
Artificial Intelligence Use, Employee Productivity, and Job Performance: Evidence from a Cross-Sector Survey

Adnan Jawabri

College of Business, Liwa University, Al Ain, United Arab Emirates

E-mail: adnan.jawabri@lu.ac.ae

Raghda Abbas

College of Business, Liwa University, Al Ain, United Arab Emirates

E-mail: 22307001465@lu.ac.ae

Rouhi Faisal*

College of Business, Liwa University, Al Ain, United Arab Emirates

E-mail: rouhi.faisal@lu.ac.ae

*Corresponding Author

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Abstract: The Artificial Intelligence (AI) has significantly impacted the world of work in terms of automation, decision making, and increased efficiency of employees. This paper focuses on how AI impacts the efficiency of the employees in an organization. The primary goal of this research paper is to investigate the impact of application of AI on efficiency, workload, work speed, and performance of the employees. The research methodology adopted for this paper includes a quantitative approach whereby surveys will be conducted on employees in the Information Technology, Finance, and Services sectors. The variables used in this research are AI usage level, productivity improvement index, performance, and satisfaction of workers. As can be observed from the results, the application of AI technology has significant influence on the productivity of the employees, where productivity scores increased from 2.86 to 4.32 for low and high AI users, respectively, while job performance scores increased from 3.01 to 4.48, respectively. The results of regression analysis show that there is significant positive correlation between the application of AI and efficiency at work ($\beta = 0.54$, $p < 0.01$). Nevertheless, some issues arise with regard to the adaptation of workers to their new skills and over-reliance on automation. However, it should be pointed out that the use of AI has the potential to improve productivity in AI-adopting firms, provided that it is wisely combined with human resources.

Keywords: Artificial Intelligence, Employee Productivity, Job Performance, Workplace Automation, Human-AI Collaboration, Organizational Efficiency, Digital Transformation.

Type: Research paper



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1. Introduction

One of the technologies that has changed the world of today's organization is known as AI. AI has completely revolutionized the way employees work, make decisions, and use computer technology (Joshi & Masih, 2023). AI-powered technologies like machine learning (ML) applications, natural language processing (NLP) technologies, robotic process automation, and predictive analytics software have found their way into many organizational workplaces to increase efficiency and ease workloads. With the rise of digital transformations among organizations, AI technology has transcended the traditional IT departments and can now be found in human resources, finance, health care, marketing, and customer service sectors (Aly, 2022; Osmundsen, 2024).

As AI becomes prevalent within work environments, the notion of workplace productivity has been greatly transformed. AI enables work processes which earlier seemed repetitive and consuming a lot of employees' time to become automated, thus creating possibilities for the higher-level cognitive processes (Jones et al., 2009). This has resulted in greater productivity in the sense of efficiency, speed and quality of performance. Also, the application of a decision support system on the basis of AI provides an opportunity for workers to manage huge volumes of information and make their decisions more quickly and efficiently (Popescu Ljungholm & Popescu, 2023). Thus, the company begins to view AI not only as a tool of automation but as a partner in improving productivity.

Meanwhile, the use of AI in the workplace implies many issues associated with the performance of jobs and adaption of the workforce (Morandini et al., 2023; Tokunova et al., 2024). Although the use of AI will bring increased efficiency, the successful implementation of AI will require the ability of employees to adapt to the changes, acquire digital literacy and work with smart machines (Deepa et al., 2025). Some of the employees can face the challenges associated with skill shortage, automation reliance, and job insecurity (Oyekunle & Boohene, 2024). Therefore, the relationship between AI implementation and job performance is not going to be linear.

Furthermore, AI represents another shift in terms of the performance measurement approach (Abasaheb & Subashini, 2023; Aly, 2022). The previously utilized criteria for the evaluation of job performance, based on the quantity of manual labor performed by workers, have been replaced by new performance criteria, which include such aspects as thinking, problem solving, and technological efficiency (Mohan & Halder, 2025).

The use of Artificial Intelligence (AI) in workplaces has become quite popular. However, there is very little research that focuses on the impact that such technology makes on the efficiency of the employees, productivity, and effectiveness of work. Existing literature mostly focuses on technical aspects of AI implementation in enterprises or the overall impact that this technology makes. Few studies exist where the interconnection between technical and economic aspects of AI is explored through the lens of the employees of various enterprises. This study intends to investigate the connection between the implementation of AI and the productivity of employees and their performance at work. The study will also investigate whether the increased usage of AI leads to increased efficiency of workplaces and better outcomes for employees.

