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GENERATIVE ARTIFICIAL INTELLIGENCE ADOPTION AND EMPLOYEE PRODUCTIVITY: IMPLICATIONS FOR ORGANIZATIONAL PERFORMANCE

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Abstract

Generative Artificial Intelligence (GenAI) is becoming more popular in businesses as a way of increasing the efficiency of the workforce, aiding decision-making processes, and improving the overall performance of the business. The research was conducted using a quantitative approach based on secondary data to explore the correlation between the use of GenAI and employee productivity as well as organizational performance. 2,000 observations of organizations in different industries, company sizes, regions and stages of AI adoption were analysed. Descriptive statistics, correlation analysis, group comparison and multiple linear regression were used to evaluate the pattern of use of GenAI and its association with productivity and performance outcomes. The results indicated that the variables of AI maturity, task automation, time savings, and variables of intensity of adoption and employee productivity are positively related. Overall, the greatest productivity change was due to AI maturity and task automation services. Increases in revenue, decreases in cost, and Customer Satisfaction were also positively correlated with productivity improvement, while AI adoption and maturity was positively correlated with Innovation performance. This implies that organizational value of GenAI is not merely about access to AI tools, but about how they're integrated, the readiness of the workforce, and strategic implementation. The study findings include augmenting AI capabilities to improve productivity and performance, helping employees adapt, and embedding GenAI into relevant business processes. Further research is needed over time and at the employee level to explore cause-and-effect relationships and the impact on the organization over time.

Keyword: - *Generative Artificial Intelligence; Employee Productivity; Organizational Performance; AI Adoption; Business Innovation*

INTRODUCTION

Generative artificial intelligence (GenAI) has become a significant technological advancement that impacts the way businesses handle information, perform day-to-day tasks, assist their workforce, and make decisions. The text-generating, summarising, problem-solving and automation aspects of knowledge-based tasks render these generative systems—such as ChatGPT, Claude, Gemini and others—useful tools for organizations. This has created a whole new setting for prevailing management theories, impacting the way employees interact with technology and the organization of work and decision-making processes (Korzynski et al., 2023). However, with the growing proliferation of GenAI in different industries and careers, there's also been an increased curiosity in understanding how this technology can positively impact organizational effectiveness, innovation, and productivity (Ooi et al., 2025; Korzynski et al., 2023). There are several technological, managerial and organizational conditions that affect the adoption of GenAI by the organizations. Adopting AI is not merely about access to AI tools, but also involves the development of the appropriate infrastructure, upskilling of employees, the design of integration strategies and the establishment of governance frameworks.

Thus, strategic alignment with organizational goals is crucial to ensure that GenAI delivers value and addresses technical and operational challenges (Al-Kfairy, 2025). Employees and managers' perceptions of usefulness, ease of use, and expected performance benefits, as well as compatibility, also play a role in organizational adoption (Prasad Agrawal, 2024). The literature on technology adoption also indicates that perceived value and organizational readiness may play a crucial role in influencing the adoption of generative technologies in business environments (Gupta, 2024). Trust in AI and senior management support are also crucial factors, as these capacities empower employees to make the most of GenAI, given that they are more willing to adopt GenAI when they feel supported by their leadership in the process (Korzyński et al., 2024).

Among the priorities in GenAI implementation is better employee productivity. GenAI can help employees by saving them time on repetitive tasks, making information more accessible, aiding in content creation, and speeding up knowledge-intensive tasks. Despite the presence of existing research that indicates GenAI can have significant impact on workplace productivity if capabilities are matched with employees and organizational processes (Al Naqbi et al., 2024), this is not currently the case for the majority of GenAI uses. GenAI is also reshaping HRM practices by enhancing the efficiency of recruitment, training, talent development, performance management and workforce planning, allowing for innovative employee–technology collaboration (Budhwar et al., 2023). It might be more impactful in HR practices if organizations foster an environment that promotes innovation, experimentation, and responsible application of new technologies (Ahmad & Khan, 2024).

