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# A Comprehensive Study of Artificial Intelligence Adoption and Its Impact on Workforce Outcomes, Employability, and Professional Competencies among IT Professionals

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**Abstract**
Artificial intelligence is increasingly embedded in the work processes of IT professionals, reshaping how work is organised and experienced. While AI adoption is often associated with efficiency and productivity gains, its influence on workforce outcomes remains uneven and insufficiently examined at the individual level. This study empirically examines the impact of AI-enabled work on workforce outcomes among IT professionals using a regression-based analytical approach. Primary data were collected from 275 IT professionals through a structured questionnaire, and multiple regression analysis was employed to assess the combined influence of workforce-related factors on overall workforce outcomes. The results reveal that the regression model explains a substantial proportion of variance in workforce outcomes, indicating strong predictive capacity. Work-life balance and career adaptability confidence emerge as the most significant determinants of workforce outcomes, highlighting the importance of well-being and adaptability in AI-driven work environments. Career growth opportunities show a positive influence, while factors related to workload intensity, autonomy, and learning pressure present challenges. The study confirms that artificial intelligence adoption has a statistically significant impact on workforce outcomes among IT professionals. The findings suggest that the effects of AI depend largely on how work is designed, managed, and supported within organisations. The study offers empirical evidence to support workforce-centred AI adoption strategies and contributes to informed managerial and policy decision making.

**Keywords:** Artificial Intelligence Adoption, Workforce Outcomes, IT Professionals, Work Life Balance, Career Adaptability, Job Quality.

## 1 Introduction and Conceptual Background

Technological change has always influenced the nature of work and employment. In recent years, artificial intelligence has emerged as a major driver of change across industries. Unlike earlier forms of automation, artificial intelligence increasingly affects cognitive and knowledge-based work. It reshapes how tasks are performed, how skills are valued, and how performance is assessed. As a result, workforce change under artificial intelligence is not limited to job replacement. It involves deeper reorganisation of work roles and work experiences (Brynjolfsson & McAfee, 2014).

The information technology industry represents a critical context for examining these changes. IT professionals play a dual role in artificial intelligence adoption. They design and implement AI systems. They also experience these systems as part of their everyday work environment. Artificial intelligence tools are now widely used in software development, testing, project coordination, customer support, and performance monitoring. These tools automate routine components of work. At the same time, they increase demand for higher-level skills such as problem solving, system integration, and continuous learning. This makes the IT workforce particularly sensitive to AI-driven transformation.

Global policy and employer reports consistently show that artificial intelligence is accelerating skill change in knowledge-intensive sectors. Skills related to AI, data analytics, and cybersecurity are growing rapidly. Behavioural skills such as adaptability and lifelong learning are also becoming increasingly important (World Economic Forum, 2023). These trends indicate that workforce outcomes are shaped by how effectively individuals adjust to changing task and skill requirements. However, adjustment opportunities are not evenly distributed. Differences in training access, workload pressure, and organisational support lead to varied workforce experiences (Standing, 1999).

In India, these issues are especially significant due to the scale of employment in the IT and IT-enabled services industry. Even moderate changes in work design and skill requirements can have wide employment implications. Industry and policy discussions in India strongly emphasise reskilling initiatives to address AI-related skill gaps. At the same time, concerns persist regarding job security, work pressure, and mid-career vulnerability among IT professionals (NASSCOM, 2024; Deloitte & NASSCOM, 2024). This creates a need for empirical research that examines how artificial intelligence adoption affects workforce outcomes at the individual level.