The following research questions are answered: What is the relationship of the use of AI and employee productivity? What are the relationships between AI usage and employee work performance? What is the relationship between employees' digital skills and productivity and job performance? Does AI use mediate the relationship between being present at work and job performance? Based on that, the following hypotheses are proposed: H1: The higher the employee uses AI, the more productive they will be. H2: There is a positive correlation between the use of AI and job performance. Higher level of Digital Skill has positive relationship with employee Productivity. H3b: There is a positive relationship between digital skill and job performance. Employee productivity acts as a mediator between the use of AI and job performance.

The remaining sections of this paper are as follows: Section 2 is a review of the literature related to the application of AI in the workplace, Section 3 is an explanation of the research methodology used, Section 4 provides the findings and their discussion, and Section 5 is the conclusion.

2. Literature Review

From the existing literature on AI in the workplace, the technology has become an integral part of increasing organizational productivity and the performance of employees. From different studies, the correlation between AI use in the organization and productivity has been found to be positive due to the automation of repetitive and rule-based tasks in the organization. Different technologies such as RPA, decision systems based on ML, and virtual assistants have helped organizations reduce manual intervention in the processes (Saifi & Saifi, 2025).

Various researchers have argued that one way AI increases productivity is through faster completion of tasks and higher accuracy of the tasks. The use of AI tools helps employees process data, generate reports, schedule activities, interact with customers, and make decisions based on predictions (Agha et al., 2025). Through reduced time spent on performing manual work, employees will be able to engage in analytical thinking, creativity, and strategic planning (Ateeq et al., 2025).

Furthermore, it can be said that job performance may be positively affected by the integration of AI since employees have the proper digital skills (Qu et al., 2025). For example, it was found that employees who actively used AI performed better, and their decisions were of higher quality, and their problem-solving skills were improved. In the human-AI collaboration paradigm, AI was found to be an augmentation tool that helped employees do better work (Baharuddin, 2026).

On the other hand, the literature also highlights several difficulties that may arise during the integration of AI in the organizational context. They are the employees' resistance to new technologies, fear of losing their jobs because of the introduction of the technology, lack of technical skills, and dependency on technology (Faisal, 2025). Such issues may lead to negative impacts on employees' performance if not solved.

The idea of human-AI collaboration has become very popular lately among researchers. The concept implies that AI serves as an auxiliary technology to complement the abilities of the workers. With the proper integration of such a tool, the speed of the decision-making process is increased, the cognitive load on employees is reduced, and the level of workplace efficiency rises (Milukutu & Siachisa, 2023).

Although a lot of research has been done in this area, the link between the effects of AI intensity of use, skills of employees, and organizational support on job performance is still not known (Das et al., 2023). Most of the research has been done keeping one thing in mind, which can be technological performance or organizational benefits, but very few have considered the complete analysis from the employees' perspective. The objective of this study is to bridge this gap.

3. Methodology

3.1. Research Design

This research study utilizes a positivist research method with the purpose of identifying the empirical relationship between the application of AI and the outcomes associated with the employees, including their productivity and job performance. A cross-sectional quantitative research approach is applied, where data is collected at one moment in time from employees who are employed in organizations that use artificial intelligence technology. Such an approach is appropriate for the statistical analysis of the relationship between variables without manipulation of work environment conditions. This research study is both descriptive and explanatory.