But productivity gains rely not just on technology; they also rely on adaptation to technology by the workforce. Skills development, employee engagement, job redesign, and responsible AI use are thus issues that need to be addressed in human resource strategies. A strategic use of HRM emphasizes that GenAI should not merely replace labor but enhance human capabilities (Chowdhury et al., 2024). Furthermore, trust is crucial in how AI-driven HR practices are received by employees, as they are more likely to accept and interact with GenAI if they believe that its applications are trustworthy and supportive (Prasad & De, 2024). Simultaneously, broader societal issues related to shifts in work, bias, accountability, privacy, and uneven benefits of AI mean that the adoption should be handled with care (Sabherwal & Grover, 2024). Research on the adoption of GenAI, HRM, workplace productivity and its use in organizations are done in isolation. Still, there is a gap for empirical research to establish the links between GenAI adoption and productivity and business performance improvements. It is important because the productivity gains can lead to increased revenues, savings, innovation, customer satisfaction and effectiveness in the overall organization. Hence, analysing GenAI adoption alongside employee productivity offers a more holistic view of the potential impact of this technology on company performance.

Research Objectives:

- To examine the level and patterns of Generative AI adoption across organizations.
- To assess the relationship between Generative AI adoption and employee productivity.
- To evaluate the implications of Generative AI adoption and employee productivity for organizational performance.

2. Methodology

2.1 Research Design

This study employed a quantitative approach with a cross sectional, secondary data research design to explore the relationship between generative artificial intelligence adoption, employee productivity and organizational performance. Due to the study's intention to assess the measurable organisational attributes and the relationship between any differences in AI adoption and the changes in productivity and business results, the analytical approach was chosen. The design also enabled comparisons to be made among organizations in different industry groups, geographic areas and company-size groups.

2.2 Data Source and Study Sample

A secondary data set with organizational data on AI adoption, workforce factors, productivity, and business impact (Thalla, 2026) was used. A final analysis data set has 2,000 observations and 43 variables. The observations spanned a range of industries, geographic regions and organizations across 30 countries from 2023 to 2026. The business was

categorized into Startups, Small and medium enterprises or Enterprises. The data was gathered using online surveys, phone interviews, research compilations and other sources of structured data.

2.3 Study Variables

Organizational indicators used to represent generative AI adoption were the AI adoption rate, adoption stage, years of AI use, primary AI tool, number of AI tools used, number of active AI projects, AI training hours, AI budget percentage, AI maturity score, and AI investment per employee. The main AI tools that did emerge in the data set were ChatGPT, Claude, Gemini, GitHub Copilot, custom in-house AI systems and other AI tools. While custom internal AI and other tools were still included as other, wider AI categories, ChatGPT, Claude, Gemini, and GitHub Copilot were classified as explicit generative AI applications. Productivity was mainly measured as productivity change percentage of the employees. Other workforce-related measures included the number of reskilled employees and number of jobs displaced, the number of tasks automated, and the time saved per week, and employee satisfaction score, and hours spent training AI. These variables were employed to measure not just the direct impact on productivity but also the broader impact on the workforce stemming from the adoption of organizational AI. The revenue growth percentage, cost reduction percentage, innovation score, customer satisfaction and annual revenue were used as indicators of organizational performance. These measures were associated with the financial, operational, innovation and customer aspects of an organization's performance. Organizational characteristics that may affect the relationships observed were company size, number of employees, industry, geographic region, company age, and remote-work percentage.

2.4 Data Preparation and Quality Assessment

The data set was reviewed prior to analysis to check for data inconsistencies and completeness. Names of variables and the types of data were checked and categorized as categorical and numerical data based on their use in analysis. No observations were missing and no exact duplicate observations were found in the final dataset. For descriptive and comparative analysis, categorical variables, such as, primary AI tool, stage of AI adoption, industry, region and company size were kept in the same categories. Before inferential testing, continuous variables were investigated for their distribution and ranges observed.

