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Generative AI Adoption and Organizational Performance: The Mediating Role of HR Digital Transformation

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Abstract

This study explored the correlation between the adoption of Generative Artificial Intelligence (GenAI) and organizational performance, with HR digital transformation proposed as a mediating variable. The quantitative cross-sectional survey design was based on positivist paradigm with an explanatory approach, and data were gathered from 175 employees and middle level managers of organizations from five industry sectors (information technology, banking, telecommunication, healthcare, higher education, consulting and manufacturing) that had implemented AI-based digital solutions. This was a purposive sampling technique, followed by analysing the data by Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 software, in line with the two stages of assessment recommended by Hair et al. (2022). All the items in the measurement model achieved the recommended values for the indicator loading, composite reliability and average variance extracted respectively, thereby establishing the reliability and validity of the model. The outcomes of the structural model showed that the use of Generative AI had a positive significant influence on HR digital transformation, which in turn significantly predicted organizational performance. Moreover, it was determined that HR digital transformation played a partial mediation between the adoption of Generative AI and organizational performance. By elucidating the pathway between GenAI capabilities and organizational outcomes, the findings contribute to technology adoption and HRM research by providing new insights into the process by which GenAI can drive tangible results in organizations. Theoretical and managerial implications are discussed, and limitations and directions for future research are discussed.

Introduction

Generative Artificial Intelligence (GenAI) is a category of AI tools that can generate text, code, images, and content relevant to decision-making processes with minimal human intervention (Dwivedi et al., 2023), transforming organizations in every industry. The unique feature of GenAI tools like large language models is their ability to complement cognitive and administrative functions that were traditionally human-only, such as creating communications, producing reports, and assisting managers in decision-making (Chatterjee et al., 2024). The rate of this diffusion is faster than many organizations can systematically investigate how these technologies relate to measurable organizational outcomes, and there is a need for empirical studies that link constructs of technology adoption to organizational outcomes (Chowdhury et al., 2023).

Given the amount of routine tasks involving language that are part of the recruitment, training, performance assessment and communication in the workplace, human resource management (HRM) is among the first and most apparent spaces where the use of GenAI has been experimented with (Malik et al., 2022). This meeting of the two has created what scholars call HR digital transformation – the systemic reconfiguration of HR processes, structures and employee experiences using digital tools (Strohmeier, 2020). Despite the widespread research on digital HR in the frameworks of enterprise resource planning (ERP) systems and HR analytics platforms (Bondarouk & Brewster, 2016), less empirical research has focused on how digital HR more specifically enables the acceleration or reshaping of this transformation process and whether the resulting digital capability adds value to organizational performance (Budhwar et al., 2023).

Despite its varied nature, organizational performance continues to be one of the most important outcome variables studied in management research, which includes operational efficiency, innovation capacity, employee productivity and service quality (Venkatraman, 1989; Delaney & Huselid, 1996). Contrary to this, an increasing volume of technology management literature suggests that the performance gains from emerging technologies are less direct, and are achieved through intermediate organizational capabilities – those that are necessary for transforming the potential of emerging technologies into operational performance (Wamba-Taguimdje et al., 2020). This is consistent with the resource-based view and the dynamic capabilities view, which argue that technology cannot provide competitive advantage without accompanying organizational routines (Mikalef & Gupta, 2021). HR digital transformation could be just such a complementary routine, serving as the pipeline for GenAI use to become actionable results.

While this is a plausible mediation pathway, there is very little empirical evidence to support the pathway, especially in developing economies where digital infrastructure, regulations, and organizational readiness are far removed from those of advanced economies (Khan & Zafar, 2023). A growing number of platforms are being developed in Pakistan's service and technology industries that utilize artificial intelligence to boost performance, and there is limited systematic evidence to connect AI-based investment with HR digitization and its impact on performance (Ahmed et al., 2021). This is exacerbated by the methodological approach of most previous research, which typically views technology adoption and organizational performance as a simple bivariate relationship without considering intervening organizational processes that mediate their relationship (Rana et al., 2022).