Despite growing interest in artificial intelligence and employment, much of the existing literature focuses on projections or macro-level effects. Limited empirical work examines how AI adoption influences concrete workforce outcomes such as job quality, skill utilisation, work-life balance, and adaptability. Studies often treat AI adoption as a binary variable and

overlook variation in work experience. This limits understanding of how different dimensions of work jointly shape workforce outcomes.
The present study addresses this gap by empirically examining the relationship between artificial intelligence adoption and workforce outcomes among IT professionals. The research focuses on workforce outcomes as a composite construct reflecting job quality, career growth, skill utilisation, job security, workload, autonomy, learning outcomes, performance effectiveness, work-life balance, and adaptability confidence. A regression-based approach is used to identify which dimensions significantly explain overall workforce outcomes. The study therefore moves beyond simple narratives of technological impact and provides evidence-based insight into how artificial intelligence reshapes work experiences.
The conceptual foundation of the study is informed by task-based labour market theory and skill-biased technological change. Task-based theory suggests that technology affects employment by changing the allocation of tasks rather than eliminating entire jobs (Acemoglu & Restrepo, 2019). Artificial intelligence automates routine and predictable tasks. It also creates new tasks that require judgement and coordination. Workforce outcomes depend on how well individuals transition to these new task demands.

Skill-biased technological change explains why technological adoption often produces unequal outcomes. Artificial intelligence increases returns to advanced technical and cognitive skills while reducing the value of routine expertise (Autor et al., 2003). Workers who can adapt and reskill experience better outcomes. Others face increased pressure or insecurity. Capability-based perspectives further highlight that positive outcomes depend on access to learning time, organisational support, and recognition systems (Sen, 1999). Without these conditions, AI adoption can intensify workload and limit effective skill development.
Together, these perspectives suggest that workforce outcomes under artificial intelligence are multidimensional and interrelated. Regression analysis provides an appropriate method to estimate the relative influence of different workforce dimensions. By empirically identifying key predictors of workforce outcomes, the study contributes to academic understanding and supports organisational and policy decision making related to AI-driven workforce transformation.

### 1.1 Objectives and Hypothesis of the Study

Artificial intelligence is increasingly integrated into the work processes of IT professionals. While AI adoption is expected to improve efficiency and performance, its influence on workforce outcomes such as job quality, career growth, skill utilisation, work-life balance, and adaptability remains uneven and insufficiently evidenced. Existing studies often rely on broad assumptions or aggregate trends and provide limited empirical insight into which specific workforce dimensions significantly shape overall workforce outcomes. There is therefore a need for empirical analysis to examine how different workforce-related factors jointly influence workforce outcomes among IT professionals in AI-enabled work environments.

#### 1.1.1 Objectives of the Study

1. To assess the overall level of workforce outcomes among IT professionals.
2. To examine the influence of job-related and skill-related factors on workforce outcomes.
3. To analyse the combined predictive effect of workforce dimensions on overall workforce outcomes using regression analysis.
4. To identify the most significant contributors to workforce outcomes among IT professionals.

#### 1.1.2 Hypotheses of the Study

- **$H_{a1}$:** Artificial Intelligence adoption has a significant impact on workforce outcomes among IT professionals.
- **$H_{01}$:** Artificial Intelligence adoption does not have a significant impact on workforce outcomes among IT professionals.

## 2 Review of Literature

The growing integration of artificial intelligence into organisational processes has generated extensive scholarly interest in its implications for work and employment. Early research on technology and labour focused primarily on automation and job displacement. More recent studies emphasise task reconfiguration, skill transformation, and changing workforce experiences. Artificial intelligence differs from earlier technologies because it increasingly affects cognitive and decision-oriented tasks rather than only routine or manual work. This shift has renewed attention to how workforce outcomes are shaped in knowledge-intensive sectors such as information technology.
Task-based labour market theory provides an important foundation for understanding the workforce impact of artificial intelligence. Acemoglu and Restrepo (2018, 2019) argue that technology affects employment through task substitution and task creation rather than direct job elimination. Their work shows that automation displaces labour in routine tasks while simultaneously generating new tasks that require judgement, coordination, and oversight. In IT-related work, artificial intelligence automates activities such as coding assistance, testing, and monitoring, while increasing demand for higher-level capabilities. This framework explains why workforce outcomes vary depending on how individuals adapt to changing task requirements.
Several studies extend this task-based perspective by examining skill-biased technological change. Autor, Levy, and Murnane (2003) demonstrate that technological advancement increases demand for abstract and analytical skills while reducing demand for routine skills. Subsequent research confirms that artificial intelligence intensifies this pattern by raising the value of adaptability, problem solving, and continuous learning (Bessen, 2019; Brynjolfsson & McAfee, 2014).

