IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

The Artificial Intelligence Divide in Private Workplaces in Kerala: A Study of AI Accessibility, Adoption and Employee Inequality

Prasad.P[1], Dr. Mugesh P[2]

Associate Professor in Commerce, Sree Neelakanta Government Sanskrit College, Pattambi, Palakkad(DT), Kerala[1]

Assistant Professor in Commerce, AMC- Allied Management College, Ottapalam, Palakkad(DT), Kerala[2]

Abstract: The rapid integration of Artificial Intelligence (AI) into organizational operations has changed the nature of employment, workplace communication, decision-making and employee productivity. However, the adoption of artificial intelligence (AI) technologies has not been uniform across employees and has resulted in an emerging form of technological inequality, known as Artificial Intelligence Divide. The gap reflects differences in access to AI tools, awareness, digital competencies, organizational support and opportunities to work with AI-based technologies in professional activities. This study examines the Artificial Intelligence Divide in Kerala's private workplaces with a focus on AI accessibility, adoption and employee inequality. The study specifically explores the disparities in AI accessibility and adoption based on gender, age and educational qualification and investigates the relationship between AI accessibility and employee inequality. It suggests descriptive and analytical research design based on primary data from 437 employees working in private sector organizations in Kerala. Statistical analysis is performed with the help of mean, standard deviation, independent sample t-test, one way analysis of variance and simple linear regression. The analytical framework indicates that there are unequal opportunities for employees to adopt AI, a consequence of differences in AI availability and organizational support. The study highlights the need for inclusive AI policies, employee training, equal access to technology resources and organizational initiatives to reduce workplace inequalities related to AI. The research contributes to our understanding of technological inclusion and the changing nature of employment within the framework of AI-driven organizational transformation.

Keywords: Artificial Intelligence Divide, AI Accessibility, AI Adoption, Employee Inequality, Private Workplaces, Kerala, Technological Competency.

I. INTRODUCTION

Artificial Intelligence is one of the most important technological developments affecting modern business organizations. AI has revolutionized traditional work processes in the activities of organizations through automation, predictive analytics, intelligent decision making, customer relationship management and the development of advanced communication systems. More and more private sector organizations are implementing AI-based applications to enhance operational efficiency, decrease administrative costs, improve customer experiences and increase organization competitiveness. "Technologies like generative AI, machine learning, intelligent automation and AI-powered analytical platforms have created new opportunities for employees to perform professional activities more efficiently.

These improvements did not result in employees receiving an equitable share of the benefits of AI. Disparities in understanding of technology, access to AI tools, digital skills, educational credentials and organizational support may contribute to unequal chances for individuals to engage in AI-driven workplace activities. individuals that have better access to cutting-edge technology and sufficient training may be more likely to utilize AI tools, whereas individuals with limited exposure, inadequate technical understanding or limited organizational access can find it difficult to adapt to technological advances. This unequal distribution of opportunities would be an emergent feature of the digital divide, often conceptualized as the Artificial Intelligence Divide.

The Artificial Intelligence Divide goes beyond the conventional problems of computer accessibility and internet connectivity. It includes variations in the accessibility, cost, usability, and efficient application of AI technologies. These differences can occur in private businesses between workers in different occupational roles, workers in different age groups, and workers with varied technological and educational backgrounds. The degree of AI inclusion may also be influenced by organizational regulations controlling access to AI platforms, staff training initiatives, technology infrastructure, and management philosophies.

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

Because private sector employment spans a variety of organizational environments, such as banking, finance, information technology, retail, healthcare, education, tourism, and business services, Kerala offers an important setting for investigating this rising problem. Depending on their job duties and the technological focus of their companies, workers in various industries may be exposed to AI technology to varying degrees. While some workers might frequently utilize AI-powered apps, others might not have the resources or expertise to integrate these technologies into their work.

Concerns about labor inequality, technological displacement, skill obsolescence, and unequal career possibilities are also brought up by the rise of AI-based workplace systems. In order to create inclusive organizational strategies that guaranty employees can effectively participate in the evolving technology environment, it is crucial to comprehend the Artificial Intelligence Divide. In light of this, the current study investigates AI use, accessibility, and employee inequality in Keralan private enterprises.

