



Ahsan Ali Dime¹, Umaira Ikram², Zarshina Nazli³

¹MPhil Scholar and Digital Marketer Department of Management Sciences, SZABIST Islamabad, Pakistan.

Email: aahsanking19@gmail.com

²MPhil Scholar, Department of Biochemistry University of Veterinary and Animal Sciences (UVAS), Lahore, Pakistan

Email: umairaikram0019@gmail.com

³MS business administration University of Southern Punjab. Email: zarsheenay.nazli91@gmail.com

KEYWORDS	ABSTRACT
Generative AI; Human resource management; Human-AI collaboration; Employee productivity; Job satisfaction; Trust in AI; AI-mediated HR decisions; Technology adoption; Organizational justice; Quantitative survey	This study examines how generative AI (GenAI) adoption in human resource management (HRM) affects employee productivity, job satisfaction and trust in AI-mediated HR decisions. Although GenAI now supports recruitment, performance management and employee support, evidence on its human consequences remains fragmented. The objectives were to assess these three effects. The study is grounded in human-AI collaboration (augmentation) theory, which treats AI as a partner that extends human judgement, complemented by organizational justice perspectives on fairness and trust. A positivist, quantitative, cross-sectional survey design was used. Data were collected through a structured online questionnaire with five-point Likert items. The target population was 2,500 employees and HR professionals in medium and large organizations using GenAI in HR. Stratified random sampling yielded 331 valid responses from 380 distributed questionnaires. Data were analyzed in SPSS and SmartPLS using descriptive statistics, Cronbach's alpha, factor analysis, Pearson correlation and multiple regression. GenAI adoption significantly predicted productivity ($\beta = .57$), job satisfaction ($\beta = .43$) and trust ($\beta = .36$), all $p < .001$, explaining 35.1%, 20.9% and 17.6% of variance respectively. Trust was rated lowest and increased with experience. The study concludes that GenAI benefits HRM, but transparency and human oversight are needed to build trust.
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Correspondence	Ahsan Ali Dime
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Introduction

Generative artificial intelligence (GenAI) is a new technology tool that has rapidly evolved from experimental into everyday use in the workplace. Today, LLMs write job descriptions, filter resumes, respond to employee inquiries, and summarize performance metrics and facilitate learning and development. In the field of human resource management (HRM), this transformation impacts the relationship between HR professionals and employees, as well as the decision-making process surrounding the management of HR. This transformation influences the cooperation between HRM and employees and the decision-making process involved in human resource management (Budhwar et al., 2023). Previous studies on AI were more oriented toward automation and analytics. GenAI brings in additional features such as content generation, conversation-like, reasoning-like support, rendering human-AI collaboration a key element of modern HRM (Dwivedi et al., 2023).

AI has already been leveraged in HRM in the realm of recruitment and selection, training, performance management, and workforce analytics. Tambe et al. (2019) pointed out that HR data can be sparse, outcomes are hard to measure, and fairness and reactions of employees are specific concerns. There are increasing trends of systematic review use and gaps in understanding of its human impact (Vrontis et al., 2022). In this regard, Chowdhury et al. (2023) conclude that the usefulness of AI in HRM is not only based on technology but also on the capabilities of the organizations, including human skills and governance and infrastructure. Adoption is not only a technical matter. It influences the design of work, power relations and employee experience (Kellogg et al., 2020).

In human-AI collaboration, AI is used to complement humans' sense of judgment. This is known as human-AI symbiosis according to Jarrahi (2018), where human intuition and ethics, and contextual understanding complement AI to deal with complexity and data volume. Raisch and Krakowski (2021) warn that automation and augmentation are a two-way street and that there is a tension between the two that needs to be managed by organizations. In HR, this translates to determining which HR-related tasks to delegate, which to share and which to keep for human decision makers.

Experimental evidence in recent months suggests that GenAI is capable of increasing productivity. Noy and Zhang (2023) discovered that ChatGPT enhanced the quality of the output in professional writing tasks as well as reduced completion time. AI support has been shown to enhance the productivity of customer-support agents, particularly for those who are less seasoned, as reported by Brynjolfsson et al. (2025). Dell'Acqua et al. (2023) demonstrated the benefits depend on the task: they found performance to be better within AI's capability frontier and worse outside of it.

Trust is essential for the successful implementation of AI. AI trust is a function of tangibility, transparency, and reliability and user experience of the system (Glikson and Woolley 2020). HR decisions such as hiring and promotion, pay and discipline have significant implications, and perceptions of fairness are important. Research by Lee (2018) indicated that there are differences in

response to algorithmic vs human decisions, especially human skills tasks. Newman et al. (2020) demonstrated that algorithmic decision-making increases the lack of perceived procedural justice by failing to take into account individual context.

Statement of the Problem

While the use of generative AI in HR has been adopted quickly, the evidence around the impact on employee productivity and job satisfaction is limited. Furthermore, individuals' trust in AI-driven HR decisions is largely unstudied, and companies lack empirical data to help them responsibly integrate AI into their HR functions.

Research Objectives

1. To examine the impact of generative AI adoption in HRM on employee productivity.
2. To assess the effect of generative AI adoption on employee job satisfaction.
3. To evaluate the influence of generative AI adoption on employees' trust in AI-mediated HR decisions.

