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THE IMPACT OF GENERATIVE AI TOOLS ON EMPLOYEE PERFORMANCE AND HUMAN RESOURCE MANAGEMENT

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ABSTRACT :

Generative Artificial Intelligence (GenAI) tools such as ChatGPT, Microsoft Copilot and Google Gemini are increasingly capable of supporting content creation, information processing, communication and routine workplace tasks. This paper examines perceived generative AI use, employee performance and Human Resource Management (HRM) support using the questionnaire and spreadsheet files supplied for this project. The available workbook contains 80 synthetic practice records and 15 Likert-type items, with some question-number gaps and duplicated or overlapping constructs. Descriptive statistics, a chi-square test, one-way ANOVA, Pearson correlation, ordinary least-squares linear regression and a limited internal-consistency check were conducted for demonstration. In this synthetic dataset, the AI-usage index had a mean of 3.50 (SD = 0.95), the performance-perception index had a mean of 3.90 (SD = 0.74), and the HRM-perception index had a mean of 3.96 (SD = 0.46). The relationship between AI usage and performance perception was weak and not statistically significant, $r = 0.138$, $p = 0.223$. The regression model explained approximately 1.9% of the variation in the performance index ($R^2 = 0.019$). The chi-square test and age-group ANOVA were also not statistically significant at the 5% level. These outputs are illustrative only because the dataset is synthetic and cannot support claims about real employees or causal impact. The paper therefore provides a research structure and an analysis template that should be rerun with authentic data.

Keywords: Generative AI; employee performance; productivity; work efficiency; Human Resource Management; regression; chi-square; ANOVA.

1. Introduction

Generative Artificial Intelligence is changing how people access information, prepare written material, develop ideas and complete knowledge-based tasks. Unlike conventional software that follows predefined instructions, generative AI systems produce new text and other outputs in response to prompts. In workplaces, employees may use these systems to draft reports, summarize information, improve communication, structure presentations and support problem-solving.

These capabilities may help employees work more quickly and can provide a starting point for routine documentation. In HRM, possible uses include drafting job descriptions, creating training resources, preparing employee communications and supporting performance-management documentation. However, benefits depend on the quality of prompts, employee skills, task suitability and organizational guidance. AI-generated output may be inaccurate, biased or unsuitable, so human review remains important.

This study brings together two areas: employee performance and HRM support. It considers perceptions of regular use, ease of use, professional use, productivity and selected HR-related applications. Because the supplied data file contains synthetic responses and does not fully match the complete questionnaire in the paper, the statistical results in this draft are presented as a worked example rather than evidence about a real population.

2. Review of Literature

2.1 Generative AI and productivity

Research on generative AI in professional tasks suggests that AI assistance can reduce time spent on certain writing and information-processing activities. Noy and Zhang's experimental work on writing tasks reported faster completion and improved output quality for tasks supported by ChatGPT. Brynjolfsson, Li and Raymond studied AI assistance in customer-support work and reported productivity benefits, with gains varying by worker experience. These studies indicate that the value of generative AI can depend on the task and the user.

2.2 Human–AI collaboration and task boundaries

Research on human–AI collaboration emphasizes that AI can augment human work, but it does not remove the need for contextual judgment. Studies

of consultants using generative AI have highlighted that performance may improve on tasks within the system's capabilities while deteriorating when users rely on AI beyond those boundaries. Organizations therefore need to identify suitable tasks and retain human review.

2.3 Generative AI in HRM

Potential HRM applications include recruitment support, employee communication, training and development, performance-management documentation and routine administrative work. Adoption raises questions about privacy, bias, transparency, data quality and accountability. HR professionals must avoid entering confidential employee information into unapproved systems and should ensure that consequential employment decisions remain subject to appropriate human oversight.

2.4 Summary and research gap

The literature supplied in the original draft indicates that AI productivity and HR applications are often studied separately. A combined employee-level examination of perceived AI usage, performance and HRM support is therefore relevant. The current project aims to contribute an organized survey-based analysis, while recognizing that genuine primary data and a questionnaire aligned with the intended constructs are required for valid empirical conclusions.

3. Research Gap

The study focuses on the need to examine generative AI usage, employee performance and HRM support together, including employees' perceptions of productivity, efficiency and HR-related applications. The dataset supplied for this draft cannot yet close this empirical gap because it contains synthetic records and incomplete alignment with the full questionnaire. The gap can be addressed only after collecting real responses from a clearly defined target population.