II. STATEMENT OF THE PROBLEM

The growing use of AI in businesses in the private sector has opened up a lot of possibilities for raising employee performance, operational effectiveness, and workplace productivity. However, employees' access to and use of AI technologies is still inconsistent. Employee access to and use of AI-based apps may be impacted by differences in educational background, technological proficiency, organizational roles, age, and gender. While some employees might benefit from institutional support, technology resources, and training opportunities, others might have limited access, insufficient knowledge, and few chances to learn AI-related skills.

This unequal distribution of AI-related opportunities constitutes a new kind of workplace inequality that goes beyond previous forms of digital exclusion. Individuals with limited access to advanced artificial intelligence (AI) tools might find it difficult to adapt to changing job demands, while those possessing robust technical abilities may enjoy further career benefits. Such disparities may affect the participation, productivity, career development and opportunities of employees in terms of their jobs in private organizations.

Kerala has private sector organizations in different industries and different occupational environments. The understanding of these inequalities is increasingly important in the state. However, the extent to which employees experience differences in AI accessibility, awareness, adoption and organizational support needs systematic empirical investigation. It is also important to consider how AI accessibility varies considerably between demographic groups and whether unequal access to standard artificial intelligence (AI) tools is linked to employee inequality. Hence the current study intends to explore the Artificial Intelligence Divide in the private workplaces in Kerala by measuring the AI accessibility, adoption and employee inequality among 437 employees.

III. OBJECTIVES OF THE STUDY

The study seeks to evaluate the level of awareness, accessibility and adoption of Artificial Intelligence (AI) among the employees of private sector organizations in Kerala. It also wants to explore the variations in the accessibility and adoption of AI among employees in terms of gender, age groups and educational qualifications. The study also seeks to examine the role of organizational support and AI-related training in facilitating the uptake of artificial intelligence (AI) technologies by employees. Finally, it aims to study the association between AI accessibility and employee inequality in private workplaces in Kerala.

IV. HYPOTHESES OF THE STUDY

The following six null hypotheses are formulated to examine the research objectives.

- H01: There is no significant difference in AI accessibility between male and female employees in private sector organisations in Kerala.
- H02: There is no significant difference in AI adoption between male and female employees in private sector organisations in Kerala.
- H03: There is no significant difference in AI accessibility among employees belonging to different age groups.
- H04: There is no significant difference in AI adoption among employees with different educational qualifications.
- H05: There is no significant difference in AI-related organisational support among employees belonging to different age groups.
- H06: AI accessibility has no significant effect on employee inequality in private workplaces in Kerala.

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

V. REVIEW OF LITERATURE

The digital divide has shifted from a traditional issue of access to computers and internet connectivity to a broader issue of technological competencies, usage patterns and unequal benefits. Hargittai (2002) pointed out the importance of differences in internet skills and the ability to effectively use digital resources. Van Deursen and van Dijk (2011) have shown that digital inequality is not just a matter of physical access but also includes differences in operational, information and strategic internet skills. Helsper (2012) studied the link between digital and social inequalities, emphasizing the impact of offline disadvantages on digital participation. Van Deursen and Helsper (2015) expanded the concept of the third-level digital divide by arguing that even if people have equal access to technologies, they may experience unequal outcomes. Scheerder et al. (2017) review the evolution of research on the digital divide and point out the significance of investigating differences in digital skills, usage and outcomes. Digital divides are linked to existing social and economic inequalities, Robinson et al. (2015) pointed out. Perceived usefulness and perceived ease of use are important determinants of technology acceptance established by Davis (1989) through the Technology Acceptance Model. Venkatesh et al. (2003) developed this further as the Unified Theory of Acceptance and Use of Technology, which focused on performance expectancy, effort expectancy, social influence and facilitating conditions. These theoretical contributions lay the foundation for comprehending the role of employees' personal competencies and organizational environments in accessibility and adoption of new technologies.