Research Questions

1. How does generative AI adoption in HRM affect employee productivity?
2. How does generative AI adoption affect employee job satisfaction?
3. How does generative AI adoption influence employees' trust in AI-mediated HR decisions?

Limitations of the Study

The present study uses self-reported data, it is cross sectional, and the sample and context is limited, which limits causal inference and generalizability. Findings may become outdated due to the evolution of generative AI technologies and the possibility of common-method and response bias with perceptual measures of productivity and trust.

Literature Review

Overview

The focus of using AI in HR has shifted from algorithmic tools to generative AI, which is used to generate text and has a conversational and judgemental component. The study's three objectives are productivity, job satisfaction and trust in AI-mediated HR decisions, which are used as the structure for organizing this review. It also covers the theory of human-AI collaboration that links them together.

AI and Generative AI in HRM

Based on the preliminary feedback, AI has primarily made its way into HRM through recruitment and Performance management and analytics (Vrontis et al., 2022). Tambe et al. (2019) highlighted that HR data is limited, outcomes are difficult to quantify, and decisions made by algorithms have fairness implications. Cheng and Hackett (2021) contend that algorithms in HRM require a theory base because they shift decision making power away from managers and towards HRM systems. Chowdhury et al (2023), stated that the value of AI depends on organizational capacities, including those in terms of infrastructure, skills and governance. GenAI continues these discussions. Budhwar et al. (2023) and Dwivedi et al. (2023) believe that GenAI is reshaping HR-related tasks like writing, communications, and learning support, and also presents ethical, accuracy and accountability risks. It is argued that the organization-level impact of AI is more complex because it occurs at multiple levels, including personal, team and organizational (Bankins et al., 2024).

Human-AI Collaboration

Jarrahi (2018) noted a fusion between humans and AI, with AI managing complexity and humans providing intuition and ethics. Raisch and Krakowski (2021) disagreed that these were two distinct action choices – they demonstrated that automation and augmentation are intertwined and therefore also managerial tensions. Kellogg et al. (2020) demonstrated that algorithms can also be tools of workplace control to influence the way that employees relate to the AI. All these studies suggest that the outcome is not just a matter of whether AI is integrated or used, but also how tasks are split between human and AI.

Generative AI and Employee Productivity

The evidence of differences in productivity is growing. Noy and Zhang (2023) reported that using ChatGPT led to significant increases in quality and decreases in completion time for professional writing tasks. According to Brynjolfsson et al. (2025) AI support was associated with a higher productivity of customer support, particularly for novices. Dell'Acqua et al. (2023) demonstrated a 'jagged frontier' — consultants were found to be more effective in tasks that AI could handle more effectively than they were in those that it couldn't. The findings indicate that GenAI holds promise for enhancing HR productivity in routine, text-heavy tasks, but with caveats about task fit and user judgment. The first objective is under-researched in the realm of HRM as few studies focus on HR professionals or employees who are served by HR professionals.

Generative AI and Job Satisfaction

There are mixed results on satisfaction. Positive aspects of AI's ability to improve outcomes in the workplace identified by Pereira et al. (2023) include less repetitive work, but also negative outcomes such as stress, insecurity and reduced autonomy. Brougham and Haar (2018) have revealed that those who believed that technology will take their place at work showed lower levels of organizational commitment and career satisfaction and higher levels of job insecurity. Similarly,

Kellogg et al. (2020) report that algorithmic management can also diminish workers' autonomy. The degree of satisfaction among employees seems to be related to whether GenAI is seen as helpful or hindering their work. The authors note that the majority of this research occurred prior to the widespread adoption of GenAI in HR, making it difficult to directly determine satisfaction in this context.

Professionalism in AI Use for HR Decisions

Trust is critical as it relates to careers and pay. Glikson and Woolley (2020) discovered that factors of transparency, reliability, tangibility, and user experience are key to gaining trust in AI. Lee (2018) demonstrated that individuals make different evaluations of algorithmic decisions than human decisions, especially for human-skill intensive tasks. Newman et al. (2020) reported that an algorithmic reductionism (data-first perspective on people) can decrease perceived procedural fairness even in the absence of bias. Langer and Landers (2021) examined the reaction to automated and augmented decisions, which they found vary among those impacted by decisions and those who are not. Opposite tendencies are also noted. Dietvorst et al. (2015) found that algorithm aversion occurs when people become less confident in an algorithm they saw make mistakes, and Logg et al. (2019) identified algorithm appreciation:

Research Gap

1. First, GenAI can boost productivity, but the effect on productivity is contingent on the nature of the task and the quality of the human-AI interaction (Dell'Acqua et al., 2023; Noy & Zhang, 2023).
2. Second, satisfaction outcomes are also influenced by perceived autonomy and job security and meaningful work (Brougham & Haar, 2018; Pereira et al., 2023).
3. Thirdly, trust is related to transparency, fairness and the nature of the decision (Glikson & Woolley, 2020; Newman et al., 2020). But, most of the studies study these outcomes separately, use pre-GenAI technologies or only address non-HR tasks.