4. Objectives of the Study

1. To examine the extent to which employees use generative AI tools in workplace activities.
2. To identify common purposes for which employees use generative AI tools.
3. To examine perceived associations between generative AI use and employee productivity or work efficiency.
4. To assess perceptions of generative AI support for HRM practices.
5. To identify perceived benefits and concerns associated with workplace generative AI.

5. Conceptual Framework

The proposed framework treats generative AI usage as the independent variable. AI-assisted work is shown as an intervening mechanism through which usage may support information processing, content creation and task assistance. Employee performance and perceived HRM support are the outcome variables. AI literacy, training, organizational guidance and human oversight are contextual factors that may influence adoption and outcomes.

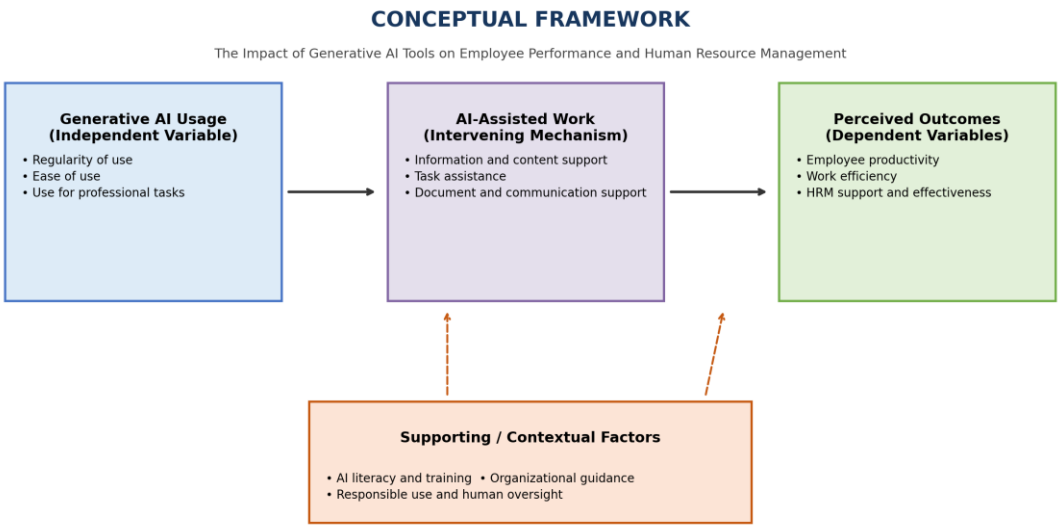


Figure 1. Conceptual framework for the study.

6. Hypotheses

- H01: There is no significant relationship between generative AI usage and employee productivity.
- H11: There is a significant relationship between generative AI usage and employee productivity.
- H02: There is no significant relationship between generative AI usage and employee work efficiency.
- H12: There is a significant relationship between generative AI usage and employee work efficiency.
- H03: There is no significant relationship between generative AI usage and perceived HRM effectiveness.
- H13: There is a significant relationship between generative AI usage and perceived HRM effectiveness.
- H04: There is no significant relationship between AI literacy/training and effective use of generative AI tools.
- H14: There is a significant relationship between AI literacy/training and effective use of generative AI tools.

7. Research Methodology

7.1 Research design

The proposed design is a quantitative, cross-sectional survey using a structured questionnaire. The original paper proposes employees and HR professionals as respondents. The final report should specify the actual study location, target population, sampling method, collection period and inclusion criteria once genuine data have been collected.

7.2 Data source and sample

The spreadsheet supplied for this analysis contains 80 records. Its own READ ME sheet explicitly identifies the entries as fictional/synthetic sample data. Therefore, the number 80 refers to rows in the practice dataset, not to verified human participants. No claim about a real sample, response rate or population can be made from this file.

7.3 Instrument and measurement

The original questionnaire uses a five-point agreement scale from 1 = Strongly Disagree to 5 = Strongly Agree. The available spreadsheet includes demographic categories and 15 Likert-type columns, but does not contain all 25 attitudinal questions listed in the Word draft. Several questions are missing, question numbering skips items, and some statements are duplicated or overlap. Consequently, composites used here are provisional: AI Usage Index is the mean of available items Q6–Q8; Performance Perception Index is the mean of available Q10 and Q17; HRM Perception Index is the mean of available Q13, Q15, Q18 and Q20. These are not validated scales.