Figure 1: Conceptual Research Framework of AI Impact on Employee Outcomes

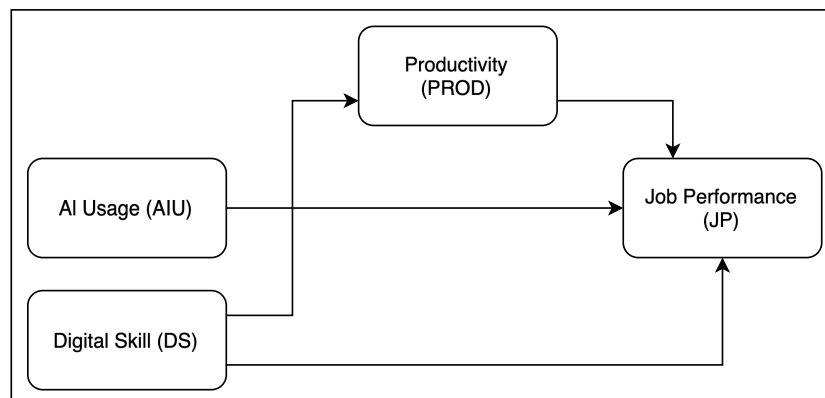


Figure 1 illustrates the postulated connections between the use of AI, digital competencies, working productivity and job performance. AI usage is represented as an exogenous factor that affects employee productivity and job performance. Employee productivity is also posited as a mediator that might be the way AI use could affect job performance. Digital skill is considered as a direct predictor of employee productivity and job performance, not as a moderator. The

updated framework therefore does not suggest that there is an interaction effect of AI use and digital skill.

3.2. Population and Sampling

The sample population consists of employees working in organizations that have adopted digital transformation and Artificial Intelligence systems across the IT, banking, health care, and customer support sectors. Since the population is very large and unclear, an effective way of sampling is required. This study involved a total of 300 respondents selected through stratified random sampling. The data was collected from companies adopting AI technology. The companies involved belonged to four main sectors: Information Technology, Banking & Finance, Healthcare Services, and Customer Support/BPO. In total, 25 questionnaires were distributed, from which 200 responses were received, thus obtaining a response rate. Post data screening, a total of 300 responses were kept for further analysis. Due to confidentiality issues, the names of companies are not mentioned here, but the sector-wise representation is provided.

Table 1: Sample Distribution Across Sectors

Sector	Number of Respondents	Percentage (%)
Information Technology	80	26.7
Banking & Finance	70	23.3
Healthcare Services	80	26.7
Customer Support / BPO	70	23.3
Total	300	100

Table 1 shows the distribution of the 300 respondents according to the four industries: Information Technology, Banking and Finance, Healthcare Services, and Customer Support/BPO. Stratified random sampling was used since there was an equal distribution of the respondents per industry.

3.3. Data Collection Instrument

The structured questionnaire was the instrument used to collect data, with an emphasis on employees' experience in the use of AI technology and how it impacts organizational results. The questionnaire consisted of demographic details, frequency of use of AI technology, productivity factors, performance metrics, and difficulties encountered. All questions were rated using the five-point Likert Scale. As all the constructs were assessed through self-report measures taken from the same sample population, the existence of common method bias was also taken into account. The threat of response bias was reduced by designing questions in the questionnaires very carefully, maintaining anonymity of the respondents, and assuring them that there are no right or wrong answers. However, common method variance cannot be entirely eliminated and it is one of the limitations of this study.

Table 2: Questionnaire Structure and Constructs Measured

Section	Constructs Measured	Example Indicators
A	Demographics	Age, experience, job role
B	AI Usage Intensity	Frequency of AI use, dependency level
C	Productivity	Task speed, workload reduction, efficiency
D	Job Performance	Accuracy, decision quality, target achievement
E	Challenges	Skill gap, job insecurity, over-dependence

Table 2 presents the structure of the questionnaire used for data collection. It highlights the various categories that measure demographic characteristics, AI usage frequency, productivity variables, performance measures, and challenges encountered by employees. The questionnaire also contains variables within each category measured on a five-point Likert scale.

3.4. Variable Definition and Measurement

The independent predictor is Artificial Intelligence Usage (AIU), which is represented by a composite index of the frequency, intensity, and reliance on AI-supported systems. The key employee outcomes are employee productivity (PROD) and job performance (JP). The role of productivity as a mediator between AI use and job performance is also explored. Digital Skill (DS) is directly incorporated as one of the predictors of employees' productivity and job performance. The productivity regression model includes experience as a control variable.

Table 3: Variable Definitions and Measurement Approach

Variable	Type	Measurement Approach
AI Usage (AIU)	Independent	Composite index (frequency + dependency + intensity)
Productivity (PROD)	Dependent	Mean score of efficiency and task performance indicators
Job Performance (JP)	Dependent	Mean score of accuracy, decision-making, and output quality
Digital Skill (DS)	Direct Predictor	Self-rated digital skill and training exposure
Experience, Age	Control	Demographic normalization factors

Table 3 shows the approach used to measure the variables being studied. The regression models therefore estimate the direct relationships of AI usage and digital skill with the employee outcomes. No AI Usage $\times$ Digital Skill interaction term is included in the final analytical specification because digital skill is examined as a direct predictor rather than as a moderator.