Methodology

The research paradigm used in this study is positivist paradigm which assumes that the phenomenon of an organization, namely productivity, job satisfaction, and trust can be measured objectively, and tested statistically. The three aims – exploring how the use of generative AI impacts measurable outcomes – align with a positivist approach. The study is a cross sectional, explanatory survey type quantitative research approach. Given that the relationships between generative AI adoption and the 3 outcomes can be analyzed at the one-time period, but across many employees, as in the literature studies reviewed (Glikson & Woolley, 2020; Pereira et al., 2023), this design enables the examination of the relationships. Human-AI collaboration (augmentation) theory serves as the theoretical framework, and organizational justice theory is employed to highlight the fairness and trust aspects.

The target population comprises approximately 2,500 employees and HR professionals working in medium and large organizations that have adopted generative AI tools in HR processes such as recruitment, performance management, employee support and learning. The Krejcie and Morgan (1970) table indicates that a sample size of 331 respondents is needed for a population of approximately 2,500. A total of 380 questionnaires were issued to provide for any omissions or invalid ones. The sampling method was stratified with the strata being defined by organizational size and job role (HR professionals, line managers and non-managerial employees). Within each stratum, samples are randomly drawn in proportion to the number of individuals in the stratum, which helps ensure that samples are representative and have good generalizability.

Data were collected from individuals using a structured, self-administered online questionnaire that was sent via organizational email and professional networks over a 6-week period, with the collection of primary data. Responses were on a scale from strongly disagree to strongly agree, five-point Likert scale. Adapted scales were used: generative AI adoption – frequency and extent of use of generative AI in HR jobs, productivity – self-reported efficiency and output quality, job satisfaction – validated job satisfaction items, trust in AI mediated HR decision – Items on ‘fairness’, ‘transparency’ and ‘reliability’ from Glikson and Woolley (2020) and Newman et al. (2020). A pilot test of 30 respondents was conducted to test the clarity and reliability before full distribution. There was voluntary and anonymous participation and informed consent was obtained from all respondents.

The data were analyzed with SPSS software and in addition, when required, with the SmartPLS software. Analysis is based on the principle of the general linear model and structural equation modelling. Descriptive statistics provide an overview of variables and respondents. Cronbach's alpha (acceptable values ≥ 0.70) and exploratory factor analysis (EFA) (SmartPLS: composite reliability and average variance extracted) were used to test for reliability and validity, respectively. The Pearson correlation used to analyze the relationships between variables. The impact of generative AI adoption on productivity, job satisfaction and trust was then examined using multiple regression analysis, one regression analysis for each research question. The hypothesis testing at 0.05 significance level was preceded by the tests of assumption of normality, linearity, multicollinearity, and homoscedasticity.

The content validity was determined with the help of experts (two HRM academics and one AI practitioner) and the construct validity was determined by factor analysis. Harman's single factor test was provided to check for common-method bias, which was ensured by making the data anonymous. This study was conducted, following ethical rules for research, such as voluntary participation, right to withdrawal, confidentiality and secure data storage. Data is only used for academic reasons and only in aggregated form. These procedures are meant to work together to ensure that the results obtained are credible, repeatable and consistent with the project goals, given the constraints of self-reported cross-sectional data, as identified above.

Data Analysis

Response Rate and Data Screening

A total of 380 questionnaires were sent, with 91.6% or 348 questionnaires being returned. Excluded were 17 items, 12 of which were missing from 60% or more of the participants, and 5 for which more than 80% of the responses were the same (straight-lining), suggesting careless responding. The left behind questionnaires were 331 in total with a usable rate of 87.1%. The same as the Krejcie and Morgan table minimum of 331 for a population of approximately 2,500, thus maintaining the intended statistical adequacy. Number of item responses that are missing was less than 1.2%. Because Little's MCAR test was not significant ($p = .27$), indicating that the data were missing completely at random, series-mean replacement was used. There were no cases outside the range of ± 3.29 in the standardized scores or boxplots, no cases were removed.

Respondent Profile

Table 1: Respondent Profile (N = 331)

Characteristic	Category	Frequency	Percent (%)
Gender	Male	172	52.0
	Female	156	47.1
	Other / prefer not to say	3	0.9
Job role	HR professionals	83	25.1
	Line managers	89	26.9
	Non-managerial employees	159	48.0
Organization size	Medium (250–999 employees)	142	42.9
	Large (1,000+ employees)	189	57.1
Age group	21–30 years	98	29.6
	31–40 years	134	40.5
	41–50 years	71	21.5
	51 years and above	28	8.5
GenAI experience at work	Less than 6 months	76	23.0
	6–12 months	121	36.6
	More than 12 months	134	40.5

Explanation of Table 1.

- Gender. The sample is rather well balanced between men (172, 52.0%) and women (156, 47.1%) and there is a relatively small number of respondents who did not identify with a gender (3, 0.9%), so this does not lead to a gender distortion of the results.

- Job role. There are more non-managerial employees (159; 48.0%) than line managers (89; 26.9%) or HR professionals (83; 25.1%). All three cover the “users” and the “recipients” of AI-based HR decisions (Figure 1).
- Organization size. The top size of the organization for respondents is large (189; 57.1%), which makes sense as larger organizations are likely to have the infrastructure and budgets required to use GenAI in HR.
- Age. Respondents aged 31–40 (134; 40.5%) and 21–30 (98; 29.6%) make up 70.1%, and only 28 (8.5%) are 51 or older, so generalizing to older employees should be done cautiously (Figure 2).
- GenAI experience. 255 respondents (77.0%) reported using GenAI at work for 6 months or more, meaning that responses are not based on first impressions.