To fill this gap, the present study proposes and tests a mediation model that links the adoption of GenAI with the organizational performance of both direct and indirect effects through HR digital transformation. The study adopts a technological adoption theory (Venkatesh et al., 2016) and digital transformation literature (Vial, 2019) to build a theoretically sound framework for quantitative validation. The research objective was to predict, which fits well with the use of the Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2022).

Based on this, the three aims of this study are as follows: The first aim of this study was to examine the direct effect of Generative AI adoption on HR digital transformation. The second aim of this study was to examine the direct effect of Generative AI adoption and HR digital transformation on organizational performance. The third aim of this study was to test the mediation effect of HR digital transformation between Generative AI adoption and organizational performance. The study is focused on these objectives, which can be seen as contributions to the technology management and the HRM literature. It is theoretically a nominalization of digital HR capability as a mediating variable between emerging AI technologies and organizational outcomes, thus extending the nomological network between these factors (Budhwar et al., 2023). It is empirically grounded and offers quantitative data from an underrepresented organizational environment, thereby adding to the generalizability of the findings on technology adoption, particularly beyond Western and East Asian contexts (Malik et al., 2022). In practice, the findings can guide organizational leaders and HR practitioners in justifying and designing GenAI investments by making internal capabilities transparent to support investments in performance gains (Chowdhury et al., 2023).

Literature Review

The theoretical underpinning of this study of Generative AI adoption in organisations was based on two well-established technology acceptance models: Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2016), and the Technology Acceptance Model (Davis, 1989). This framework was designed for traditional information systems, but further research has developed the concept to inform support for the use of AI-powered systems, which also requires a sense of trust, transparency, and confidence in the reliability of the systems' output (Chatterjee et al., 2024). Another stream of research on GenAI adoption draws on diffusion of innovation theory which provides insights into how GenAI tools' relative advantage, compatibility, and observability will affect organizational uptake (Wamba-Taguimdje et al., 2020; Rogers, 2003). Combined, these suggest that the adoption of GenAI is a social and organizational process that is not uniform and may occur at different levels and across departments.When taken together, these frameworks imply that GenAI adoption is a process that happens in the social and organizational context and is not straightforward or evenly spread across departments and hierarchical levels (Dwivedi et al., 2023).

Alongside this, there is a parallel body of literature on the digital transformation of HRM, which has moved from the first use of electronic HR (eHR) systems for transactional efficiency to the use of predictive analytics, algorithmic support in decisions making and personalisation of employee experiences (Strohmeier, 2007). Bondarouk and Brewster (2016) state that digital

HRM should not be seen as the replacement of existing HRM processes but as an entire reconfiguration of HRM value creation and delivery in organizations. This rethinking is also reflected in more recent literature that focuses on the changes required in organizational structure, competencies and leadership attitudes to create digital HR transformation vs. technology adoption (Marler & Boudreau, 2017). This shift is now being amplified by the rise of GenAI, which has ushered in new features like automated candidate screening, AI-based performance feedback, and chat-based learning platforms that were previously unimaginable at scale that GenAI brings to the table (Budhwar et al., 2023).

According to empirical research, factors that have been found to be consistently associated with HR digital transformation success include organizational readiness, top management support, and employee digital literacy (Iqbal et al., 2019). In this literature, the adoption of technology is often the precursor factor that paves the way for more comprehensive HR digitalization, rather than an end goal (Malik et al., 2022). This is aligned with the concept of sociotechnical systems theory, which states that organizational changes must be manifested through co-evolution of technological and social subsystems to achieve success (Sarker et al., 2019). In the context of GenAI, this implies that organizations need to invest in rebuilding HR processes, training and education initiatives, and governance frameworks to fully harness the technology's potential for change (Vial, 2019).

The link between digital transformation and the performance of the organization has been extensively studied in various industry settings. The authors Mikalef and Gupta (2021) show the major role played by AI capability in firm performance as its impact on process innovation and organizational creativity, rather than a direct technological impact. Likewise, Wamba-Taguimdje et al (2020) conclude that the value created by AI-based transformation mainly occurs when there is also a change in business processes and roles. The results suggest that the digital transformation phenomenon is not a direct driver of performance but instead represents an intervening capability in the relationship between capabilities and performance (Chowdhury et al., 2023).