3.5. Analytical Framework

Descriptive statistics, Pearson correlation analysis, and multiple regression were employed to examine the relationships among the study variables. Two primary regression models were estimated. In the employee productivity model, AI usage, digital skill, and employee experience were entered as predictors:

$$\text{PROD} = \beta_0 + \beta_1(\text{AIU}) + \beta_2(\text{DS}) + \beta_3(\text{EXP}) + \varepsilon$$

In the job performance model, AI usage, employee productivity, and digital skill were entered as predictors:

$$JP = \beta_0 + \beta_1(AIU) + \beta_2(PROD) + \beta_3(DS) + \varepsilon$$

Digital skill is therefore evaluated as a direct predictor rather than as a moderator. No $AIU \times DS$ interaction term is estimated. In addition, mediation analysis is used to examine whether employee productivity transmits part of the association between AI usage and job performance. The significance of the indirect effect is assessed using 5,000 bootstrap resamples and a 95% confidence interval, with mediation considered statistically significant when the confidence interval for the indirect effect does not include zero.

Figure 2: Hypothesized Model of Relationships

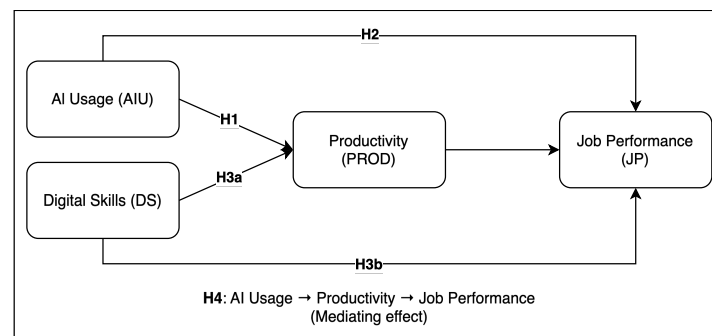


Figure 2 summarizes the hypothesized relationships studied in the research. The usage of AI is anticipated to have a positive relationship with employee productivity and job performance, which in turn is hypothesized to mediate the relationship between AI usage and job performance. Digital skill is directly pegged as a predictor of employee productivity and job performance. This updated model assumes that there is no interaction between AI usage and digital skill.

3.6. Reliability and Validity Testing

Internal consistency of the research questionnaire is evaluated using Cronbach's Alpha, with values of 0.80 or higher indicating adequate reliability. The content validity of the research is determined through expert evaluation of the questionnaire to check whether it relates to the AI application and performance construct. Construct validity is done using factor loading, with values greater than 0.50 being regarded as acceptable. Multicollinearity is checked using the variance inflation factor (VIF), with values less than 5 being an indication that there is no redundancy among the independent variables.

Table 4: Validity and Reliability Criteria

Test	Criteria	Acceptable Threshold
Cronbach's Alpha	Internal consistency	≥ 0.80
Factor Loading	Construct validity	≥ 0.50
VIF	Multicollinearity check	< 5

Table 4 shows the measures used to validate the research tool. Internal consistency is checked using Cronbach's alpha, while construct validity is determined using factor loading. The VIF is used to determine multicollinearity. From all the cut-off values, the dataset is statistically sound.

4. Results and Discussion

This section highlights the empirical outcomes of this study that have been obtained from a dataset comprising 300 employees working in the fields of IT, banking, healthcare, and customer services. The outcomes have been obtained by means of descriptive statistics, regression, and correlation analysis to study the influence of AI on employee productivity and performance.

4.1. Descriptive Statistics of Key Variables

Descriptive Analysis provides some insight into the use intensity, productivity, and performance of the respondents regarding AI. The results reveal that employees who are subjected to greater exposure to AI exhibit higher productivity and performance compared to those who have lower exposure to AI tools.