2.5 Statistical Analysis

Descriptive statistics were used to summarize the characteristics of the participating organizations and their AI-adoption patterns. For categorical data, frequencies and percentages were calculated and for continuous data means and standard deviation were summarized. Where there was significant skewness, median and interquartile range was used. When the assumptions of approximate linearity and approximate normality were met, Pearson correlation analysis was used to examine relationships among the continuous measures of AI adoption and productivity and organizational performance. Where these assumptions were not considered to be fulfilled, Spearman rank correlation was used. Independent-samples t-tests were used to analyse continuous outcomes between relevant two categories of classification, with non-parametric alternatives using the Mann–Whitney U test when necessary. Chi-square tests were used to test association for categorical variables. Multiple linear regression analysis was employed to determine the factors related to the employees' productivity and the organizational performance. The dependent variable in the first model was productivity change percentage, and the variables of interest in this model were AI adoption rate, AI maturity score, AI investment per employee, AI training hours, number of AI tools used, and task automation rate. The following models have the organizational performance indicators (revenue growth percentage, cost reduction percentage and innovation score) as dependent variable. Predictors included productivity change percentage and key measures of AI adoption as well as relevant organizational characteristics. A two-sided p value of < 0.05 was considered statistically significant.

2.6 Ethical Considerations

This study relied on secondary organizational data only, without recruiting, intervening or interacting with people. The analytical data set lacked Personally Identifiable Information (PII) data regarding employees. Data was only utilized for academic analysis and was interpreted at the organizational level. Great care was taken not to show organizational-level productivity measures as measurements of individual employee productivity.

3. Results

3.1 Organizational Characteristics and Generative AI Adoption

The final dataset included 2,000 organizational observations across various company sizes, industries, and geographic regions, along with varying levels of AI adoption. The highest company size group was small and medium enterprises followed by startups and enterprises. The highest percentages of observations were from Asia and Europe. But some of the better represented industries were technology, finance, healthcare, manufacturing and retail. When it came to AI adoption, many organisations were either at the partial-adoption or pilot stage, and there were relatively few full adoptions. The organized and AI adoption characteristics are detailed in Table 1.

Table 1. Organizational and Generative AI Adoption Characteristics of the Study Sample

Characteristic	Category	n	%
Company size	SME	839	41.9
	Startup	768	38.4
	Enterprise	393	19.7

Region	Asia	669	33.4
	Europe	539	27.0
	Africa	294	14.7
	South America	243	12.2
	Oceania	139	7.0
	North America	116	5.8
AI adoption stage	Partial	997	49.8
	Pilot	904	45.2
	None	77	3.8
	Full	22	1.1
Primary AI tool	ChatGPT	625	31.2
	Custom Internal AI	334	16.7
	Claude	319	16.0
	Gemini	315	15.8
	GitHub Copilot	275	13.8
	Other	132	6.6

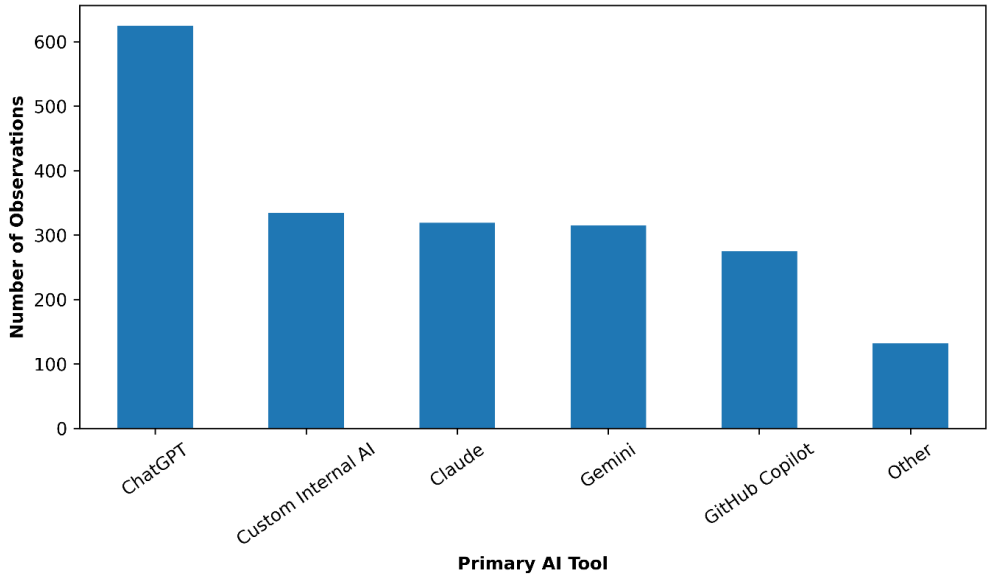


Figure 1. Distribution of Primary AI Tools Used by Organizations

The distribution of primary AI tools is further illustrated in Figure 1. ChatGPT represented the largest individual category, while Claude, Gemini, GitHub Copilot, and custom internal systems were also widely represented.