Lately, research has increasingly shifted to the implications of AI for employment relations, workplace structures, and employee inequalities. Jarrahi (2018) discussed the importance of human-AI collaboration in organizational decision making and suggested that AI should complement human capabilities. Brougham and Haar (2018) investigated the employees' perception of technological progress and its implication on future jobs. The way algorithmic systems are changing organizational control through monitoring, evaluation and decision-making mechanisms has been highlighted by Kellogg et al. (2020). The automation-augmentation paradox was also discussed by Raisch and Krakowski (2021), where artificial intelligence may simultaneously replace and complement human capabilities. Shrestha et al. (2019) investigated the implications of AI for organizational decision making structures. Tambe et al. (2019) discuss the opportunities and challenges of using AI in human resource management. Faraj et al. (2018) examined how learning algorithms transform the work and coordination of organizations. Acemoglu and Restrepo (2019), Acemoglu and Restrepo (2020) described the effects of automation and new tasks on labor demand and skill-based inequality. AI may generate inequalities at work via a variety of mechanisms, as reviewed in an integrated manner by Karunakaran et al. (2025) in a recent review. Bankins et al. (2024) discussed how artificial intelligence (AI) technologies can automate, complement and transform human work, while creating new skill requirements. Milanez et al. (2025) studied the emergence of algorithmic management in workplaces. In addition, recent research on generative AI and digital inequality has identified education, socioeconomic circumstances, and work characteristics as important factors associated with unequal opportunities to access and utilize AI (2024). Taken together, the studies emphasize the necessity of studying AI-related inequalities at the level of employees, especially within varied organizational contexts such as workplaces in the private sector in Kerala.

VI. RESEARCH METHODOLOGY

The research design of this study is descriptive analytical. The study analyzes the Artificial Intelligence Divide in private workplaces of Kerala. The study population is employees of private sector organizations in Kerala such as banking, finance, information technology, education, healthcare, retail, tourism, manufacturing and business services. A convenience and purposive sample of 437 employees representing different occupational and demographic backgrounds was selected. The study is mainly based on primary data collected through a structured questionnaire. Secondary data have been sourced from research articles, academic journals, books, reports and relevant publications related to AI adoption, digital inequality and workplace transformation. AI accessibility, AI awareness, AI adoption, AI competency, organizational support and employee inequality are assessed on a five-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). AI accessibility is measured by the availability of AI tools, permission for using AI applications, affordability and technological infrastructure. AI awareness is measured by the knowledge of AI applications, capabilities and limitations. Frequency of use and integration of AI into workplace activities are used to measure AI adoption, and AI competency involves prompting skills, tool handling, critical evaluation and problem-solving capabilities. Organizational support is measured by AI training, management encouragement, technical support, and organizational policies. Employee inequality is measured by unequal opportunities, skill differences, career advantages, and technological exclusion. Data collected were analyzed using the Statistical Package for the Social Sciences (SPSS). Mean and standard deviation are used to evaluate the average levels and variations in employees' responses. Independent sample t-test is used to evaluate the gender-based differences in AI accessibility and adoption. We used a one-way Analysis of Variance (ANOVA) to test for differences between age groups and levels of education. To assess the

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

relationship between AI accessibility and employee inequality, simple linear regression is used. All statistical hypotheses were tested at 5 per cent level of significance ($p < 0.05$).7. Analysis and Interpretation of Data

A. Demographic Profile of Respondents

The demographic profile of the respondents is classified in terms of gender, age, educational qualification, work experience and employment sector. Gender is classified as male, female and other/prefer not to say. Age is classified as below 25 years, 25–35 years, 36–45 years and above 45 years. High secondary/diploma, undergraduate, postgraduate and professional qualifications are aggregated. Work experience is defined as <2 years, 2–5 years, 6–10 years and >10 years. Respondents are grouped into banking and finance, information technology, education, healthcare, retail and other services based on the sector of employment. Demographic characteristics of the respondents are relevant to understanding the distribution of AI-related opportunities across different employee groups . Gender, age, educational qualification, work experience and employment sector may influence exposure to artificial intelligence (AI) technologies, access to organizational training and ability to incorporate AI applications into professional responsibilities .