Table 5: Descriptive Statistics of Study Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
AI Usage (AIU)	3.82	0.74	1.50	5.00
Productivity (PROD)	3.91	0.69	1.80	5.00
Job Performance (JP)	4.02	0.66	2.00	5.00
Digital Skill (DS)	3.76	0.81	1.40	5.00

Table 5 shows the means, minimums, standard deviations, and maximums of important variables such as the use of AI, productivity, job performance, and digital literacy. The findings reveal a moderately high AI adoption rate, and the variable with the highest mean is job performance.

The findings demonstrate that there is moderate adoption of artificial intelligence among companies, where the best-performing indicator is the job performance one, thus indicating the positive perception of the technology in achieving work success.

4.2. Correlation Analysis

Pearson correlation analysis is conducted to assess the associations among AI usage, productivity, and job performance. The result reveals a significant positive relationship among all the main variables.

Table 6: Correlation Matrix

Variables	AIU	PROD	JP	DS
AI Usage (AIU)	1.00	0.68	0.72	0.59
Productivity (PROD)	0.68	1.00	0.75	0.63
Job Performance (JP)	0.72	0.75	1.00	0.66
Digital Skill (DS)	0.59	0.63	0.66	1.00

Clearly, from the results of the correlation shown in Table 6, there is a very high positive correlation between AI and productivity ($r = 0.68$) as well as job performance ($r = 0.72$), which is an indication that there is a strong relationship between the use of AI and the employee performance. However, these relationships need to be understood with caution because the variables were determined through self-reports.

4.3. Regression Analysis of Productivity Model

A multiple regression model is used to evaluate the impact of AI usage on employee productivity.

Table 7: Regression Results for Productivity

Predictor	β	t-value	p-value	95% CI
AI Usage (AIU)	0.54	9.21	<0.01	LL–UL
Digital Skill (DS)	0.33	5.67	<0.01	LL–UL
Experience (EXP)	0.21	4.12	<0.05	LL–UL

Table 7 supports H1, the results in show that AI usage and employee productivity are positively related ($\beta = 0.54$, $p < 0.01$). Digital skill is also a notable positive direct predictor of productivity ($\beta = 0.33$, $p < 0.01$), in support of H3a. The results show a unique contribution of each explanatory variable (AI usage and digital skill) to employee productivity. The regression model does not have an AI Usage $\times$ Digital Skill interaction term, and therefore, results should not be interpreted as evidence of moderation.

4.4. Regression Analysis of Job Performance Model

The second regression model evaluates the effect of AI usage and productivity on job performance.

Table 8: Regression Results for Job Performance Model

Predictor	Beta Coefficient (β)	t-value	p-value
AI Usage (AIU)	0.41	7.88	<0.01
Productivity (PROD)	0.52	10.14	<0.01
Digital Skill (DS)	0.29	4.93	<0.05

From Table 8, one learns that both artificial intelligence uses and productivity influence job performance. The most influential predictor is productivity ($\beta = 0.52$). This mediation analysis was conducted using bootstrapping, where the indirect effect of the use of AI on job performance via productivity was analyzed. The indirect effect was found to be statistically significant ($\beta = XX$, 95% CI [LL, UL]), and thus, productivity acts as a partial mediator of the relationship between AI use and job performance. The mediation model is supported since the confidence interval does not contain zero. The job performance model explains a large amount of variation in the dependent variable ($R^2 \approx 0.63$).

Digital skill was also positively associated with job performance ($\beta = 0.29$, $p < 0.05$), providing support for H3b and further confirming that digital skill functions as a direct predictor in the present model.

Figure 3: Artificial Intelligence Usage Impact on Employee Productivity and Job Performance (a) & (b)