The ability-motivation-opportunity framework (Delaney & Huselid, 1996) has been a long-standing focus in the strategic HRM literature, and HR practices have been shown to affect organizational performance by the way they influence employee skills, motivation, and opportunities to contribute. Theorized to have a greater impact, digitally transformed HR practices are expected to improve the effects through digitally-based talent analytics, quicker feedback loops and equitable, data-driven decision-making (Marler & Boudreau, 2017). Some empirical findings from emerging markets like Pakistan provide supporting evidence, as HR digitally enabled organizations report higher HR organizational agility and employee productivity compared to their less digitally enabled counterparts (Ahmed et al., 2021; Khan & Zafar, 2023).

Despite this development, there are still some literature gaps present. Most of the existing studies focus on either the adoption of AI technologies or digitalization of HR practices but rarely combine the two constructs into a single explanatory model (Budhwar et al., 2023). Second, the research that does look at mediation mechanisms in the technology-performance relationship has largely focused on samples from the advanced economies, which cannot be readily transferred to the context of organizational conditions in developing economies where the conditions of infrastructure and institutions may differ from those in the advanced economies (Rana et al., 2022). Third, while some applications of AI in the past have involved robotic process automation or predictive analytics, Generative AI has a distinctly different purpose from both of these: creating content and engaging in natural language interactions (Chatterjee et al., 2024).

Based on these syntheses, the current study theorizes that Generative AI uptake is a pre-condition which makes and enhances HR digital transformation, in line with the sociotechnical and diffusion theories (Vial, 2019; Rogers, 2003, as cited in Wamba-Taguimdje et al., 2020). In addition, based on the capability mediated approach to technology-performance relations (Mikalef & Gupta, 2021), the study proposes that HR digital transformation was the more proximal antecedent of organizational performance, as was the case with prior technology adoption studies (Wamba-Taguimdje et al., 2020), and that GenAI adoption continued to have a direct impact on organizational performance, albeit a residual one. Based on this, the following hypotheses are proposed: H1 – Generative AI adoption has a significant positive effect on HR digital transformation; H2 – Generative AI adoption has a significant positive effect on organizational performance; H3 – HR digital transformation has a significant positive effect on organizational performance; H4 – HR digital transformation significantly mediates the relationship between Generative AI adoption and organizational performance.

Methodology

This section explains the research design, research philosophy, research strategy, population, sample, instrument for data collection, measurement of variables, data collection, and data analysis technique which were used in this research.

Research Design

This study used quantitative research and explanatory cross-sectional research design. The quantitative approach was chosen to facilitate the statistical analysis of the relationships between the variables studied, namely the use of Generative AI, HR digital transformation and organizational performance. A cross sectional design was used because all data were gathered at one time only, thus enabling the proposed mediation model to be assessed efficiently. The explanatory design was suitable in the context of the study aimed at finding the direct and indirect effect among the study variables.

Research Philosophy

The positivist research philosophy was used in the study. The positivism approach is a perspective that states that organizational phenomena can be measured objectively from observation and measured using statistical testing methods. This approach dovetailed with the aim of the study, which involved testing of the theoretical hypotheses.

Research Strategy

The survey research approach was used because it allowed for standardized data to be obtained from a large number of organizational employees within a relatively brief time. Many studies on technology adoption and organizational performance have been conducted using the survey method approach with latent constructs.

Target Population

The target population comprised employees and middle level managers in organizations that implemented Generative Artificial Intelligence technologies into their day-to-day tasks. Eligible organizations were companies in the information technology sector, banks, telecommunication companies, healthcare companies, universities, consulting companies and manufacturing companies using AI-powered digital solutions. Participants had to have at least 6 months of experience in an organization and experience with AI-assisted work processes.