3.2 Productivity and Organizational Performance Indicators

Descriptive statistics for the principal GenAI, productivity, and organizational-performance indicators are provided in Table 2. The average rate of AI adoption was 35.82%, and the average length of time organizations have adopted AI was around five years. Average productivity change was 9.39%, and the average weekly time saving was 6.19 hours, and the average task automation rate was 19.52%. Average revenue growth and reducing costs were positive organizational outcomes, and innovation and customer satisfaction were moderately different across observations.

Table 2. Descriptive Statistics of Key Study Variables

Variable	Mean	SD	Median	Minimum	Maximum
AI adoption rate (%)	35.82	14.92	35.26	0.00	82.95
Years using AI	4.93	2.48	5.00	0.00	10.00
Number of AI tools used	2.28	0.96	2.00	1.00	6.00
AI training hours	27.25	13.14	27.22	0.00	71.45
AI maturity score	0.34	0.14	0.34	0.00	0.78
Employee satisfaction score	5.59	0.82	5.58	3.03	8.23

Task automation rate (%)	19.52	9.46	19.55	0.00	51.88
Time saved per week (hours)	6.19	3.01	6.13	0.00	16.46
Productivity change (%)	9.39	5.72	9.15	0.00	27.80
Revenue growth (%)	4.56	5.40	4.28	-5.00	22.60
Cost reduction (%)	4.79	3.42	4.55	0.00	17.04
Innovation score	54.96	8.52	55.00	40.00	84.00
Customer satisfaction	5.42	1.04	5.41	2.13	8.97

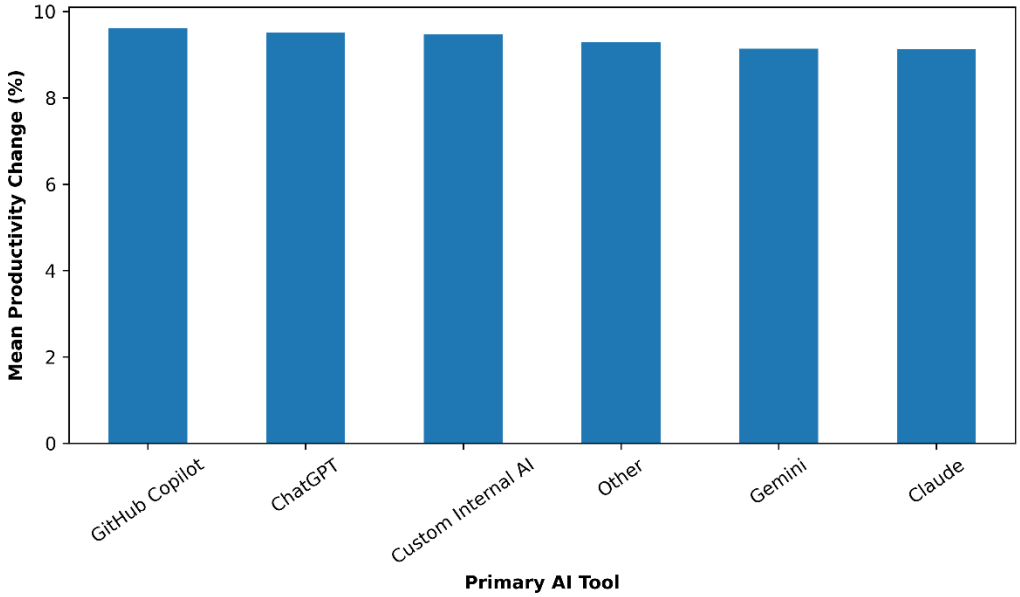


Figure 2. Mean Employee Productivity Change by Primary AI Tool

The average productivity change across the different primary AI tools is shown in Figure 2. Productivity levels were broadly similar across tool categories, with no large separation among ChatGPT, Claude, Gemini, GitHub Copilot, custom internal AI, and other systems.