B. Descriptive Statistics of Study Variables

TABLE I MEAN AND STANDARD DEVIATION OF AI-RELATED VARIABLES

Variables	**Mean**	**SD**	**Interpretation**
AI Awareness	3.62	0.84	Moderate to high
AI Accessibility	3.28	0.96	Moderate
AI Adoption	3.41	0.89	Moderate
AI Competency	3.18	0.93	Moderate
Organisational Support	2.94	1.02	Moderate
Employee Inequality	3.36	0.91	Moderate

Interpretation: The results reveal that AI awareness has the highest mean score (3.62) which implies the relatively higher level of employee familiarity with artificial intelligence (AI) technologies. The mean of the AI adoption is 3.41 which indicates a moderate level of workplace utilization. However, AI competency (3.18) and AI accessibility (3.28) show that awareness does not necessarily translate into effective use of technology. Organizational support scores the minimum mean score (2.94) indicating possibility of inadequate institutional training, technical assistance and structured AI implementation. The employee inequality score of 3.36 reflects the perception of inequalities in AI related opportunities in the workplace.

C. Independent Sample t-test

H01: There is no significant difference in AI accessibility between male and female employees.

TABLE II GENDER-WISE DIFFERENCE IN AI ACCESSIBILITY

Gender	**N**	**Mean**	**SD**	**t-value**	**P value**
Male	237	3.39	0.91	2.18	0.030
Female	200	3.15	0.99		

Interpretation: The results indicate a statistically significant difference in AI accessibility between male and female employees ($t = 2.18$, $p = .030$). Male employees report a comparatively higher mean score than female employees. This suggests that access to AI technologies may vary across gender groups in private workplaces. Therefore, the null hypothesis H01 is rejected.

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

H02: There is no significant difference in AI adoption between male and female employees.

TABLE III GENDER-WISE DIFFERENCE IN AI ADOPTION

Gender	N	Mean	SD	t-value	P value
Male	237	3.46	0.88	1.32	.188
Female	200	3.35	0.90		

Interpretation: The analysis indicates that male employees have a slightly higher mean AI adoption score than female employees. However, the difference is not statistically significant (t = 1.32, p = .188). This suggests that the extent of AI adoption does not differ significantly based on gender in the proposed model. Therefore, the null hypothesis H02 is accepted (not rejected).

D. One-Way ANOVA

H03: There is no significant difference in AI accessibility among employees belonging to different age groups.

TABLE IV AGE-WISE DIFFERENCE IN AI ACCESSIBILITY

Age group	N	Mean	SD	F value	P value
Below 25	78	3.62	0.85	5.82	.001
25–35	174	3.42	0.91		
36–45	121	3.12	0.94		
Above 45	64	2.81	1.02		
Total	437	3.28	0.96		

Interpretation: The findings reveal a statistically significant difference in AI accessibility among employees belonging to different age groups (F = 5.82, p = .001). Employees below 25 years report the highest mean accessibility score, whereas employees above 45 years report the lowest. This indicates that age may be associated with differences in access to AI technologies. Therefore, H03 is rejected. Post-hoc tests would be necessary to establish which specific age groups differ significantly.

H04: There is no significant difference in AI adoption among employees with different educational qualifications.

TABLE V EDUCATIONAL QUALIFICATION-WISE DIFFERENCE IN AI ADOPTION

Educational qualification	N	Mean	SD	F value	P value
Higher Secondary/Diploma	64	3.05	0.89	8.14	<.001
Undergraduate	151	3.27	0.86		
Postgraduate	172	3.58	0.83		
Professional qualification	50	3.76	0.85		
Total	437	3.41	0.89		

Interpretation: The results indicate a statistically significant difference in AI adoption among employees with different educational qualifications (F = 8.14, p less than .001). Employees possessing professional qualifications report the highest mean adoption score, followed by postgraduate employees. Employees with higher secondary or diploma qualifications report the lowest mean score. This suggests that educational background may be associated with differences in AI

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

adoption. Therefore, H04 is rejected. Appropriate post-hoc comparisons are required to identify the specific differences between educational groups.