Sampling Technique

The sampling technique used was a purposive sampling technique where only respondents who had experience of application of Generative AI and digitally transformed HR practices could provide reliable information concerning the constructs being investigated. The technique of non-probability sampling has been widely adopted in organizational technology adoption studies (Malik et al., 2022).

Sample Size

175 respondents made up the final sample. The sample size was deemed adequate since PLS-SEM is able to work well with medium sample sizes and meets the minimum sample size requirements proposed by Hair et al. (2022). In addition, the number of cases in the sample was greater than the recommended number of cases for mediation analysis, the ten-times rule.

Data Collection Instrument

A structured, self administered questionnaire was used to gather primary data. The questionnaires were divided in two sections. The first segment focused on the demographic details of the respondents, such as gender, age, education, organizational experience, industry type, and previous experience with AI. The second section used previously validated measurement scales to measure the study constructs. The items were all evaluated on a five-point Likert scale (Strongly Disagree to Strongly Agree).

Measurement of Variables

The independent variable Generative AI Adoption was measured as the degree of employees' and organizations' usage and application of Generative Artificial Intelligence tools in different work activities, such as decision making, content creation, communication, automation, and knowledge management activities. The construct was assessed with eight items adapted from literature related to recent use of AI (Dwivedi et al., 2023; Venkatesh et al., 2016; Chatterjee et al., 2024) which include aspects of AI integration, AI utilization, AI-assisted decision-making, and AI-enabled task automation.

The mediating variable was HR Digital Transformation, which was measured by the human resource management processes' digitalization using advanced technologies that facilitated better management of the workforce and organizational capability. The construct was assessed using nine items adapted from digital HR transformation literature (Bondarouk & Brewster, 2016; Strohmeier, 2020) that spanned the dimensions of digital recruitment, digital learning and development, digital performance management, HR analytics and employee self-service systems.

Organizational Performance, the dependent variable, was measured as the overall effectiveness of organizational operations and outcomes due to the technology-enabled improvements. The construct was assessed by nine items borrowed from Delaney and Huselid (1996) and Venkatraman (1989) that reflected operational, innovation, employee productivity, organizational agility, and service quality aspects.

Data Collection Procedure

Participating organizations were contacted and permission granted before data collection. The survey was conducted online via Google Forms and organizational communication channels from February to April 2025. There was no compulsion to participate and participants were assured that the information they provided would remain anonymous and confidential. Only complete questionnaires were included in the statistical analysis and 175 questionnaires were returned and usable.

Data Analysis Technique

The data collected were analyzed by applying the two-stage approach suggested by Hair et al. (2022) in SmartPLS 4. The first stage comprised the reliability and validity assessments of the measurement model based on indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, variance inflation factor, Fornell-Larcker criterion, and heterotrait-monotrait ratio of correlations. In the second stage, the results of the structural model were evaluated through path coefficients, coefficient of determination, effect size, predictive relevance, standardized root mean square residual (SRMR) and bootstrapping (5,000 iterations) to test direct, indirect and total effects.

Results and Analysis

This section provides the results of the data analysis in two phases, as outlined in Data Analysis Technique Section. The demographic characteristics of respondents are reported in The demographic profile of respondents section. Measurement model assessment results, such as reliability, convergent validity, and discriminant validity, are reported in Measurement Model Assessment Section. The structural model assessment and hypothesis testing of the direct and indirect effects are reported in Structural Model Assessment Section.

The demographic profile of respondents

Demographic factors for the 175 respondents are summarized in Table 1. The sample was reasonably balanced across gender and included a range of organizational tenure, educational qualifications, and industry sectors that matched the study's purposive sampling to include those who are directly involved in work processes that involve Generative AI.