7.4 Statistical techniques

The workbook provides frequencies and percentages for demographic variables; mean, median and standard deviation for available Likert items and provisional composite indices; a chi-square test of association between gender and Q6 regular AI-use response; one-way ANOVA comparing Q10 productivity ratings across age groups; Pearson correlations; a simple linear regression predicting the performance index from the AI Usage Index; and Cronbach's alpha for the three available usage items. Tests are exploratory and demonstrate the workflow in Excel/SPSS; the data should be replaced before substantive interpretation.

8. Data Analysis and Interpretation

8.1 Descriptive statistics

The available synthetic records produced a mean AI Usage Index of 3.50 (median 3.67, SD 0.95), suggesting moderately positive responses on the three included usage items. The Performance Perception Index mean was 3.90 (median 4.00, SD 0.74), while the HRM Perception Index mean was 3.96 (median 4.00, SD 0.46). Because the observations are synthetic, these values describe only the constructed practice dataset.

Composite index	N	Mean	Median	SD	Range
AI Usage Index (Q6–Q8)	80	3.50	3.67	0.95	1.00–5.00
Performance Perception Index (Q10, Q17)	80	3.90	4.00	0.74	2.50–5.00
HRM Perception Index (Q13, Q15, Q18, Q20)	80	3.96	4.00	0.46	2.75–4.75

8.1.1 Demographic profile of the practice dataset

The following frequencies summarize the 80 rows in the supplied workbook. Percentages are calculated using N = 80. Because the records are synthetic, the table is a description of the practice file and not a profile of actual employees.

Demographic variable	Category	Frequency	Percentage
Gender	Prefer not to say	33	41.2%
Gender	Male	25	31.2%
Gender	Female	22	27.5%
Age	31–40	21	26.2%
Age	20–25	20	25.0%
Age	Above 40	17	21.2%
Age	26–30	12	15.0%
Age	18–20	10	12.5%
Educational qualification	Undergraduate	22	27.5%
Educational qualification	Diploma	18	22.5%
Educational qualification	Postgraduate	14	17.5%
Educational qualification	Intermediate	13	16.2%
Educational qualification	Other	13	16.2%
Work experience	4–6 years	18	22.5%
Work experience	Less than 1 year	17	21.2%
Work experience	7–10 years	16	20.0%
Work experience	More than 10 years	15	18.8%
Work experience	1–3 years	14	17.5%
Job role	IT	16	20.0%
Job role	Administration	14	17.5%
Job role	Manager	14	17.5%
Job role	Other	13	16.2%
Job role	Employee	13	16.2%
Job role	HR	10	12.5%