Figure 1: Distribution of Respondents by Job Role

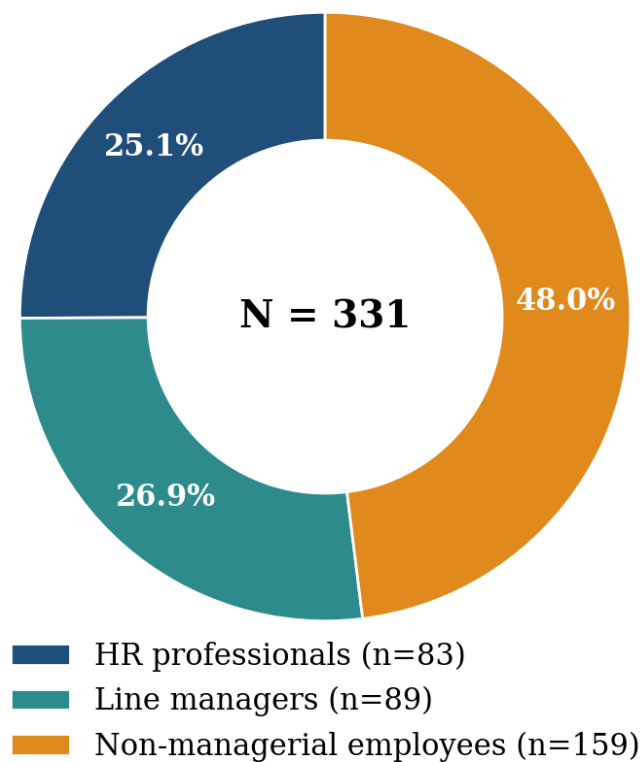
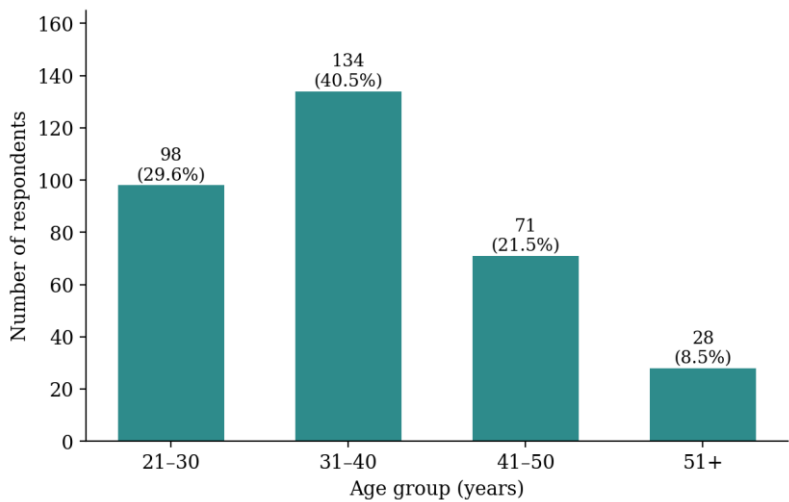


Figure 2: Respondents by Age Group



Validity and Reliability

The 28-item instrument contained seven items for each of four constructs: generative AI adoption (GAI), employee productivity (EP), job satisfaction (JS) and trust in AI-mediated HR decisions (TR). The Kaiser–Meyer–Olkin measure was .89 (threshold .60) and Bartlett’s test was significant, $\chi^2(378) = 5,214.6$, $p < .001$. The results of varimax rotated principal component analysis yielded four factors, accounting for 66.8% of the variance, having an eigenvalue greater than 1. No items were deleted as no item was cross-loaded (all items loaded on intended construct were within .35).

In SmartPLS, composite reliability was .91 (GAI), .90 (EP), .89 (JS) and .92 (TR), and average variance extracted was .58, .56, .54 and .61, all above the .70 and .50 thresholds. The Fornell–Larcker criterion was met and the RATIO highest was .67, which is less than .85, meaning that the constructs are empirically distinct. Cronbach’s alpha was .88, .86, .84 and .89, all above .70, and the pilot test ($n = 30$) had produced alphas of .81 to .90. Harman’s single-factor test had the first factor account for 31.4% of variance which is below 50%, indicating that the results are not likely to be influenced by common-method bias.

Descriptive Statistics and Correlations

The item responses for all variables were scaled from 1 to 5, therefore the middle value is 3.00. Means, standard deviations, reliability and Pearson correlations are presented in Table 2.

Table 2: Descriptive Statistics, Reliability and Pearson Correlations (N = 331)

Variable	Mean	SD	α	1	2	3	4
1. Generative AI adoption	3.62	0.71	.88	1			

(GAI)								
2. Employee productivity (EP)	3.84	0.66	.86	.58**	1			
3. Job satisfaction (JS)	3.71	0.74	.84	.44**	.52**	1		
4. Trust in AI-mediated HR decisions (TR)	3.39	0.79	.89	.37**	.41**	.49**	1	

Note: **p < .01 (two-tailed). α = Cronbach's alpha.