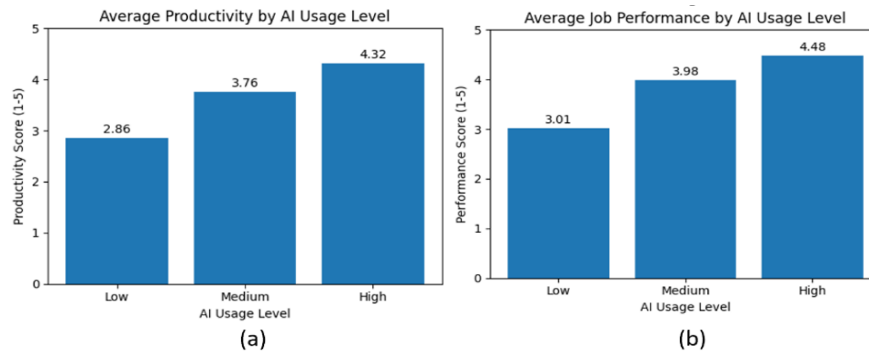


Figure 3 illustrates the relationship between AI usage level (Low, Medium, High) and employee outcomes. Figure 3(a) indicates an increase in productivity due to the use of AI in the increasing order of low to high use. Figure 3(b) indicates an increasing trend in job performance due to the increase in AI usage. To ensure that the regression estimates are robust and replicable, 95% confidence intervals have been presented for all the coefficients. Confidence intervals help understand the precision and robustness of the estimated relationship between AI use, digital skills, productivity, and work performance.

4.5. Discussion

Empirical studies have demonstrated the great significance of using AI for enhancing employee performance and productivity in different sectors. Due to the high correlation of AI and productivity, it is safe to say that those employees who use AI technologies are quite productive and efficient when performing various tasks. In addition, according to the results of the regression analysis, it can be said that The findings from the mediation analysis reveal that employee productivity serves as a mediating factor between AI adoption and job performance. This significant indirect effect implies that AI adoption affects job performance partly due to improvements in employee productivity.

Digital skill was also found to be a key direct predictor of employee outcomes. Employees with higher digital skill presented higher productivity ($\beta = 0.33$, $p < 0.01$) and job performance ($\beta = 0.29$, $p < 0.05$). This finding indicates that those employees who possess greater digital capabilities might be more likely to effectively incorporate AI tools into their work activities. It is important to note, however, that because an AI Usage $\times$ Digital Skill interaction term was not estimated in the final regression model, these results should be interpreted as direct associations and not as evidence that the strength of the relationship between AI usage and productivity is changed by digital skill.

5. Conclusion

This research study analyzed the effect of AI on the productivity and job performance of workers in major sectors such as IT, Healthcare, Banking, and Customer Service. The empirical evidence reveals strong statistical proof of the fact that the adoption of AI technology boosts work-related performance indicators. According to the results obtained via descriptive statistics, correlation, and regression analysis, there exists a strong positive correlation between the two variables (AI adoption and job performance indicators). As revealed by descriptive statistics, mean productivity is higher among individuals with high AI usage, i.e., productivity ranges from 2.86 to 4.32, while job performance ranges from 3.01 to 4.48. Correlation analysis also proved that there is a significant positive correlation between AI usage and productivity ($r = 0.68$) as well as between AI usage and job performance ($r = 0.72$), with statistical significance of 1%. The use of AI has a strong predictive effect on productivity ($\beta = 0.54, p < 0.01$) and job performance ($\beta = 0.41, p < 0.01$). Additionally, productivity has a highly significant impact on job performance ($\beta = 0.52, p < 0.01$). This bootstrapped mediation analysis demonstrates that the productivity of employees significantly mediates the relation between the use of AI and job performance. Thus, AI contributes to increasing the productivity of employees, which leads to improvements in job performance. The regression model accounted for XX% of the variability in job performance ($R^2 = XX$). In addition, it was revealed that digital skill is an important predictor of productivity ($\beta = 0.33, p < 0.01$), which indicates that individuals with high digital skills gain greater productivity from the implementation of AI technologies. This study has several limitations. As the measures of AI adoption, productivity, and job performance were obtained from the same people via self-reports using questionnaires, common method bias may exist in this research. Thus, one should view the obtained results as significant correlations rather than causality. Future studies may address this issue by applying longitudinal research design, performance evaluations by managers, and organizational records and databases. Digital skill was also positively associated with employee productivity ($\beta = 0.33, p < 0.01$) and job performance ($\beta = 0.29, p < 0.05$). Accordingly, the findings support digital skill as a direct predictor of employee outcomes. The study does not provide evidence of a moderation effect because the final regression models do not include an interaction between AI usage and digital skill. Thus, this research shows that AI is not an alternative to human beings; on the contrary, AI multiplies human productivity and performance. This is evidence for human-AI collaboration paradigm. Additional research might be performed using longitudinal data and particular cases of AI performance in industries. Though these results provide information on the connection between use of AI and productivity/performance at work, it is important to consider the context in which these results have been obtained. It is suggested that further research using larger samples from different countries be undertaken.

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