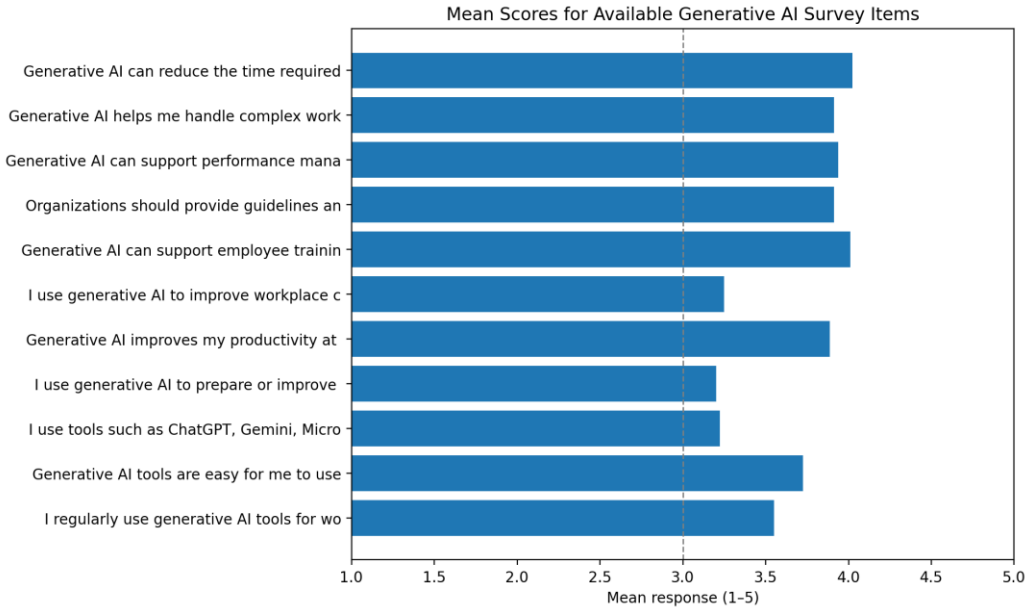
8.1.2 Item-level descriptive statistics

Table 2 reports the mean, median and standard deviation for each available Likert item. The scale is coded from 1 (Strongly Disagree) to 5 (Strongly Agree). Items in the workbook do not fully align with the 25-item questionnaire, so item labels below follow the supplied dataset rather than assuming missing questions were answered.

Dataset item	N	Mean	Median	SD	Min–Max
6.I regularly use generative AI tools for work-related activities.	80	3.55	4.00	1.30	1–5
7. Generative AI tools are easy for me to use.	80	3.73	4.00	1.20	1–5
8. I use tools such as ChatGPT, Gemini, Microsoft Copilot, or similar AI applications for professional tasks.	80	3.23	3.00	1.42	1–5
9.I use generative AI to prepare or improve documents and reports.	80	3.20	3.00	1.50	1–5
10. Generative AI improves my productivity at work.	80	3.89	4.00	1.04	1–5
12. I use generative AI to improve workplace communication.	80	3.12	3.00	1.36	1–5

13. Generative AI can support employee training and development.	80	4.01	4.00	1.04	1–5
14. Organizations should provide guidelines and training for the responsible use of generative AI.	80	3.91	4.00	1.18	1–5
15. Generative AI can support performance management activities	80	3.88	4.00	1.02	1–5
16. I use generative AI to improve workplace communication.	80	3.25	3.00	1.33	1–5
17. Generative AI helps me handle complex work-related tasks more efficiently.	80	3.91	4.00	1.07	1–5
18. Generative AI can reduce the time required for routine HR tasks and documentation.	80	4.03	4.00	0.90	2–5
19. Generative AI can reduce the time required for routine HR tasks and documentation	80	3.79	4.00	1.26	1–5
20. Generative AI can support performance management activities.	80	3.94	4.00	0.89	1–5

Figure 2. Mean scores for the available survey items.



8.2 Chi-square test

A Pearson chi-square test examined whether gender was associated with responses to the regular AI-use statement (Q6). The test result was $\chi^2(8) = 3.553$, $p = 0.895$. At the 5% significance level, the result was not statistically significant. The practice data therefore do not show evidence of an association between gender and Q6 response. Some expected cell counts may be small because the table contains multiple gender and response categories; in a real study, assumptions should be checked and categories combined only when substantively defensible.
Interpretation note: Likert items are ordinal. Means and standard deviations are commonly reported for multi-item scales but should be interpreted cautiously for single items. The composite indices used here are provisional and were defined from the items actually present in the spreadsheet.

8.3 One-way ANOVA

A one-way ANOVA compared the Q10 productivity-perception rating across the five age categories in the synthetic dataset. The result was $F(4, 75) = 1.979$, $p = 0.106$. This was not statistically significant at $\alpha = .05$. Thus, the analysis did not detect a statistically significant difference in Q10 ratings across age groups in these constructed data. Since Likert responses are ordinal and the groups are not necessarily balanced, this should be treated as an illustrative analysis; Kruskal–Wallis may be considered as a robustness check for real data.

8.4 Correlation analysis

The Pearson correlation between the AI Usage Index and Performance Perception Index was $r = 0.138$, $p = 0.223$, indicating a weak positive, non-significant association in the practice dataset. The correlation between AI Usage Index and HRM Perception Index was $r = -0.073$, $p = 0.519$, a very weak negative and non-significant association. These results do not establish that AI has no impact; they simply show that the constructed records do not demonstrate a statistically significant linear association.