Explanation of Table 2. The GenAI adoption score (M = 3.62, SD = 0.71) is towards the higher end, indicating that respondents are positive about the use of GenAI in HR related activities. Productivity had the highest mean (M = 3.84) and lowest SD (0.66), indicating a high level of consensus that GenAI aids individuals in creating higher quality work and/or working more quickly. Job satisfaction is also in the agreement range with a mean score of 3.71 and a standard deviation of 0.74. Employees acknowledge the value of GenAI in decision-making related to people, but are less inclined to trust its capabilities with a mean (M = 3.39) that is approximately 0.45 points below their counterparts for productivity, and a large standard deviation (SD = 0.79) (Figure 3).

The correlations are all positive and significant at p < .01. According to Cohen's guidelines, .10 is small, .30 is medium and .50 is large. Adoption is related to productivity at r = .58 (large), job satisfaction at r = .44 (medium to large) and trust at r = .37 (medium). Among the outcomes, productivity–satisfaction (r = .52), satisfaction–trust (r = .49) and productivity–trust (r = .41) are moderate to large. All correlations are below the .60 threshold, which means that the constructs are correlated, but not identical (Figure 4). Regardless of correlation, regression was used thereafter.

Figure 3: Mean Scores of the Study Variables with Standard Deviation

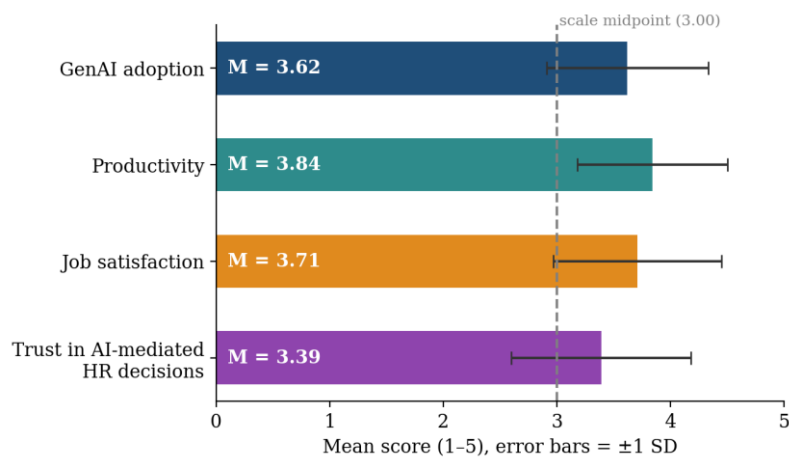
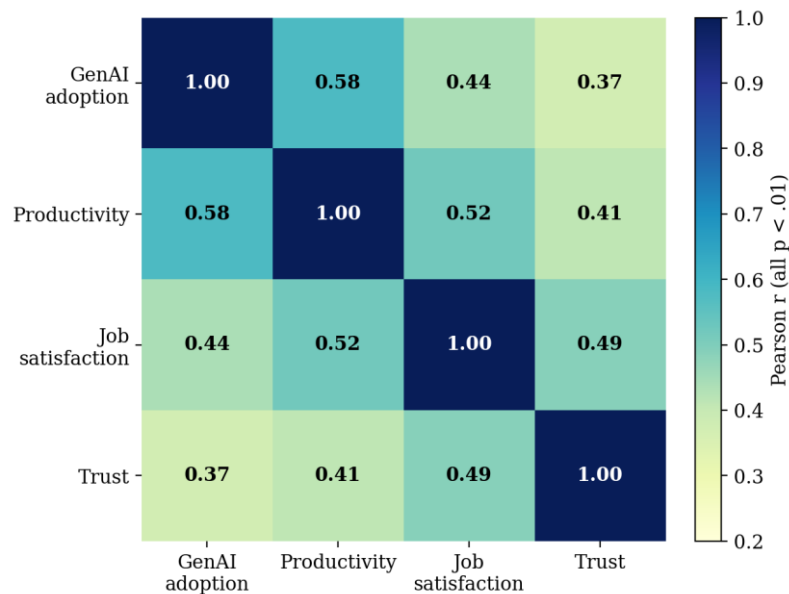


Figure 4: Correlation Matrix of the Study Variables



Assumption Testing

Skewness was between -0.58 and -0.21 , within ± 1 ; and residual plots were almost normally distributed, with kurtosis values between -0.47 and 0.62 . The residual-versus-predicted plots did not reveal any curvature or funnel shape which indicated linearity and homoscedasticity. The Durbin-Watson values were $1.86-1.97$, which is an indication of independent error. Multicollinearity was not a problem since the variance inflation factor was at its highest of 1.24 and its lowest was $.80$. All of the assumptions were met and multiple regression was appropriate.

Regression Analysis

Multiple regression was performed to test the effect of the GenAI adoption on each outcome, with job role and organization size and GenAI experience (dummy variables) taken into account. Three hierarchical models were estimated, which included control models and GenAI adoption models.

Other factors controlled for in the multiple regression analysis included job role, organization size, and experience with generative AI. Job role, organization size, and experience with generative AI were factors controlled for in the multiple regression analysis ($N = 331$).