3.3 Relationships Between GenAI Adoption and Employee Productivity

A correlation analysis revealed positive relationship between some AI-adoption indicators and productivity outcomes. AI maturity score and AI adoption rate turned out to be highly associated with productivity change, as presented in Table 3. The relationships of task automation and time saved per week with productivity were also significantly positive. The number of hours of training in AI and the number of AI tools used were directly correlated with productivity, while AI investment per employee was relatively less correlated.

Table 3. Correlations Between GenAI Adoption, Productivity, and Organizational Performance Indicators

Variable	Productivity change	Revenue growth	Cost reduction	Innovation score	Customer satisfaction
AI adoption rate	0.677***	0.417***	0.380***	0.512***	0.431***
AI maturity score	0.740***	0.405***	0.349***	0.531***	0.456***
AI investment per employee	0.239***	0.103***	0.139***	0.176***	0.149***
AI training hours	0.619***	0.347***	0.293***	0.460***	0.396***
Number of AI tools used	0.398***	0.237***	0.243***	0.283***	0.261***
Task automation rate	0.573***	0.339***	0.474***	0.375***	0.360***
Time saved per week	0.531***	0.311***	0.379***	0.358***	0.323***
Productivity change	1.000	0.502***	0.325***	0.418***	0.578***

*Note: Pearson correlation coefficients are reported. **$p < 0.001$.

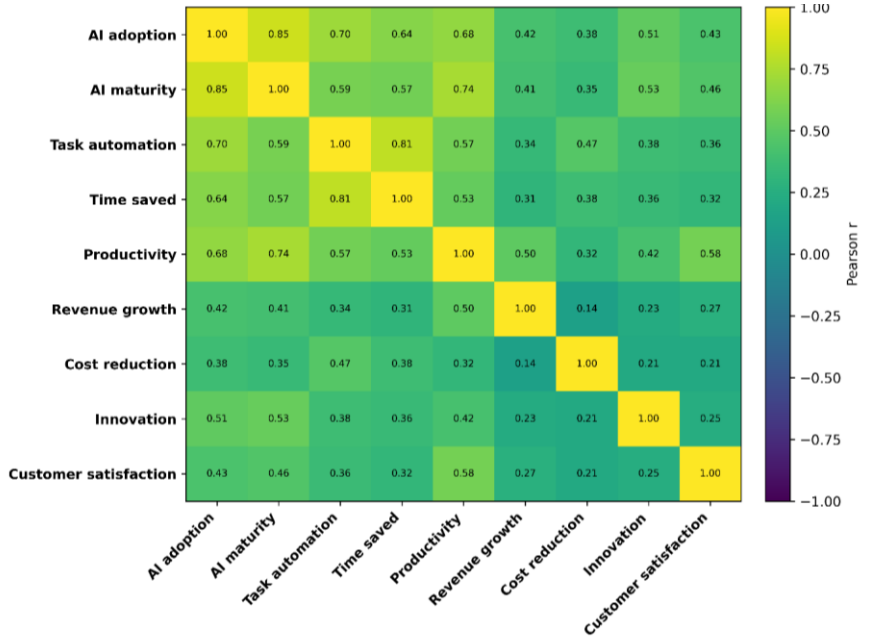


Figure 3. Correlation Matrix of AI Adoption, Productivity, and Organizational Performance

The broader correlation pattern among AI adoption, workforce productivity, and organizational outcomes is visualized in Figure 3. The heatmap demonstrates that higher AI maturity and adoption were consistently associated with stronger productivity and organizational-performance measures.