Table 1. Demographic Profile of Respondents (N = 175)

Variable	Category	Frequency	Percentage (%)
Gender	Male	101	57.7
	Female	74	42.3
Age (years)	20-29	48	27.4
	30-39	72	41.1
	40-49	39	22.3
	50 and above	16	9.1
Education	Bachelor's	63	36.0
	Master's	89	50.9
	PhD / Other	23	13.1
Organizational Experience	6 months-2 years	41	23.4
	3-5 years	68	38.9
	Above 5 years	66	37.7
Industry Sector	IT / Software	46	26.3
	Banking / Finance	38	21.7
	Telecommunication	24	13.7
	Healthcare	21	12.0
	Higher Education	27	15.4
	Manufacturing / Other	19	10.9

Measurement Model Assessment

The reliability and convergent validity were assessed and the results are shown in Table 2. The internal consistency reliability of all constructs were above 0.70, as were the Cronbach's alpha's and indicator loadings, suggesting satisfactory internal consistency reliability. The values of average variance extracted (AVE) for all constructs were higher than the recommended 0.50, indicating good convergent validity (Hair et al., 2022).

Table 2. Measurement Model: Reliability and Convergent Validity

Construct	Items	Loading Range	Cronbach's α	CR	AVE
Generative AI Adoption (GAI)	8	0.741-0.892	0.912	0.928	0.618
HR Digital Transformation (HRDT)	9	0.723-0.876	0.921	0.934	0.593
Organizational Performance (OP)	9	0.735-0.881	0.918	0.931	0.601

The discriminant validity was examined by using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) of correlation. The AVE for each construct was greater than its correlations with other constructs as presented in Table 3, meeting the Fornell-Larcker criterion. As expected of the conservative threshold of 0.85, all the HTMT values were found below that limit, which is another indicator of discriminant validity (see Table 4). The variance inflation factor (VIF) values from Table 5 were used to test for collinearity in the structural model and they were below 3.3 for all the indicators, so that there were no concerns over collinearity.

Table 3. Discriminant Validity: Fornell-Larcker Criterion

Construct	GAI	HRDT	OP
Generative AI Adoption (GAI)	0.786		
HR Digital Transformation (HRDT)	0.612	0.770	
Organizational Performance (OP)	0.541	0.598	0.775

Table 4. Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)

Construct Pair	HTMT Value
GAI ↔ HRDT	0.658
GAI ↔ OP	0.591
HRDT ↔ OP	0.634

Table 5. Collinearity Statistics (VIF)

Predictor Construct	Outcome Construct	VIF
Generative AI Adoption	HR Digital Transformation	1.000
Generative AI Adoption	Organizational Performance	1.596
HR Digital Transformation	Organizational Performance	1.596

Structural Model Assessment

Path coefficients, t-values, p-values and 95% bias-corrected confidence intervals were used to assess the structural model with bootstrapping of 5,000 resampling. Support for H1 was found as Generative AI adoption had a strong positive effect on HR digital transformation ($\beta = 0.612$, $t = 11.847$; $p < .001$) as demonstrated in Table 6. HR digital transformation also had a great positive influence on organizational performance ($\beta = 0.487$, $t = 8.213$, $p < .001$), which led to the support of H3. The direct impact on organizational performance was also considerable, but smaller ($\beta = 0.219$, $t = 3.542$, $p < .001$), and lent support to H2.

Table 6. Structural Path Results (Direct Effects)

Hypothesis	Path	β	t-value	p-value	95% CI	Decision
H1	GAI → HRDT	0.612	11.847	< .001	[0.512, 0.706]	Supported
H2	GAI → OP	0.219	3.542	< .001	[0.098, 0.339]	Supported
H3	HRDT → OP	0.487	8.213	< .001	[0.372, 0.598]	Supported

The coefficient of determination (R^2), effect size (f^2) and predictive relevance (Q^2) are reported for the endogenous constructs in Table 7. A moderate amount of variance in organizational performance (37.5%) and a moderate amount of variance in HR digital transformation (41.2%) were explained by HR digital transformation, respectively. The Q2 values of both the endogenous constructs were greater than zero, indicating the model's good predictive relevance. The standardized root mean square residual (SRMR) was 0.061 which is lower than the recommended value of 0.08 and was determined to be a good fit of the model.

Table 7. Explanatory and Predictive Power (R^2, f^2, Q^2, SRMR)

Construct	R^2	Q^2	f^2 (on OP)
HR Digital Transformation	0.412	0.284	-
Organizational Performance	0.375	0.251	GAI: 0.061; HRDT: 0.267

Model fit: SRMR = 0.061 (below the 0.08 threshold).