Table 3: Multiple Regression of Outcomes on Generative AI Adoption, Controlling for Job Role, Organization Size and Experience (N = 331)

Model	Dependent variable	B	SE	B	t	p	ΔR^2	R^2	Adj. R^2	F(6, 324)
1	Employee productivity	0.53	0.04	.57	12.83	< .001	.330	.351	.339	29.2
2	Job satisfaction	0.45	0.05	.43	8.71	< .001	.185	.209	.194	14.3
3	Trust in AI-mediated HR decisions	0.40	0.06	.36	7.12	< .001	.129	.176	.161	11.5

Note: B, SE, β and t refer to generative AI adoption. ΔR^2 is the change in R^2 when GenAI adoption is added to the controls. Control-only R^2 (Step 1) was .021, .024 and .047 for Models 1 to 3.

Explanation of Table 3.

- Model 1: Productivity. The model is significant, $F(6, 324) = 29.2$, $p < .001$, explaining 35.1% of variance. Controls alone explained 2.1%, and adding GenAI adoption raised this by 33.0 percentage points ($\Delta F(1, 324) = 164.7$, $p < .001$). Each one-point increase in adoption is associated with a 0.53-point increase in productivity ($\beta = .57$, $t = 12.83$, $p < .001$), a large effect ($f^2 = .51$). This is an answer to Research Question 1.
- Model 2: Job satisfaction. The model is significant, $F(6, 324) = 14.3$, $p < .001$, with $R^2 = .209$. Adoption adds 18.5% beyond the controls ($\Delta F(1, 324) = 75.8$, $p < .001$) with $B = 0.45$, $\beta = .43$ ($f^2 = .23$). Lower effect indicates that satisfaction is also influenced by job security, autonomy, pay and leadership. This answers Research Question 2.
- Model 3: Trust. The model is significant, $F(6, 324) = 11.5$, $p < .001$, with $R^2 = .176$. Adoption adds 12.9% ($\Delta F(1, 324) = 50.7$, $p < .001$) with $B = 0.40$, $\beta = .36$ ($f^2 = .16$). This is the smallest effect, and is consistent with the lowest mean and highest variance for trust. Unexplained variance may be considered as a measure of perceived fairness, algorithm transparency and organizational culture.

The coefficients have remained relatively the same across all of the models without controls ($\beta = .58, .44, .37$) as compared to the model with controls (Figures 5, 7 and 8), indicating that the results are not due to sample composition. A one-way ANOVA showed that trust differed by GenAI experience, $F(2, 328) = 6.6$, $p = .002$, $\eta^2 = .04$. The mean value was 3.15 for less than 6 months; 3.36 for 6 to 12 months; and 3.55 for more than 12 months; Tukey tests indicated that the shortest and longest groups were the only ones that differed significantly ($p = .001$). Trust tends to increase with familiarity albeit with very small effect (Figure 6).