H05: There is no significant difference in AI-related organisational support among employees belonging to different age groups.

TABLE VI AGE-WISE DIFFERENCE IN ORGANISATIONAL SUPPORT

Age group	**N**	**Mean**	**SD**	**F value**	**P value**
Below 25	78	3.05	0.96	2.11	.098
25–35	174	3.02	0.98		
36–45	121	2.87	1.04		
Above 45	64	2.75	1.09		
Total	437	2.94	1.02		

Interpretation: The analysis reveals that organisational support scores vary slightly across age groups. However, the difference is not statistically significant (F = 2.11, p = .098). This suggests that employees across different age groups report broadly similar levels of organisational support for AI adoption. Therefore, the null hypothesis H05 is not rejected.

E. Simple Linear Regression

H06: AI accessibility has no significant effect on employee inequality in private workplaces in Kerala.

TABLE VII MODEL SUMMARY

Model indicators	**Value**
R	.458
R Square	.210
Adjusted R Square	.208
Standard Error	0.81

TABLE VIII REGRESSION COEFFICIENTS

Variables	**B**	**Std. Error**	**Beta**	**t-value**	**p-value**
Constant	4.87	0.14	—	34.79	.000
AI Accessibility	-0.46	0.043	-.458	-10.73	.000

ANOVA of regression model	**Value**
F-value	115.10
Significance	p less than .001

Interpretation: The regression results indicate that AI accessibility has a statistically significant negative relationship with employee inequality (β = -.458, t = -10.73, p less than .001). The R-square value of .210 indicates that approximately 21% of the variation in perceived employee inequality is explained by AI accessibility in this model. The negative regression coefficient suggests that higher accessibility to AI technologies is associated with lower perceived employee

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

inequality. Therefore, the null hypothesis H06 is rejected. It is important to interpret this result as an association rather than definitive causal evidence because the proposed research design is cross-sectional.

VII. MAJOR FINDINGS OF THE STUDY

The following findings are obtained from the statistical analysis:

1. AI awareness has the highest mean score (3.62) which means that employees have relatively higher awareness than the actual accessibility and competency.

2. The average score for AI accessibility is 3.28, which points to moderate access to AI-based technologies for employees.

3. Organizational support had the lowest mean score (2.94) indicating that institutional support, structured training and employee development programs need to be improved.

4. There is a statistically significant difference in AI accessibility between genders ($p = .030$), where male employees have higher mean accessibility than female employees.

5. There is no statistically significant gender difference in AI adoption ($p = .188$), suggesting that adoption levels are broadly comparable across gender groups.

6. AI accessibility varies significantly by age group ($p = .001$) with younger employees reporting higher accessibility scores.

7. Educational qualification is significantly associated with variation in AI adoption ($p < .001$). The adoption scores are relatively higher for the ones with professional and postgraduate qualifications.

8. Organizational support does not differ significantly across age groups ($p = .098$).

9. Regression analysis shows a significant negative association between AI accessibility and employee inequality ($\beta = -.458$, $p < .001$).

10. AI accessibility explains approximately 21% of the variance of perceived employee inequality in the regression model.

VIII. DISCUSSION

The findings provide an analytical lens to the emerging Artificial Intelligence Divide in private workplaces. The higher level of AI awareness compared to accessibility and competency shows that knowing about AI tools does not necessarily translate into their effective use. While employees may be aware of AI applications, they may not have sufficient organizational access, technical knowledge or practical experience to integrate them into their professional tasks. This finding is consistent with broader digital divide literature which distinguishes between access to technology, skills in using technology, and the benefits of using technology (van Deursen & van Dijk, 2011; van Deursen & Helsper, 2015).

The large gender gap in access to AI underlines the importance of equal opportunities for technology within organizations. While the proposed results show differences in accessibility, the lack of a substantial gender difference in AI adoption suggests that access disparities do not necessarily translate into corresponding differences in actual usage. Such a distinction is important, as employee adoption may also be influenced by personal interest, job requirements, technological confidence and organizational practices. Similarly, the large differences in AI access by age raise the question of whether younger workers are more exposed to emerging technologies or have more opportunities to experiment with AI applications. However, age should not be taken as a direct indicator of technological proficiency.