The result of the mediation analysis is shown in Table 8. The indirect effect of Generative AI adoption on organizational performance via HR digital transformation was significant (β = 0.298, t = 6.104, p < .001, 95% CI [0.204, 0.392]) and did not overlap with zero, suggesting mediation. The results showed partial mediation for the direct effect, as the use of Generative AI was significant, and indirect effect of the use of Generative AI on organizational performance was significant, which confirms H4. The results collectively suggest that the HR digital transformation is a significant, but not exclusive, pathway for generative AI to drive better organizational performance.

Table 8. Mediation Analysis: Indirect and Total Effects

Hypothesis	Path	Indirect β	t-value	p-value	95% CI	Total Effect	Result
H4	GAI → HRDT → OP	0.298	6.104	< .001	[0.204, 0.392]	0.517	Partial Mediation

Discussion

This study's findings support a mediation model with the adoption of Generative AI affecting organizational performance directly and indirectly via HR digital transformation. This significant positive relationship between the adoption of generative AI tools and HR digital transformation (H1) aligns with the sociotechnical and diffusion literature, arguing that the introduction of generative tools catalyses the reconfigured nature of HR practices, structures and employee experiences (Vial, 2019; Strohmeier, 2020). It builds on existing digital HR research by empirically proving that GenAI is a significant, not just any-one of many, inputs for digital HR transformation.

The relatively greater effect of HR digital transformation on organizational performance (H3) than of the direct effect of the adoption of Generative AI on performance (H2) confirms the technology-performance capability-mediated perspective proposed by Mikalef and Gupta (2021) and Wamba-Taguimdje et al. (2020). The results indicate that the performance advantages of GenAI are achieved significantly, but not exclusively, via the organizational ability of digitalized HR practice and not directly from GenAI itself. This is further supported by the confirmation of partial mediation (H4) showing that HR transformation through the H strategy of HR technology and analytics, and HR systems for employees is more important than GenAI investment when it comes to maximizing the performance returns.

The results are also relevant for organizations in developing economy environments like Pakistan where there is a significant difference in the digital infrastructure and readiness of the organization by industries (Khan & Zafar, 2023; Ahmed et al., 2021). To realize the potential benefits of using GenAI in their work, managers need to build digital HR capability, such as digital recruitment systems, HR analytics, and employee self-service portals, alongside implementing GenAI to ensure technological capability translates to operational improvements. Theoretically, the study is a valuable contribution to the technology adoption and strategic HRM fields since it brings together the concept of GenAI adoption, HR digital transformation, and organizational performance within a single empirically supported nomological network, which was identified as a gap in the literature by previous studies (Rana et al., 2022; Chowdhury et al., 2023).

Conclusion, Limitations, and Future Research

The authors hypothesised that organizational performance is mediated by HR digital transformation and tested this hypothesis for the relationship between Generative AI adoption and organizational performance. Results from the survey of 175 employees and middle-level managers and the use of the PLS-SEM analysis in the software package SmartPLS 4 indicated that the adoption of Generative AI had a significant impact on HR digital transformation, HR digital transformation had a significant impact on organizational performance, and HR digital transformation partially mediated the relationship between the adoption of Generative AI and organizational performance. Together, these results provide a strong case for a capability-based understanding of the consequences of emerging AI technologies for organizational outcomes.

The study has some limitations that indicate the directions for further research. First, because of the cross-sectional design, the causal inferences are limited, future investigations might use longitudinal designs to better understand the relationships discussed when they become more common and prevalent in organizations. Second, the purposive sampling method, which was suitable for sampling people who had direct exposure to GenAI, could mean that the results are not generalizable to less digitally mature organizations. Third, measures of organizational performance were self-reported, which future studies might be able to incorporate objective measures if available. Future research may investigate other boundary conditions that may serve as moderators of the relationships explored in this study including organizational culture, leadership style, or industry type.

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