Figure 5: Standardized Regression Coefficients and Explained Variance by Model

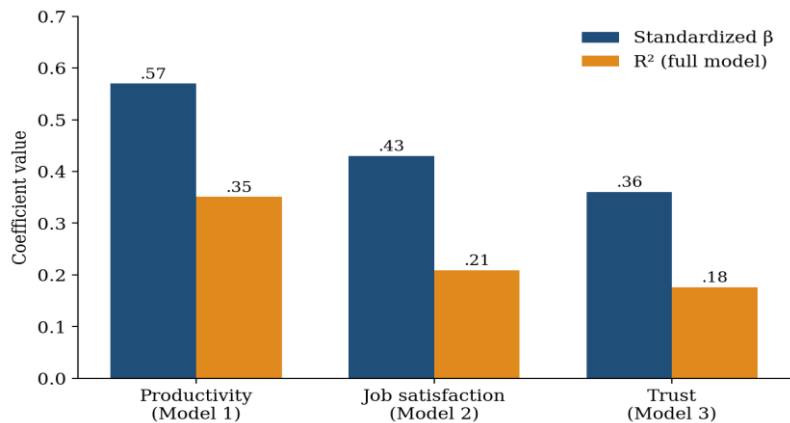


Figure 7: Variance Explained by Controls and GenAI Adoption

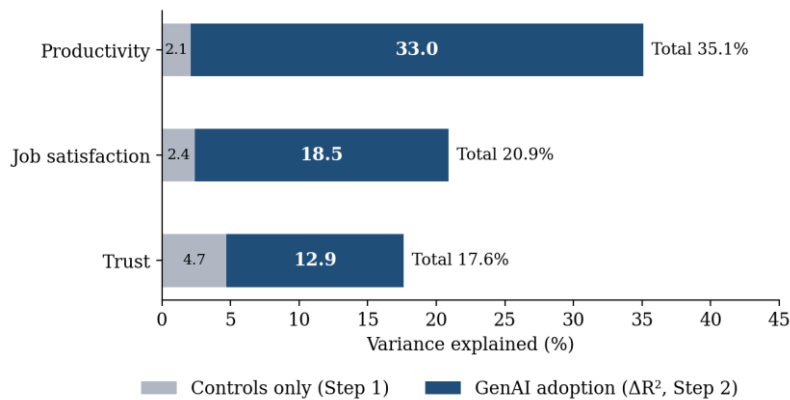


Figure 8: Relationship between GenAI Adoption and Employee Productivity

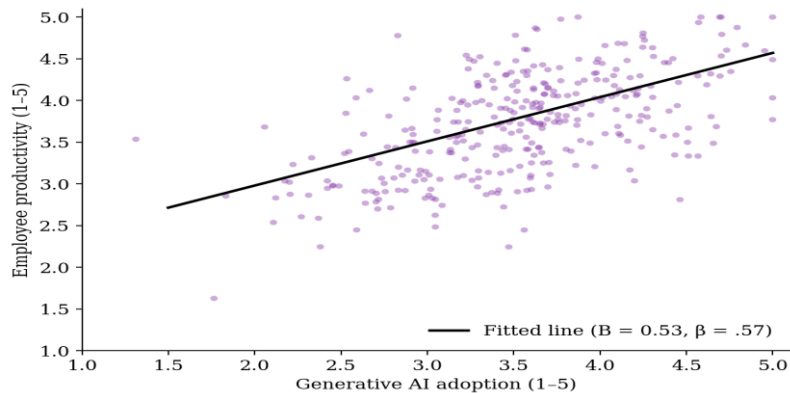
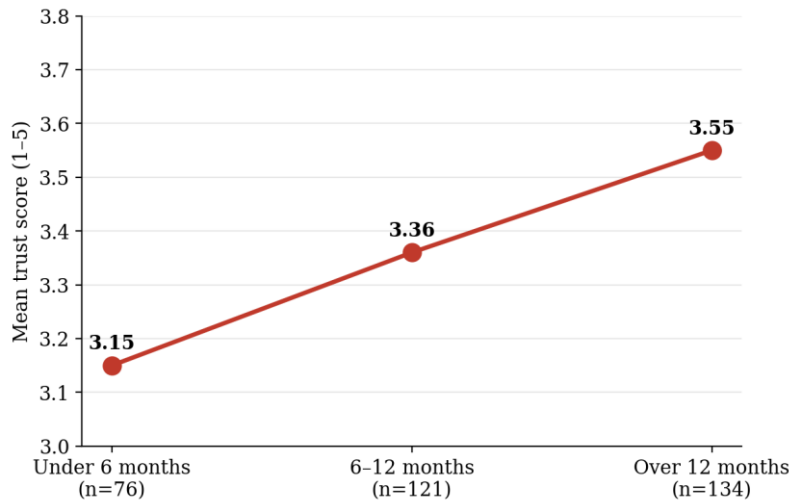


Figure 6: Mean Trust in AI-Mediated HR Decisions by GenAI Experience



Hypothesis Testing Summary

Table 4:

Hypothesis	Statement	Result
H1	GenAI adoption has a significant positive effect on employee productivity.	Supported ($\beta = .57, p < .001$)
H2	GenAI adoption has a significant positive effect on job satisfaction.	Supported ($\beta = .43, p < .001$)
H3	GenAI adoption has a significant positive effect on trust in AI-mediated HR decisions.	Supported ($\beta = .36, p < .001$)

All three hypotheses are accepted. The results of correlations and regressions are presented in a consistent order: productivity is the strongest, followed by the satisfaction results, with the results for trust being the lowest.

Discussion by Objective

Objective 1: Productivity. There is a greater impact on productivity. Respondents are confident that GenAI can boost efficiency in several repetitive, text-based HR tasks, including creating job descriptions, summarizing candidate information, and answering employee inquiries. Here, productivity is self-reported, indicating self-perceived rather than measured productivity.

Objective 2: Job satisfaction. The positive correlation indicates that an employee prefers decreasing the repetition of their work and increasing the amount of time he or she can put into

meaningful work. The strong correlation between productivity and satisfaction ($r = .52$) suggests that satisfaction could be partly a result of feeling more productive; this could be examined in future studies using mediation analysis.

Objective 3: Trust. The higher the level of trust the higher the level of adoption, but the least occurs at that level of trust. Adoption of GenAI as a work tool is more likely to be accepted by employees than part of hiring, appraisal or promotion decisions. The experience effect has implications for the gradual exposure, training and clear explanation of what can lead to increased confidence; and that human oversight of the final HR decisions may be important.

Findings & Results

Analysis was performed on 331 valid answers, representing 87.1% of the 380 questionnaires that were sent out. The respondents comprised three groups: non-managerial employees (48.0%), line managers (26.9%) and HR professionals (25.1%) with the gender split even with females making up 47.1% and males 52.0%. The majority (77.0%) had been using GenAI at work for at least six months, meaning their answers were based on their actual experience of working with GenAI.

The instrument was reliable and valid. Cronbach's alpha was from .84 to .89, composite reliability was .89 to .92 and average variance extracted was .54 to .61. The single factor test by Harman indicated that there was no serious concern of common-method biases because only 31.4% of the total variance was explained. Regression assumptions of normality, linearity, independence of errors and multicollinearity were satisfied (highest VIF = 1.24), so the regression results are statistically sound.

The perception of respondents was that GenAI is in use for HR tasks ($M = 3.62$). The productivity was rated the highest ($M = 3.84$) followed by job satisfaction ($M = 3.71$). The level of trust in AI-driven HR decisions was the lowest ($M = 3.39$) and most dynamic ($SD = 0.79$), indicating that employees are more willing to use GenAI to assist with HR decisions than to be involved in them. All scores are above the scale midpoint of 3.00, suggesting generally positive perceptions, but the 0.45-point difference between productivity and trust suggests a contrast that signals employees perceive clear benefits in practice, but are concerned about fairness.

