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EXPLORING THE IMPACT OF DEMOGRAPHIC FACTORS ON THE ADAPTATION OF TECHNOLOGY IN HUMAN RESOURCE MANAGEMENT

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A B S T R A C T

In the rapidly evolving landscape of Human Resource Management (HRM), the adaptation of technology has become a critical factor in enhancing operational efficiency, fostering innovation, and improving employee experience. This study examines the influence of demographic factors—specifically gender and education level—on the adoption of HR technology within organizations. Through a survey of 200 respondents, the findings indicate a significant correlation between these demographic factors and technology adaptation, while age does not exhibit a notable impact. The analysis utilized Chi-square tests and factor analysis, revealing that High Involvement HRM practices and digital tools play pivotal roles in transforming HRM from a traditional administrative function to a strategic partner in organizational success. The research highlights the importance of context-specific strategies for technology implementation, particularly in diverse sectors and varying organizational sizes. