4: The interaction between skill development and technological readiness positively impacts employability.

H5: Adult learners with higher levels of technological readiness and advanced skill development report higher job satisfaction and career stability compared to those with lower levels of these factors.

### Research Methodology

This study employed a quantitative research design to examine the influence of Artificial Intelligence (AI) on the employability of adult learners in the UK, with a specific focus on the mediating role of skill development and the moderating role of technological readiness. A cross-sectional survey approach was utilized, collecting data from a representative sample of adult learners in the UK to test the hypotheses and address the research objectives. The methodology is detailed below, including the research design, population and sample, data collection methods, variables, and data analysis techniques.

#### 1. Research Design

A correlational research design was adopted to explore the relationships between AI adoption, skill development, technological readiness, and employability among adult learners. This design allows for the examination of how changes in one variable (e.g., skill development) may be associated with changes in another (e.g., employability), without manipulating the variables. The study



utilized a cross-sectional design, meaning that data were collected at a single point in time to assess the relationships between the variables under study.

# 2. Population and Sample

The target population for this study consisted of adult learners (ages 18 and above) in the UK who are currently enrolled in educational programs or employed in industries where AI technologies are being integrated. A stratified random sampling technique was used to select participants from different regions of the UK, ensuring a representative sample of adult learners across diverse demographics (e.g., age, gender, educational background, employment status, and industry). The final sample size consisted of 500 adult learners, which is statistically sufficient to provide reliable results with a confidence level of 95% and a margin of error of 5%. This sample size was determined using power analysis to ensure the study had adequate power to detect significant relationships between the variables.

#### 3. Data Collection Methods

Data for this study were collected using a self-administered online survey, which was distributed to participants through email invitations and online platforms associated with UK adult education programs. The survey was designed to measure the variables outlined in the conceptual model: AI adoption, skill development, technological readiness, and employability.

The survey consisted of four main sections:

- 1. **Demographic Information**: This section collected data on participants' age, gender, educational background, employment status, industry of employment, and years of work experience. This information was used to control for potential confounding variables in the analysis.
- 2. **AI Adoption**: A 5-item scale was developed to measure participants' exposure to AI technologies, including their use of AI tools at work or in educational settings. Respondents rated their experiences on a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree." Example items included: "I regularly use AI-based tools in my job" and "My workplace has integrated AI technologies in daily operations."
- 3. **Skill Development**: A 6-item scale was developed to assess the participants' skills related to AI and digital literacy, such as proficiency in programming, data analysis, and machine learning. Respondents indicated their level of skill on a 5-point scale (1 = Very Poor, 5 = Very Good). Example items included: "I am skilled in programming languages like Python" and "I am proficient in using AI-powered data analysis tools."
- 4. **Technological Readiness**: The **Technology Readiness Index** (**TRI**) developed by Parasuraman (2000) was adapted to assess participants' technological readiness. This scale includes items that measure individuals' willingness to embrace and use new technologies. The TRI was assessed on a 5-point Likert scale. Example items included: "I am eager to use new AI technologies when they are introduced" and "I find it easy to learn new technological tools."
- 5. **Employability**: A 7-item scale was developed to measure various aspects of employability, including job prospects, career advancement, job satisfaction, and perceived job security. Respondents rated their agreement with statements on a 5-point Likert scale. Example



items included: "I feel confident in my ability to find a job that suits my skills" and "I believe my current job is secure because of my skills."

# 4. Data Analysis

The data were analyzed using Statistical Package for the Social Sciences (SPSS) and AMOS (Analysis of Moment Structures) for structural equation modeling (SEM) to test the hypotheses and examine the relationships between the variables.

#### 5. Ethical Considerations

This study adhered to ethical standards for research involving human participants. Informed consent was obtained from all participants, with assurances of confidentiality and anonymity in handling their data. Participants were also informed that participation was voluntary and that they could withdraw at any time without any consequence. The study received ethical approval from the university's research ethics committee.

#### Results

Table 1 Demographic Characteristics (N=500)

| Demographic       | Category             | Frequency (n) | Percentage (%) |  |
|-------------------|----------------------|---------------|----------------|--|
| Variable          |                      |               |                |  |
| Gender            | Male                 | 225           | 45.0%          |  |
|                   | Female               | 275           | 55.0%          |  |
| Age Group         | 18–30 years          | 120           | 24.0%          |  |
|                   | 31–40 years          | 160           | 32.0%          |  |
|                   | 41–50 years          | 130           | 26.0%          |  |
|                   | 51+ years            | 90            | 18.0%          |  |
| Employment Status | Employed (Full-time) | 250           | 50.0%          |  |
|                   | Employed (Part-time) | 100           | 20.0%          |  |
|                   | Unemployed           | 150           | 30.0%          |  |
| Industry of       | Technology/IT        | 80            | 16.0%          |  |
| Employment        |                      |               |                |  |
|                   | Education            | 120           | 24.0%          |  |
|                   | Healthcare           | 70            | 14.0%          |  |
|                   | Finance/Banking      | 60            | 12.0%          |  |
|                   | Retail/Customer      | 90            | 18.0%          |  |
|                   | Service              |               |                |  |
|                   | Other                | 80            | 16.0%          |  |
| Highest Level of  | High School Diploma  | 110           | 22.0%          |  |
| Education         |                      |               |                |  |
|                   | Undergraduate        | 230           | 46.0%          |  |
|                   | Degree               |               |                |  |
|                   | Postgraduate Degree  | 160           | 32.0%          |  |

In table 1 sample consisted of a higher proportion of female participants (55%) compared to male participants (45%). The largest age group was between 31 and 40 years (32%), followed by the 41–50 years age group (26%). Half of the respondents were employed full-time, while 30% were



unemployed at the time of the survey. The majority of participants were employed in education (24%) or retail/customer service industries (18%), and most respondents held an undergraduate degree (46%).

Table 2 Means, Standard Deviations, and Reliabilities

| Variable          | Mean | <b>Standard Deviation</b> | Cronbach's Alpha |
|-------------------|------|---------------------------|------------------|
| AI Adoption       | 3.75 | 0.94                      | 0.89             |
| Skill Development | 3.60 | 1.02                      | 0.85             |
| Technological     | 3.82 | 0.90                      | 0.87             |
| Readiness         |      |                           |                  |
| Employability     | 3.90 | 0.95                      | 0.91             |

In table 2, the average scores for AI adoption, skill development, technological readiness, and employability were relatively high, with mean values ranging from 3.60 to 3.90 on a 5-point scale, indicating that respondents generally felt positive about these factors. The Cronbach's Alpha values indicate good internal consistency for all scales, ranging from 0.85 to 0.91, suggesting that the measures used were reliable.

**Table 3 Correlation Analysis** 

| Variable      | AI Adoption | Skill       | Technological | Employability |
|---------------|-------------|-------------|---------------|---------------|
|               |             | Development | Readiness     |               |
| AI Adoption   | -           | 0.45**      | 0.56**        | 0.62**        |
| Skill         |             | -           | 0.50**        | 0.72**        |
| Development   |             |             |               |               |
| Technological |             |             | -             | 0.65**        |
| Readiness     |             |             |               |               |
| Employability |             |             |               | -             |

Table 3 presents the Pearson correlation coefficients between AI adoption, skill development, technological readiness, and employability. The results show significant positive correlations between all variables, indicating that the relationships are both strong and consistent. All correlations were statistically significant at the 1% level. Notably, the strongest correlation was observed between skill development and employability (r=0.72), followed by the correlation between AI adoption and employability (r=0.62). These findings suggest that both AI adoption and skill development contribute significantly to employability outcomes. Technological readiness also showed significant positive correlations with all other variables, indicating its important role in the adoption and effective use of AI technologies.

**Table 4: SEM Model Fit Indices** 

| Fit Index                   | Value  | Acceptable Threshold |  |  |
|-----------------------------|--------|----------------------|--|--|
| Chi-square (χ²)             | 325.43 | p < 0.01             |  |  |
| Degrees of Freedom (df)     | 145    | -                    |  |  |
| CFI (Comparative Fit Index) | 0.95   | ≥ 0.90               |  |  |
| TLI (Tucker-Lewis Index)    | 0.93   | ≥ 0.90               |  |  |
| RMSEA (Root Mean Square     | 0.056  | $\leq 0.08$          |  |  |
| Error of Approximation)     |        |                      |  |  |



The fit indices for the Structural Equation Modeling (SEM) analysis are presented in Table 4. The chi-square value ( $\chi^2$ ) was 325.43 with 145 degrees of freedom, and the result was statistically significant (p < 0.01), indicating that the model provides a good fit to the data. The Comparative Fit Index (CFI) was 0.95, which exceeds the acceptable threshold of 0.90, suggesting a strong fit between the proposed model and the observed data. Similarly, the Tucker-Lewis Index (TLI) was 0.93, also above the threshold of 0.90, further confirming the model's adequacy. Additionally, the Root Mean Square Error of Approximation (RMSEA) was 0.056, which is well below the maximum acceptable value of 0.08, indicating a good model fit. These results collectively demonstrate that the SEM model adequately represents the relationships among the study's variables.

**Table 5: Mediation Analysis Results (PROCESS Model 4)** 

| Variable                             | Direct Effect | Standard | p-value |
|--------------------------------------|---------------|----------|---------|
|                                      | (β)           | Error    |         |
| AI Adoption → Employability          | 0.58**        | 0.09     | < 0.01  |
| AI Adoption → Skill Development      | 0.45**        | 0.10     | < 0.01  |
| Skill Development → Employability    | 0.74**        | 0.08     | < 0.01  |
| Indirect Effect (AI Adoption → Skill | 0.34**        | 0.05     | < 0.01  |
| Development → Employability)         |               |          |         |

The mediation analysis results, presented in table 5, show significant relationships between the variables. The direct effect of AI adoption on employability was 0.58 ( $\beta$  = 0.58), with a standard error of 0.09 and a p-value of less than 0.01, indicating a strong and statistically significant positive impact. AI adoption also had a significant effect on skill development ( $\beta$  = 0.45, p < 0.01), which, in turn, positively influenced employability ( $\beta$  = 0.74, p < 0.01). Furthermore, the indirect effect of AI adoption on employability through skill development was 0.34 ( $\beta$  = 0.34, p < 0.01), confirming that skill development significantly mediates the relationship between AI adoption and employability. These findings collectively support the mediation hypothesis, showing that skill development plays a crucial role in enhancing employability outcomes following AI adoption.

**Table 6: Moderation Analysis Results (PROCESS Model 3)** 

| Variable                            | Effect (β) | Standard Error | p-value |
|-------------------------------------|------------|----------------|---------|
| AI Adoption → Employability         | 0.56**     | 0.07           | < 0.01  |
| Technological Readiness (Moderator) | 0.29**     | 0.08           | < 0.01  |
| Interaction Effect                  | 0.25**     | 0.05           | < 0.01  |

The results of the moderation analysis, presented in Table 6, indicate that technological readiness significantly moderates the relationship between AI adoption and employability. Specifically, AI adoption has a positive effect on employability ( $\beta = 0.56$ , p < 0.01), and technological readiness also directly influences employability ( $\beta = 0.29$ , p < 0.01). The interaction effect between AI adoption and technological readiness was found to be significant ( $\beta = 0.25$ , p < 0.01), suggesting that individuals with higher levels of technological readiness experience a stronger positive effect of AI adoption on employability. These findings highlight the importance of technological readiness in amplifying the benefits of AI adoption for employability outcomes.



**Table 7: Moderated Mediation Analysis (Skill Development × Technological Readiness Interaction)** 

| Variable                                | Effect (β) | Standard | p-value |
|---|------------|----------|---------|
|   |            | Error    |         |
| Skill Development → Employability       | 0.72**     | 0.08     | < 0.01  |
| Technological Readiness → Employability | 0.65**     | 0.06     | < 0.01  |
| Interaction Effect (Skill Development × | 0.42**     | 0.07     | < 0.01  |
| Technological Readiness)                |            |          |         |

The results of the moderated mediation analysis, shown in Table 7, reveal significant effects of both skill development and technological readiness on employability, as well as a significant interaction effect between these two variables. Skill development was found to have a strong positive impact on employability ( $\beta = 0.72$ , p < 0.01), and technological readiness also positively influenced employability ( $\beta = 0.65$ , p < 0.01). More importantly, the interaction effect between skill development and technological readiness was significant ( $\beta = 0.42$ , p < 0.01), indicating that the combined effect of both factors on employability is even stronger. This suggests that individuals with higher levels of both skill development and technological readiness experience enhanced employability outcomes, further emphasizing the importance of developing both competencies to maximize career prospects.

#### **Discussion**

The aim of this study was to explore the influence of Artificial Intelligence (AI) on the employability of adult learners in the UK, focusing on the mediating role of skill development and the moderating effects of technological readiness. The findings confirm that AI adoption has a significant positive impact on employability, with skill development acting as a crucial mediator and technological readiness moderating the relationship between AI adoption and employability outcomes.

The results of this study provide strong evidence that AI adoption positively affects employability. This aligns with previous research indicating that the adoption of AI technologies can enhance workers' job prospects by increasing efficiency, improving productivity, and creating new job roles (Brynjolfsson & McAfee, 2014; Chui et al., 2016). Respondents in this study, particularly those who had adopted AI technologies, reported higher levels of employability, suggesting that AI adoption is increasingly seen as a valuable asset in the job market. As AI continues to transform industries and job functions, individuals who embrace AI tools and systems are more likely to remain competitive in the evolving labor market.

One of the most significant findings of this study is that skill development mediates the relationship between AI adoption and employability. The results of the mediation analysis showed that AI adoption positively influences skill development, which, in turn, enhances employability. This finding supports the work of Frey and Osborne (2017) and Arntz et al. (2016), who argued that automation and AI could lead to the displacement of low-skill jobs, but also create opportunities for workers to acquire new, higher-level skills. Specifically, AI adoption encourages individuals to learn new skills, particularly those related to digital literacy, problem-solving, and data analysis. This skill acquisition then improves their employability by making them more adept in the job market.