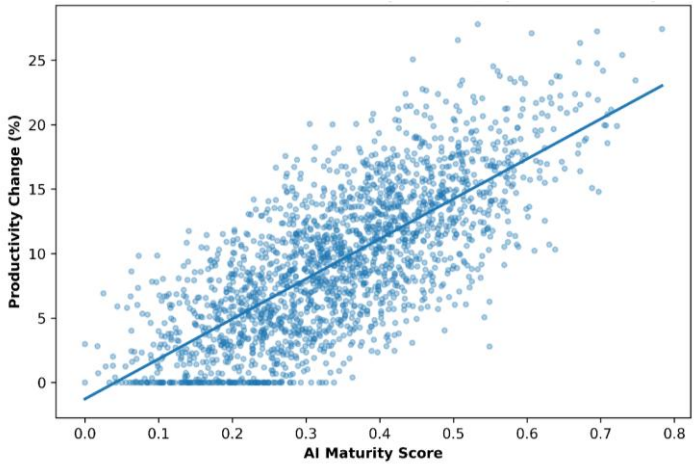


Figure 4. Association Between AI Maturity and Employee Productivity

A particularly strong positive relationship was observed between AI maturity and employee productivity. This association is illustrated in Figure 4, where increases in AI maturity generally corresponded with higher productivity-change percentages.

3.4 Predictors of Employee Productivity

Multiple linear regression was performed to determine those factors related to GenAI that were independently associated with productivity change. The entire model was statistically significant with an R2 value of 0.577, accounting for 57.7% of the variation in employee productivity. AI maturity score was the most powerful predictor followed by task automation rate, as shown in Table 4. Once the other variables were accounted for in the simultaneous model, all these variables were not individually significant: AI adoption rate, AI investment per employee, AI training hours, and number of AI tools used.

Table 4. Multiple Linear Regression Predicting Employee Productivity Change

Predictor	B	Standardized β	t	p-value
AI adoption rate	0.011	0.028	0.846	0.398
AI maturity score	24.911	0.594	17.673	<0.001
AI investment per employee	<0.001	0.002	0.108	0.914
AI training hours	-0.000	-0.001	-0.030	0.976
Number of AI tools used	0.059	0.010	0.564	0.573

Task automation rate	0.121	0.201	9.760	<0.001

Model $R^2 = 0.577$; Adjusted $R^2 = 0.575$; overall model $p < 0.001$.

3.5 Implications for Organizational Performance

Additional regression models tested the relationship between organizational performance and GenAI adoption and productivity. Productivity change was a significant positive predictor of revenue growth, cost reduction and customer satisfaction, as demonstrated in Table 5. The rate of AI adoption was a significant, independent predictor of both revenue growth and cost reduction as well as innovation performance. The most independent association with innovation was seen with AI maturity. Once other AI-related and organizational factors were factored in, there was no separate link between innovation and productivity.

Table 5. Regression Models for Organizational Performance Outcomes

Predictor	Revenue Growth β	Cost Reduction β	Innovation β	Customer Satisfaction β
Productivity change	0.429***	0.118***	0.033	0.522***
AI adoption rate	0.174***	0.293***	0.229***	0.068
AI maturity score	-0.042	0.030	0.324***	0.003
AI investment per employee	-0.034	0.027	0.003	0.001
Employee satisfaction	-0.046*	-0.024	0.018	0.032
Company age	0.003	-0.029	0.037	-0.010
Remote-work percentage	0.024	-0.031	-0.042	-0.007
Model R^2	0.267	0.156	0.299	0.338

*Note: Standardized regression coefficients are reported. *$p < 0.05$; **$p < 0.001$.

The results showed that overall, the adoption of GenAI had a positive relationship with workforce productivity and several aspects of organizational performance. The independent relationships that were most significant with productivity were AI maturity and automation of tasks, and productivity change was particularly relevant to revenue growth and customer satisfaction. There were also direct relationships between AI adoption and maturity and cost efficiency and innovation, implying that there could be organizational performance benefits through productivity related as well as other organizational mechanisms.

4. Discussion

In the present study, the results revealed positive relationships between Generative AI adoption and employee productivity and various aspects of organizational performance. Of the predictors reviewed, AI maturity and task automation came out as the most robust independent variables that were associated with the change in productivity. This suggests that companies could gain more productivity gains when AI wasn't just available, but was already part of existing processes and workflows, and backed by a more mature technology ecosystem. Other findings indicate that generative AI tools can enhance the performance of individual employees when they have access and support for using these tools in their job roles (Cohran, 2025). The results align with the wider literature which points to the impact of AI-enabled systems on employee performance, such as increasing information accessibility, saving time on repetitive tasks, and assisting with quicker task completion (Gupta et al., 2024).