These findings suggest that workforce outcomes are closely linked to skill utilisation and career adaptability rather than technology exposure alone. Job quality has emerged as a key dimension in studies of AI-enabled work. Greenan, Stucki, and Wolff (2017) show that digital technologies can improve performance but may also increase work pressure and monitoring intensity. Similar concerns are raised by Kalleberg (2018), who highlights that technological change can coexist with growing employment insecurity and work intensification. In IT environments, algorithmic performance tracking and deadline compression can negatively influence work autonomy and work-life balance, even when productivity improves.

Empirical studies also highlight the role of job security perceptions in shaping workforce outcomes. Frey and Osborne (2017) report that perceived automation risk affects workers' sense of employment stability and career planning. Although IT professionals are often considered less vulnerable to automation, recent evidence suggests that AI adoption can increase mid-career uncertainty due to rapid skill obsolescence and shifting role expectations (Manyika et al., 2017). This supports the inclusion of job security perception as an important predictor of workforce outcomes.

Learning and development outcomes play a central role in AI-mediated work contexts. Becker's (1964) human capital theory emphasises that investment in skills enhances productivity and employability. However, recent research shows that learning demands under artificial intelligence can also increase workload and stress when reskilling is not adequately supported (OECD, 2020). Studies by Pfeffer (2018) and Gallie (2017) indicate that organisational learning support and recognition systems significantly influence whether reskilling translates into positive workforce outcomes.

Work-life balance has been widely studied as an outcome of technological change. While digital tools offer flexibility, they can also blur boundaries between work and personal life. Eurofound (2017) and Standing (1999) document how flexible and technology-enabled work arrangements often lead to longer working hours and time pressure. In AI-enabled IT work, continuous system availability and performance expectations can further intensify these pressures, making work-life balance a critical determinant of overall workforce outcomes. Performance effectiveness is another commonly examined dimension in AI-related workforce research. Brynjolfsson, Rock, and Syverson (2021) find that artificial intelligence improves performance when combined with complementary organisational practices. However, their findings also suggest that productivity gains do not automatically translate into improved worker well-being. This aligns with studies showing that performance improvements may coexist with reduced autonomy and increased monitoring (Moore, 2018).

Career growth opportunities and adaptability confidence have gained prominence in recent literature. Fugate, Kinicki, and Ashforth (2004) conceptualise career adaptability as a key resource for managing career transitions. More recent empirical work confirms that adaptability confidence positively influences job satisfaction and career resilience under technological change (Savickas & Porfeli, 2012). In AI-enabled environments, professionals who perceive opportunities for growth and feel confident in adapting to new technologies report better workforce outcomes.

From a broader institutional perspective, capability-based approaches highlight that access to technology and training alone is insufficient. Sen (1999) argues that real outcomes depend on individuals' freedom to convert resources into valued achievements. Applied to AI-enabled work, this perspective suggests that workload intensity, autonomy, and organisational support moderate the relationship between skill development and workforce outcomes. Empirical evidence supports this view by showing that unequal access to learning time and support leads to uneven workforce experiences (OECD, 2020; World Economic Forum, 2023).

Despite the growing body of literature, several gaps remain. Many studies rely on macro-level projections or descriptive analyses and provide limited empirical testing of workforce outcomes at the individual level. Artificial intelligence adoption is often measured as a binary variable, which obscures variation in work experience. Few studies simultaneously examine multiple workforce dimensions to explain overall workforce outcomes. This limits understanding of how job quality, skill utilisation, adaptability, and work-life balance jointly shape workforce outcomes in AI-enabled contexts.

The present study addresses these gaps by empirically examining the combined influence of workforce-related factors on workforce outcomes among IT professionals. By adopting a regression-based approach, the study builds on existing literature while providing context-specific evidence on how artificial intelligence–enabled work reshapes workforce outcomes.