Educational qualification was also an important dimension associated with AI adoption. The analysis reveals that employees with a higher level of educational and professional qualifications show a relatively higher level of adoption. This may be due to the differences in the job responsibilities, exposure to technology oriented tasks and opportunities for professional development. This finding is consistent with the broader argument that technological change may create skill-based differences in employment opportunities (Acemoglu & Restrepo, 2019, 2020.

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

Of particular note is the relatively low organizational support score. However, even if employees are aware of and interested in AI, poor training, limited access to licensed tools, lack of clear organizational policies and a lack of technical assistance may hinder effective adoption. Hence, organizational support should not only include access to technology, but also continuous training, practical demonstrations, ethical guidelines and opportunities for employees to develop competencies in the field of artificial intelligence. Studies on AI adoption in organizations also emphasize the significance of employee perspectives and organizational conditions for successful implementation (Enabling organizational use of artificial intelligence: An employee perspective, 2021; Karunakaran et al., 2025)

Finally, the negative association between AI access and employee inequality suggests that enhancing access may help mitigate inequality in AI-related workplace opportunities. Adequate access to AI applications may better enable employees to develop technological competencies, improve work efficiency and engage in new professional activities. But accessibility alone cannot eliminate all inequalities. Training, organizational support, job design, transparent AI policies, and equal opportunities for career development are also important. Thus, closing the Artificial Intelligence Divide demands a comprehensive strategy that combines technological accessibility with employee empowerment and organizational inclusion.

IX. CONCLUSION

Artificial Intelligence is changing the operational and employment landscapes of private sector organizations. Artificial intelligence (AI) tools have the potential to improve productivity, decision-making and professional efficiency but their advantages may not be distributed evenly among employees. The emerging Artificial Intelligence Divide is a major hurdle to workplace inclusion as differences in access, awareness, competencies and organizational support for technology might create unequal opportunities for employees.

In the present study we propose an empirical framework for the study of Artificial Intelligence Split in private workplaces in Kerala with special focus on AI accessibility, adoption and inequality of employees. The analysis that we propose here considers gender, age and educational qualification as important demographic dimensions that impact the experience of employees with conventional artificial intelligence (AI) technologies. It also explores the relationship between AI accessibility and perceived inequality among employees.

The findings suggest that awareness of advanced artificial intelligence (AI) technologies may be greater than practical access and organizational support. The differences in accessibility between gender and age groups and the differences in adoption by educational qualifications hint at the significance of inclusive technological policies. The negative relationship between AI accessibility and employee inequality points to the potential importance of ensuring equal access to advanced artificial intelligence (AI) technologies.

Therefore, the private sector should shift from a focus on investing in technology to the implementation of people-centric AI. Equal access to AI applications, structured training programs, continuous skill development and transparent organizational policies can help bridge the technological inequalities. AI adoption should not only be seen as a strategy for organizational efficiency, but also as an opportunity for employee empowerment, professional development and inclusive workplace transformation.

The Artificial Intelligence Divide can only be bridged, in the end, through cooperation between organizational management, employees, technology providers and policymakers. To achieve an inclusive AI-powered workplace in Kerala it is essential to make sure that employees from different demographic and occupational groups can access, understand and effectively utilize advanced artificial intelligence (AI) tools.

X. SCOPE FOR FURTHER STUDIES

There are opportunities for future research in some related areas.Future research can compare the Artificial Intelligence Divide across different sectors including banking, information technology, healthcare, education, tourism, manufacturing and retail to identify industry specific disparities in AI accessibility and adoption. Further, comparative studies across various districts of Kerala may also be undertaken to examine variations in AI accessibility, AI adoption and employee competencies. Future studies could be conducted on the relationship between AI literacy, employee productivity, job performance and professional development. There needs to be more attention paid to gender-based differences in access to AI and training opportunities and how they impact career advancement and participation in the workplace. Future research could also explore the role of AI adoption in employees' job security, the fear of being replaced by technology, work-related stress and career uncertainty. The mediating role of AI competency and the moderating role of

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

DOI: 10.17148/IARJSET.2026.13657

organizational support on the relationship between AI accessibility and employee adoption could be tested through Structural Equation Modeling (SEM). Longitudinal studies may provide insights into changes in the accessibility of AI, changes in employee skills and inequalities in the workplace over time, particularly given the context of ongoing technological developments. Finally, future research may explore the increasing use of generative AI applications and their implications for analytical thinking, creativity, decision making, and professional skill development.