Task automation, time savings, and productivity are closely related, indicating that one of the greatest values of GenAI is the time saved in performing repetitive tasks that demand knowledge. This aligns with empirical data that reveals generative AI's capabilities to boost the efficiency and quality of specific professional tasks (Noy & Zhang, 2023). The findings also align with the studies that highlight how GenAI can boost the efficiency of the workforce, especially when it comes to content creation, analysis, communication, and problem solving (Rayhan, 2024). Similarly, in the operational and supply-chain context, GenAI has been associated with potential efficiency gains, enhanced information processing, and decision support, but it is equally important to consider implementation hurdles (Fosso Wamba et al., 2024).

The results also showed that there is a significant relationship between productivity change and revenue growth and customer satisfaction. This indicates that efficiency improvements at the employee level can be more than just a benefit to the internal workings of the company and can have a broader impact on the entire organization. Past studies have also correlated the use of GenAI for workplace innovation with better performance in organizations where AI is integrated into business processes, as opposed to being a stand-alone technological solution (Alghamdi, 2025). Furthermore, GenAI and innovation capability have been linked to superior organizational performance, suggesting that the benefits of AI might be further compounded by organizational innovation practices (Khan et al., 2025). Similarly, digital performance studies have demonstrated that using GenAI effectively can have a positive impact on employee performance as long as they have the necessary skills to use it in a suitable way (Qi et al., 2025).

The other key observation was the link between the maturity of AI and Innovation Performance. This indicates that organisations with higher AI maturity levels might be more likely to use AI to generate novel concepts, optimise operations and build knowledge. This interpretation is aligned with the findings that GenAI can help enterprises

innovate by enhancing their knowledge management and organizational learning processes (Zhang et al., 2025). GenAI can also impact decision-making by providing information, offering alternatives, and aiding in the entrepreneurial evaluation, but one still needs managerial judgement (López-Solís et al., 2025).

The results should also be interpreted in the context of conditions related to employees. The use of generative AI can alter work routines, responsibilities, and ways of working together, impacting performance and employee experience (Lozie et al., 2024). Trust and engagement are especially crucial as employees tend to gain more value out of GenAI when they view it as helpful, reliable, and supportive of their job (Marimon et al., 2025). In service contexts, it has been found that the incorporation of GenAI in pertinent work tasks has been linked to the creativity and performance of employees (Wang & Zhang, 2025), with similar trends observed in other areas.

The results indicate that the value of GenAI within organizations is multifaceted and requires more than just adoption. There seems to be a correlation between increased AI maturity, the automation of appropriate tasks, employee support, and increased productivity and performance. Hence, managers should prioritize capability building, implementation with responsibility and impactful integration instead of merely fostering greater access to GenAI technologies.

5. Conclusion

This study investigated the relationship between Generative Artificial Intelligence Adoption, employee productivity and organizational performance using secondary data for 2000 organizational observations. The findings showed positive correlations between the adoption of GenAI and various indicators of the workforce and business. AI maturity and task automation were the most salient predictors of productivity change, suggesting that AI tools are more likely to enhance productivity when they are integrated into current workflows compared to being used at a basic level. Productivity changes also positively related to revenue growth, cost reduction and customer satisfaction indicating that productivity gains can also result in better organisational performance. The results further indicated that AI adoption and maturity levels were correlated to innovation performance, implying that this increased adoption and maturity of AI can assist in improving operational efficiency and increasing innovation in new ideas and processes. Meanwhile, the results highlight the importance of technology, without being technology centric. To successfully integrate GenAI into the workplace, employers should educate their staff on the technology, design appropriate tasks, offer company support, use it responsibly, and integrate it with their business strategies. In sum, Generative AI can greatly boost productivity and enhance the performance of organisations when implemented with the right process. Therefore, organisations need to invest in building the ability of AI to help the people to adapt and work with GenAI for relevant activities in the business. Longitudinal and employee level data should be used in the future to better capture long term causal effects.

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