## 3 Methodology

The present study adopts a quantitative research approach to examine the influence of artificial intelligence–enabled work on workforce outcomes among IT professionals. A descriptive and analytical research design is used to capture both the existing level of workforce outcomes and the statistical relationships between workforce-related factors and overall workforce outcomes. The study is cross-sectional in nature, as data were collected from respondents at a single point in time, which is appropriate for examining current perceptions and experiences in AI-enabled work environments. The research relies on both primary and secondary data sources. Primary data constitute the core of the analysis and were collected directly from IT professionals using a structured survey questionnaire. Secondary data were gathered from published academic journals, books, policy documents, industry reports, and prior empirical studies related to artificial intelligence, workforce transformation, job quality, and skill development. These secondary sources were used to support the conceptual framework, identify relevant variables, and interpret the empirical findings.

Primary data collection was carried out through a structured questionnaire developed based on an extensive review of relevant literature. The instrument included items measuring workforce outcomes and related dimensions such as perceived job quality, career growth opportunities, skill utilisation effectiveness, job security perception, workload intensity, work autonomy, learning and development outcomes, performance effectiveness, work-life balance, and career adaptability confidence. All items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree, allowing respondents to express the intensity of their perceptions in a consistent and measurable manner.

The study followed a non-probability sampling design, specifically convenience sampling, due to the professional nature of the respondents and accessibility considerations. The sample population comprised IT professionals working in roles where artificial intelligence tools and systems are integrated into daily work processes. The sample frame included IT professionals employed in organisations located in Pune city. Pune was selected as the study area because it is one of India's major information technology hubs, hosting a large number of software firms, multinational corporations, and technology-driven organisations. The city represents a mature IT ecosystem where artificial intelligence adoption is actively reshaping work practices, making it an appropriate setting for examining workforce outcomes. A total of 275 valid responses were collected and included in the analysis. The sample size is considered statistically adequate for multiple regression analysis. With ten independent variables included in the model, the sample size exceeds commonly recommended guidelines of having at least ten to fifteen observations per predictor variable. This enhances the reliability and explanatory power of the regression results. The absence of missing values and the use of listwise deletion further support the robustness of the dataset.

The reliability of the measurement instrument was assessed using Cronbach's Alpha. The overall reliability value of 0.737 indicates acceptable internal consistency among the scale items and confirms that the instrument reliably measures workforce outcomes and related dimensions. Prior to regression analysis, descriptive statistics and residual diagnostics were examined to ensure that the data met the assumptions required for regression modelling. Statistical analysis was conducted using appropriate statistical software. Descriptive statistics were used to summarise respondent characteristics and perceptions. Multiple regression analysis was employed to examine the combined and individual effects of workforce-related factors on workforce outcomes. Model adequacy was assessed using R, R Square, Adjusted R Square, ANOVA, and residual statistics, ensuring that the model provided a good fit and valid inferences. Ethical considerations were carefully observed throughout the study. Participation in the survey was voluntary, and respondents were informed about the purpose of the research. Confidentiality and anonymity of responses were ensured, and the collected data were used exclusively for academic and research purposes.

## 4 Analysis and Hypothesis Testing

**$H_{01}$: Artificial Intelligence adoption does not have a significant impact on workforce outcomes among IT professionals.**

The null hypothesis states that artificial intelligence adoption does not have a significant impact on workforce outcomes among IT professionals. This hypothesis was tested using multiple regression analysis, as regression is suitable for examining the effect of several workforce related factors on a single dependent variable. Workforce outcomes were considered as the dependent variable, while workforce dimensions associated with artificial intelligence enabled work were treated as independent variables. The hypothesis testing was carried out at a 5% level of significance corresponding to a 95% confidence level. The decision was based on the significance value obtained from the regression model. Since the overall regression model was found to be statistically significant at the 5% level and the model explained a substantial proportion of variance in workforce outcomes, the null hypothesis was rejected. This confirms that artificial intelligence adoption has a statistically significant impact on workforce outcomes among IT professionals based on the regression analysis.