8.5 Linear regression

A simple ordinary least-squares regression predicted the Performance Perception Index from the AI Usage Index. The fitted equation was: Performance Index = 3.521 + (0.108 × AI Usage Index). The model had $R^2 = 0.019$ (adjusted $R^2 = 0.006$), $F(1, 78) = 1.509$, $p = 0.223$. The usage coefficient was 0.108, $p = 0.223$, and was not statistically significant. The model explains approximately 1.9% of the variation in the performance index in this synthetic dataset.

8.6 Reliability check

Cronbach's alpha for the three available AI-usage items (Q6–Q8) was $\alpha = 0.541$. This is modest/low and suggests that the three items may not form a sufficiently consistent scale in this dataset. Given the synthetic nature of the records and the mismatch between the workbook and the questionnaire, this value should not be used to validate the instrument. Reliability must be recalculated using genuine responses and a finalized questionnaire.

8.6.1 Decision rule and model specification

All inferential tests used a nominal significance level of $\alpha = .05$. A p-value below .05 would be treated as evidence against the relevant null hypothesis, subject to assumptions and design limitations. A p-value above .05 means the analysis did not detect a statistically significant result; it does not prove that no relationship exists. For regression, the model is Performance Perception Index = $\beta_0 + \beta_1$(AI Usage Index) + ε. The model is exploratory and cannot establish causality.

8.7 Summary of tests

Analysis	Result	Decision at $\alpha = .05$
Chi-square: gender × Q6	$\chi^2(8) = 3.553$, $p = 0.895$	Not significant
One-way ANOVA: Q10 by age	$F(4, 75) = 1.979$, $p = 0.106$	Not significant
Correlation: usage × performance	$r = 0.138$, $p = 0.223$	Not significant
Regression: usage predicting performance	$R^2 = 0.019$, slope $p = 0.223$	Not significant
Cronbach's alpha: Q6–Q8	$\alpha = 0.541$	Low/modest; use cautiously

9. Findings

- The constructed dataset contains 80 records, but all are marked as synthetic and do not represent verified survey respondents.
- The provisional AI Usage Index mean is 3.50; the performance and HRM perception indices have means of 3.90 and 3.96 respectively.
- The chi-square test did not identify a statistically significant association between gender and the regular AI-use response.
- The one-way ANOVA did not identify a statistically significant difference in the productivity-perception item across age categories.
- The AI usage index showed a weak, non-significant correlation with the performance perception index, and the simple regression model was not statistically significant.

- The reliability estimate for the three available usage items was modest/low, so the composite measure requires reconsideration.
- The spreadsheet does not contain all questions in the original questionnaire, so conclusions about all study objectives cannot be made from the current file.

10. Suggestions / Recommendations

1. Collect genuine responses from employees and HR professionals after obtaining informed consent and explaining the purpose of the study.
2. Align the spreadsheet columns with the finalized questionnaire, using one unique column per item and consistent question numbering.
3. Define and document composite scales before testing hypotheses; do not combine items solely because they are available.
4. Pilot-test the questionnaire and assess reliability using real data. Review item-total statistics and revise weak or ambiguous items.
5. Encourage responsible AI use through training, approved tools, privacy rules, fact-checking and human review.
6. Use AI as an assistant for suitable tasks rather than as the sole decision-maker for recruitment, appraisal or other consequential HR decisions.
7. Report effect sizes, confidence intervals, assumptions and exact p-values alongside significance decisions in the final study.

11. Limitations

- The 80 records are synthetic sample data, not genuine participant responses; no population-level inference is valid.
- The available workbook includes only part of the original questionnaire, with missing questions and overlapping/duplicated items.
- The provisional composite indices are not validated measures.
- The cross-sectional design, even with real data, would support associations rather than strong causal claims.
- The chi-square test may have small expected counts; ANOVA assumptions and ordinal-scale considerations require checking.
- Demographic coding differs in places from the options in the Word questionnaire, so the instrument and codebook must be reconciled.

12. Conclusion

The supplied materials establish a relevant topic: how generative AI may support employee performance and HRM. The worked analysis shows how descriptive statistics, chi-square, ANOVA, correlation, regression and reliability checks can be reported. In the synthetic dataset, none of the inferential tests showed a statistically significant association at the 5% level, and the regression explained little variation in the provisional performance index. These are demonstrations of the analysis procedure, not empirical conclusions about employees. The most important next step is to replace synthetic entries with authentic survey data, correct the questionnaire-to-dataset mapping, rerun the analysis and revise the findings accordingly.

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