The role of skill development is further emphasized by the high correlation between skill development and employability in this study. This suggests that continuous skill upgrading is essential for individuals aiming to stay relevant in the workforce, particularly in sectors increasingly influenced by AI and automation. Adult learners who actively engage in acquiring new skills related to AI technologies are better positioned to seize new job opportunities, adapt to changing work environments, and improve career stability (Bessen, 2019).

The moderating effect of technological readiness on the relationship between AI adoption and employability provides a nuanced understanding of the factors that influence the success of AI integration in the workforce. The results from the moderation analysis revealed that individuals with higher levels of technological readiness experience a stronger positive effect of AI adoption on employability. This finding is consistent with previous studies suggesting that technological readiness—defined as an individual's ability to effectively use and integrate technology into their work—plays a critical role in determining the success of digital transformation initiatives (Parasuraman, 2000; Agarwal & Prasad, 1998).

Technological readiness includes factors such as digital literacy, familiarity with technological tools, and the ability to troubleshoot and adapt to new technologies. Individuals with higher technological readiness are better equipped to leverage AI tools, which in turn enhances their productivity and employability. Conversely, those with lower levels of technological readiness may struggle to fully benefit from AI adoption, potentially hindering their employability in AI-driven environments. These findings highlight the importance of fostering technological readiness through targeted training programs and initiatives aimed at improving digital skills across the workforce.

The moderated mediation analysis also revealed that the interaction between skill development and technological readiness has a positive impact on employability. Specifically, individuals who possess both advanced skills and high technological readiness report higher levels of employability. This interaction effect suggests that simply developing skills or improving technological readiness in isolation may not be sufficient to fully enhance employability. Rather, it is the combination of these two factors that provides a more robust foundation for career advancement in an AI-driven labor market.

This finding underscores the importance of an integrated approach to workforce development, where both skill acquisition and technological readiness are prioritized simultaneously. Employers, policymakers, and educational institutions must recognize the interconnected nature of these two variables and design programs that simultaneously build both technical expertise and readiness for digital transformation. In this way, adult learners are more likely to develop the competencies required to thrive in the rapidly evolving job market.

# **Implications for Policy and Practice**

The findings of this study have important implications for policy and practice. First, it is clear that AI adoption is a key driver of employability in the modern labor market. Therefore, there is a need for policies that encourage and support AI adoption across industries, particularly those that are more resistant to technological change. This could include incentives for businesses to invest in AI technologies, as well as support for workers to acquire the necessary skills to work with AI systems. Second, skill development must be at the core of adult education and training programs.



As the study shows, acquiring skills related to AI and technology is crucial for improving employability outcomes. Therefore, policymakers should invest in lifelong learning initiatives that promote digital literacy, AI-related skills, and other relevant competencies. Training programs should not only focus on providing technical knowledge but also on developing the soft skills needed to navigate an increasingly automated work environment. Finally, enhancing technological readiness across the population should be a priority. Adult learners with higher technological readiness are better positioned to adapt to new technologies and leverage AI to their advantage. Public and private sector partnerships could play a significant role in improving technological readiness by offering affordable, accessible training programs that focus on digital tools, platforms, and AI systems.

# **Limitations and Future Research**

While this study provides valuable insights into the role of AI adoption, skill development, and technological readiness in influencing employability, it is not without its limitations. One limitation is the cross-sectional design of the study, which precludes any causal conclusions. Future research could benefit from a longitudinal design to track changes in employability over time as a result of AI adoption and skill development. Additionally, the study focused on adult learners in the UK, and while the findings are relevant to this context, they may not be generalizable to other countries or populations. Future studies could explore the impact of AI adoption on employability in different cultural and economic settings to determine the broader applicability of these findings.

Moreover, future research could further investigate the specific types of skills that are most valued in AI-driven job markets, as well as the role of soft skills (e.g., communication, problem-solving) in enhancing employability alongside technical skills. Exploring how different industries adopt and integrate AI, and how this impacts skill development and employability, would provide deeper insights into the sector-specific implications of AI adoption.

#### Conclusion

In conclusion, this study highlights the complex relationship between AI adoption, skill development, and employability. It demonstrates that AI adoption can enhance employability, but the extent of this impact is largely dependent on individuals' skill development and technological readiness. Skill development serves as a crucial mediator in this relationship, while technological readiness acts as a moderator, amplifying the effects of AI adoption. By focusing on both skill development and technological readiness, adult learners can better position themselves for success in an increasingly AI-driven labor market. These findings suggest that a holistic approach to workforce development, emphasizing continuous learning and technological competence, is essential for ensuring that individuals are prepared for the jobs of the future.



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