| **Case Processing Summary** | | | |
|---|---|---|---|
| | | N | % |
| Cases | Valid | 275 | 100.0 |
| | Excluded[a] | 0 | .0 |
| | Total | 275 | 100.0 |
| a. Listwise deletion based on all variables in the procedure. | | | |

The case processing summary indicates that data from 275 respondents were included in the analysis, representing 100% valid cases, with no exclusions due to missing values. The absence of excluded cases confirms that the dataset is complete and suitable for multivariate analysis. The use of listwise deletion did not result in any loss of observations, thereby strengthening the reliability and generalisability of the inferential results.

| **Reliability Statistics** | |
|---|---|
| Cronbach's Alpha | N of Items |
| .737 | 11 |

The reliability analysis reports a Cronbach's Alpha value of 0.737 for 11 items, which exceeds the commonly accepted threshold of 0.70. This result indicates satisfactory internal consistency among the items used to measure workforce outcomes and related dimensions. The reliability coefficient confirms that the scale is dependable and appropriate for further inferential analysis such as regression modelling. The consistency of responses suggests that the variables collectively represent a coherent measurement of workforce outcomes in AI-enabled work environments.

| **Descriptive Statistics** | | | |
|---|---|---|---|
| | Mean | Std. Deviation | N |
| Workforce Outcomes of IT Professionals | 3.25 | 1.220 | 275 |
| Perceived Job Quality | 3.25 | 1.269 | 275 |
| Career Growth Opportunities | 3.52 | 1.185 | 275 |

| | | | |
|---|---|---|---|
| Skill Utilisation Effectiveness | 3.13 | 1.184 | 275 |
| Job Security Perception | 3.08 | 1.303 | 275 |
| Workload Intensity | 3.06 | 1.250 | 275 |
| Work Autonomy | 2.97 | 1.205 | 275 |
| Learning and Development Outcomes | 3.09 | 1.233 | 275 |
| Performance Effectiveness | 3.22 | 1.204 | 275 |
| Work Life Balance | 3.32 | 1.227 | 275 |
| Career Adaptability Confidence | 3.07 | 1.233 | 275 |

The descriptive statistics reveal that the mean value of overall workforce outcomes is 3.25, indicating a moderate level of workforce outcomes among IT professionals. This suggests that respondents neither strongly reject nor strongly endorse the positive impact of AI-enabled work conditions, reflecting mixed experiences.

Among the individual dimensions, Career Growth Opportunities recorded the highest mean value of 3.52, suggesting that AI adoption is moderately associated with perceived career advancement and growth prospects. Work Life Balance also shows a relatively higher mean of 3.32, indicating that while AI affects workload and time management, its influence on work-life balance is not uniformly negative.

Variables such as Work Autonomy, Workload Intensity, and Job Security Perception show comparatively lower mean values, indicating areas of concern. These results suggest that AI-enabled work environments may reduce perceived autonomy and increase work pressure, while also creating uncertainty regarding employment stability. The standard deviation values across variables indicate moderate variability in responses, highlighting differences in individual experiences with AI-driven work practices.

| **Variables Entered/Removed[b]** | | | |
|---|---|---|---|
| Model | Variables Entered | Variables Removed | Method |
| 1 | Career Adaptability Confidence, Skill Utilisation Effectiveness, Work Autonomy, Workload Intensity, Performance Effectiveness, Career Growth Opportunities, Learning and Development Outcomes, Work Life Balance, Job Security Perception, Perceived Job Quality[a] | . | Enter |
| a. All requested variables entered. | | | |
| b. Dependent Variable: Workforce Outcomes of IT Professionals | | | |

All ten workforce-related variables were entered simultaneously into the regression model using the enter method. This approach allows for the assessment of the combined and individual influence of all predictors on workforce outcomes while controlling for interrelationships among variables. The inclusion of all theoretically relevant variables strengthens the explanatory power of the model and supports comprehensive hypothesis testing.