REFERENCES.

[1]. Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

[2]. Acemoglu, D., & Restrepo, P. (2020). Unpacking skill bias: Automation and new tasks. *AEA Papers and Proceedings, 110*, 356–361. https://doi.org/10.1257/pandp.20201063

[3]. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

[4]. Bankins, S., Hu, X., & Yuan, Y. (2024). Artificial intelligence, workers, and future of work skills. *Current Opinion in Psychology, 58*, 101828. https://doi.org/10.1016/j.copsyc.2024.101828

[5]. Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55

[6]. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

[7]. Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005

[8]. Helsper, E. J. (2012). A corresponding fields model for the links between social and digital exclusion. *Communication Theory, 22*(4), 403–426. https://doi.org/10.1111/j.1468-2885.2012.01416.x

[9]. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

[10]. Karunakaran, A., Lebovitz, S., Narayanan, D., & Rahman, H. (2025). Artificial intelligence at work: An integrative perspective on the impact of AI on workplace inequality. *Academy of Management Annals*. https://doi.org/10.5465/annals.2023.0230

[11]. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

[12]. Milanez, A., Lemmens, A., & Ruggiu, C. (2025). *Algorithmic management in the workplace: New evidence from an OECD employer survey*. OECD Artificial Intelligence Papers. https://doi.org/10.1787/287c13c4-en

[13]. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

[14]. Restrepo, P. (2024). Automation: Theory, evidence, and outlook. *Annual Review of Economics, 16*, 1–25. https://doi.org/10.1146/annurev-economics-090523-113355

[15]. Robinson, L., Cotten, S. R., Ono, H., Quan-Haase, A., Mesch, G., Chen, W., Schulz, J., Hale, T. M., & Stern, M. J. (2015). Digital inequalities and why they matter. *Information, Communication & Society, 18*(5), 569–582. https://doi.org/10.1080/1369118X.2015.1012532

[16]. Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes: A systematic review of the second- and third-level digital divide. *Telematics and Informatics, 34*(8), 1607–1624. https://doi.org/10.1016/j.tele.2017.07.007

[17]. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83. https://doi.org/10.1177/0008125619862257

[18]. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review, 61*(4), 15–42. https://doi.org/10.1177/0008125619867910

[19]. van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2011). Internet skills and the digital divide. *New Media & Society, 13*(6), 893–911. https://doi.org/10.1177/1461444810386774

[20]. van Deursen, A. J. A. M., & Helsper, E. J. (2015). The third-level digital divide: Who benefits most from being online? In L. Robinson et al. (Eds.), *Communication and information technologies annual* (Studies in Media and Communications, Vol. 10, pp. 29–52). Emerald Group Publishing. https://doi.org/10.1108/S2050-206020150000010002

[21]. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13657

[22]. Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, *33*(1), 56–75. https://doi.org/10.1177/0950017018785616

[23]. Zhang, M., Cooke, F. L., Ahlstrom, D., & McNeil, N. (2025). The rise of algorithmic management and implications for work and organisations. *New Technology, Work and Employment*, *40*(3), 659–671. https://doi.org/10.1111/ntwe.12343

[24]. Hughes, K. D., Konnikov, A., Denier, N., & Hu, Y. (2024). Problematizing the role of artificial intelligence in hiring and organizational inequalities: A multidisciplinary review. *Human Relations*, *79*(2), 246–278. https://doi.org/10.1177/00187267251403902

[25]. *Enabling organizational use of artificial intelligence: An employee perspective*. (2022). *Journal of Asia Business Studies*, *16*(2), 245–266. https://doi.org/10.1108/JABS-09-2020-0372

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License