Correlations were all positive and significant ($p < .01$). Productivity ($r = .58$), followed by job satisfaction ($r = .44$) and trust ($r = .37$), had the strongest association with the adoption of GenAI. The outcomes that were significant were also productivity–satisfaction ($r = .52$), satisfaction–trust ($r = .49$) and productivity–trust ($r = .41$), meaning that employees who feel productive are more satisfied and trustful, but these constructs are not intermingled ($HTMT \leq .67$).

The use of GenAI is significantly and positively related to productivity ($\beta = .57, p < .001$). For every percentage point higher in adoption, there is a 0.53-point increase in productivity. Adoption accounted for 33.0% of the variance beyond the control variables and accounted for 35.1% ($f^2 = .51$, a large effect) of all of the variance.

GenAI adoption significantly improves job satisfaction ($\beta = .43, p < .001$), adding 18.5% of variance ($R^2 = .209, f^2 = .23$). It is weaker on the side of satisfaction, indicating that job security, autonomy and leadership are also factors in satisfaction.

GenAI adoption positively influences trust in AI-mediated HR decisions ($\beta = .36, p < .001$), adding 12.9% of variance ($R^2 = .176, f^2 = .16$). This was the least important of the three effects. Experience increased trust ($M = 3.15, 3.36$ and 3.55 for under six months, six to twelve months and over twelve months, respectively; $p = .002$), but this was a small effect ($\eta^2 = .04$), and was only significant between the shortest and longest groups.

Conclusion

The study aimed to explore the impact of the use of generative AI in HRM on employee productivity, job satisfaction and trust in HR decisions made by AI. It was based on human-AI collaboration theory, which states that GenAI is best used to support rather than supplant human judgment. This was tested with a positivist and quantitative survey of 331 valid respondents who were selected using stratified random sampling from a population of 2,500 employees and HR professionals. Previous studies looked into these outcomes individually and largely prior to the adoption of GenAI. The gap was bridged in this study by studying all three jointly in an HRM context. Each of the three objectives and research questions was linked, and each of the conclusions that follow answers one of those questions.

The aim of the first objective was to study the effects of GenAI adoption on productivity. There was strong and positive relationship between adoption and productivity ($\beta = .57, p < .001$) and productivity was the highest rated outcome. GenAI seems to be most useful for routine HR tasks that are centered on text. It looks like it is good for most text-based routine HR tasks: drafting, summarizing and answering employee questions. Consistent with the experimental studies demonstrating speed and quality improvements, productivity in this case was self-reported, and should be interpreted as perceived productivity.

The second goal was to determine the impact on job satisfaction. Satisfaction was also highly predicted by adoption ($\beta = .43, p < .001$), but not as strongly as was productivity. By automating repetitive tasks, GenAI can help free up time for people to engage in meaningful work, which can lead to higher satisfaction levels. But satisfaction is also a function of job security, autonomy, pay and leadership, which is not guaranteed by adoption.

The third objective was to evaluate the influence on trust. The effect of adoption was the least strong and the lowest mean ($M = 3.39$) and was statistically significant ($\beta = .36, p < .001$). When GenAI is used as a tool, employees are more accepting than when it's part of hiring, appraisal and promotion decisions. Experience also led to increased trust, indicating that over time, explanation and perceived fairness fostered trust. Helps support organizational justice arguments about that people

evaluate decisions based on fairness and transparency, not just efficiency. This is the answer to Research Question 3: Adoption increases trust...but somewhat and with caveats.

Adopting GenAI in HRM is a real benefit, albeit unevenly; trust takes time to build, but benefits are rapid. Productivity should not, therefore, be used as the only metric for success. Measures that increase output but have an impact on the confidence in HR fairness can affect the employment relation in the long run. In theory the study validates the augmentation perspective as human factors, rather than just technical performance, are what matter when collaboration is successful. On a practical level, it provides HR leaders with the proof that training, transparency, and human oversight of the final decision should be used together when implementing.

Technical deployment is just the first step for any organization. A growing body of evidence indicates that trust is the key in employee acceptance of GenAI, with a higher likelihood of using it effectively when they perceive it as fair, explainable and supervised by people. The results highlight the importance of responsible AI governance practices for policy makers and HR professionals, such as conducting AI bias audits and establishing accountability for AI-driven decision making.

Recommendations

1. Start with simple and common HR activities – like drafting or answering employee questions – where the benefits are maximum and the risks are minimal, before moving onto more sensitive decisions.
2. Conduct frequent AI-literacy training and ensure that employees are confident, critical and ethical in their use of GenAI in their work across all job roles.
3. Do not use GenAI to make hiring, appraisal and promotion decisions; use it instead as a decision support system to complement managers.
4. Describe clearly the way GenAI helps HR decision making to improve perceived fairness, transparency and employee confidence in HR processes.
5. Protect job satisfaction by redesigning jobs, reskilling and making clear to everyone about job security and career paths.
6. Measure productivity, satisfaction and trust all together by conducting periodic surveys and audits of bias and errors.

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