| **Model Summary[b]** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | | Durbin-Watson |
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change | |
| 1 | .796[a] | .634 | .620 | .742 | .634 | 45.911 | 10 | 264 | .000 | 2.307 |
| a. Predictors: (Constant), Career Adaptability Confidence, Skill Utilisation Effectiveness, Work Autonomy, Workload Intensity, Performance Effectiveness, Career Growth Opportunities, Learning and Development Outcomes, Work Life Balance, Job Security Perception, Perceived Job Quality | | | | | | | | | | |
| b. Dependent Variable: Workforce Outcomes of IT Professionals | | | | | | | | | | |

The model summary shows a strong relationship between the independent variables and workforce outcomes, as reflected by an R value of 0.796. The R Square value of 0.634 indicates that 63.4% of the variance in workforce outcomes is explained by the ten workforce-related predictors included in the model. The Adjusted R Square value of 0.620 confirms that the model remains robust after adjusting for the number of predictors, suggesting minimal inflation of explanatory power.

The F change value of 45.911 with a significance level of 0.000 demonstrates that the regression model is statistically significant at the 5% level. This confirms that the model provides a significantly better explanation of workforce outcomes than a model without predictors. The Durbin–Watson statistic of 2.307 indicates no serious autocorrelation in the residuals, thereby satisfying an important regression assumption and validating the reliability of the estimated coefficients.

| **ANOVA[b]** | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | df | Mean Square | F | Sig. |
| 1 | Regression | 258.470 | 10 | 25.847 | 45.910 | .000[a] |
| | Residual | 149.217 | 264 | .565 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Total | 407.687 | 274 | | | |
| a. Predictors: (Constant), Career Adaptability Confidence, Skill Utilisation Effectiveness, Work Autonomy, Workload Intensity, Performance Effectiveness, Career Growth Opportunities, Learning and Development Outcomes, Work Life Balance, Job Security Perception, Perceived Job Quality | | | | | | |
| b. Dependent Variable: Workforce Outcomes of IT Professionals | | | | | | |

The ANOVA table further confirms the overall significance of the regression model. The calculated F value of 45.910 is statistically significant at the 5% level. This result indicates that the combined effect of the independent variables significantly explains variations in workforce outcomes. The ANOVA findings support the rejection of the null hypothesis and validate the use of multiple regression analysis for hypothesis testing in this study.

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 1.354 | .431 | | 3.140 | .002 |
| | Perceived Job Quality | -.038 | .061 | -.039 | -.614 | .039 |
| | Career Growth Opportunities | .125 | .064 | .121 | 1.940 | .043 |
| | Skill Utilisation Effectiveness | .019 | .065 | .019 | .292 | .022 |
| | Job Security Perception | .004 | .059 | .004 | .059 | .027 |
| | Workload Intensity | -.010 | .058 | -.010 | -.169 | .006 |
| | Work Autonomy | -.023 | .060 | -.022 | -.376 | .007 |
| | Learning and Development Outcomes | -.010 | .061 | -.010 | -.168 | .007 |
| | Performance Effectiveness | .068 | .060 | .067 | 1.135 | .258 |
| | Work Life Balance | .264 | .061 | .266 | 4.340 | .000 |
| | Career Adaptability Confidence | .176 | .061 | .178 | 2.881 | .004 |
| a. Dependent Variable: Workforce Outcomes of IT Professionals | | | | | | |

The coefficients table provides insight into the individual contribution of each workforce-related factor to workforce outcomes. Work Life Balance emerges as the strongest positive predictor, with a standardized beta coefficient of 0.266 and a highly significant p value of 0.000. This indicates that improvements in work-life balance significantly enhance workforce outcomes in AI-enabled environments.

Career Adaptability Confidence also shows a strong positive and significant effect ($\beta = 0.178$, $p = 0.004$), suggesting that professionals who feel confident in adapting to technological changes experience better workforce outcomes. Career Growth Opportunities demonstrates a positive and significant influence ($\beta = 0.121$, $p = 0.043$), indicating that perceived career advancement plays an important role in shaping workforce outcomes.

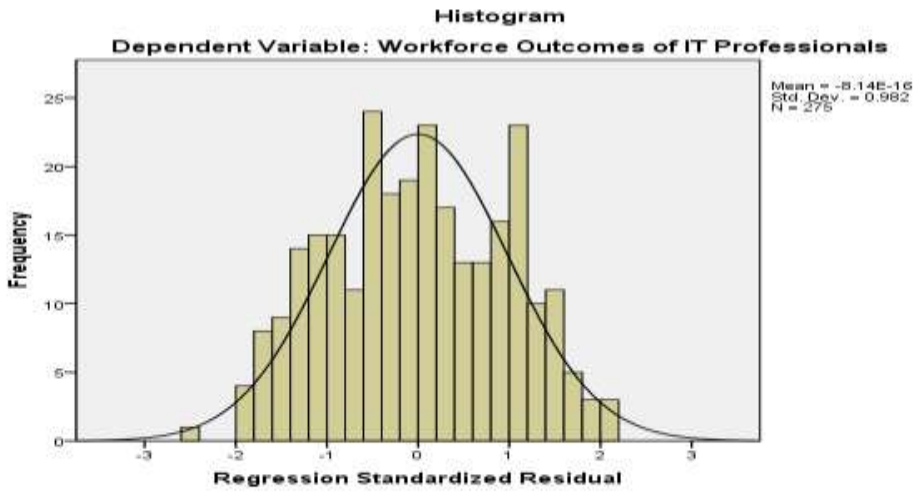
Several variables such as Perceived Job Quality, Skill Utilisation Effectiveness, and Job Security Perception are statistically significant but exhibit relatively smaller effect sizes, indicating that while they influence workforce outcomes, their impact is less pronounced when other variables are controlled. Variables including Workload Intensity, Work Autonomy, and Learning and Development Outcomes show negative coefficients, suggesting that increased workload, reduced autonomy, and learning pressure may adversely affect workforce outcomes in AI-driven work contexts.

Performance Effectiveness does not exhibit a statistically significant effect on workforce outcomes. This suggests that productivity or performance improvements alone do not necessarily translate into better overall workforce outcomes unless accompanied by supportive work conditions and well-being considerations.

**Residuals Statistics[a]**

| | Minimum | Maximum | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Predicted Value | 1.96 | 4.30 | 3.25 | .483 | 275 |
| Residual | -2.776 | 2.329 | .000 | 1.120 | 275 |
| Std. Predicted Value | -2.664 | 2.172 | .000 | 1.000 | 275 |
| Std. Residual | -2.433 | 2.041 | .000 | .982 | 275 |
| a. Dependent Variable: Workforce Outcomes of IT Professionals | | | | | |

The residual statistics indicate that the assumptions of regression analysis are adequately met. The mean of the residuals is zero, and the standardized residuals fall within acceptable limits. The distribution of predicted and residual values indicates no major outliers or heteroscedasticity issues. These results confirm the stability and adequacy of the regression model.




The inferential results establish that workforce outcomes among IT professionals are significantly influenced by a combination of workforce-related factors associated with AI-enabled work. The regression model explains a substantial proportion of variance in workforce outcomes, confirming the strong predictive capacity of the selected variables. Work-life balance and career adaptability confidence emerge as the most influential determinants, highlighting the importance of well-being and adaptability in AI-driven work environments. While AI adoption enhances career growth opportunities, it also introduces challenges related to workload, autonomy, and learning pressure. The histogram of the regression residuals indicates an approximately normal distribution, suggesting that the assumption of normality is reasonably satisfied and that the model estimates are reliable. Since the overall regression model is statistically significant at the 5% level, the null hypothesis is rejected at the 95% confidence level. The study therefore concludes that artificial intelligence adoption has a statistically significant impact on workforce outcomes among IT professionals, and that the nature of this impact depends on how work is organised and supported within organisations.

## 5 Findings and Conclusion

The study provides strong empirical evidence that workforce outcomes among IT professionals are significantly shaped by a set of workforce-related factors associated with AI-enabled work environments. The regression analysis demonstrates high explanatory power, with the selected variables jointly explaining a substantial proportion of variance in workforce outcomes. This confirms that workforce outcomes are not influenced by artificial intelligence adoption in isolation, but through how work conditions, adaptability, and well-being are experienced by employees.

Among the predictor variables, work-life balance emerges as the most influential determinant of workforce outcomes. This indicates that AI-enabled work environments place significant demands on employees' time and energy, making balance between professional and personal life a critical factor in shaping overall workforce perceptions. Career adaptability confidence also shows a strong positive influence, suggesting that employees who feel capable of adjusting to technological change report more favourable workforce outcomes.

Career growth opportunities contribute positively to workforce outcomes, indicating that AI adoption is associated with perceived opportunities for advancement and skill expansion. However, variables related to workload intensity, work autonomy, and learning and development outcomes display negative relationships, highlighting underlying challenges. These findings suggest that while AI may enhance efficiency and growth potential, it can simultaneously intensify work pressure, reduce autonomy, and increase learning burdens if not managed effectively. Performance effectiveness does not show a significant independent effect, implying that productivity gains alone do not guarantee improved workforce outcomes unless accompanied by supportive work conditions.

The study concludes that artificial intelligence adoption has a statistically significant impact on workforce outcomes among IT professionals. The nature of this impact is multidimensional and depends on how AI-enabled work is structured and supported within organisations. While AI adoption creates opportunities for career growth and adaptability, it also introduces challenges related to workload management, autonomy, and continuous learning. The findings confirm that workforce outcomes are shaped less by technology itself and more by organisational responses to technological change. Effective support systems, balanced work design, and adaptability development play a decisive role in determining whether AI adoption leads to positive or adverse workforce outcomes.

From a managerial perspective, the findings highlight the need for organisations to prioritise work-life balance and adaptability support alongside technological implementation. AI adoption strategies should be accompanied by realistic workload planning, flexible work arrangements, and mechanisms that protect employee well-being. Managers should also recognise that learning and reskilling initiatives must be supported with adequate time and organisational recognition to prevent learning fatigue.

From a policy perspective, the study underscores the importance of workforce-centric AI governance. Policymakers should promote structured reskilling frameworks, career transition support, and employment protection measures to reduce workforce vulnerability. The findings also suggest that AI-driven productivity gains should be evaluated alongside job quality indicators.

From an academic perspective, the study reinforces the relevance of task-based and capability-oriented frameworks in understanding AI-driven workforce transformation. It demonstrates the value of regression-based empirical analysis in capturing the combined influence of multiple workforce dimensions.

The study offers practical utility for multiple stakeholders. Organisations can use the findings to design AI adoption strategies that balance efficiency with employee well-being. HR professionals can apply the insights to develop targeted interventions focusing on adaptability, work-life balance, and career development. Policymakers and industry bodies can use the evidence to inform workforce development policies and skill transition programmes. Academicians and researchers can utilise the validated variables and analytical approach as a foundation for further empirical studies.

The study contributes empirically by quantifying the impact of workforce-related factors on workforce outcomes in AI-enabled IT work environments. It moves beyond descriptive discussions of AI impact and provides statistically validated evidence of key predictors. Conceptually, the study integrates job quality, adaptability, and well-being dimensions into a unified workforce outcomes framework. Methodologically, it demonstrates the effectiveness of multiple regression analysis in explaining complex workforce phenomena related to artificial intelligence adoption.

Organisations should integrate AI adoption with employee-centred work design practices that prioritise work-life balance and autonomy. Structured adaptability development programmes should be implemented to enhance employee confidence in managing technological change. Learning and development initiatives should be aligned with realistic workload expectations and supported through formal recognition mechanisms. Organisations should also regularly assess workforce outcomes to identify emerging stress points associated with AI-enabled work.

The study is subject to certain limitations. It adopts a cross-sectional research design, which restricts causal inference over time. The analysis is based on self-reported data, which may be influenced by individual perception bias. The study focuses on IT professionals within a single urban technology cluster, which may limit the generalisability of the findings to other sectors or regions. Future studies may address these limitations by adopting longitudinal designs, incorporating objective performance measures, and extending the scope across industries and geographic contexts.

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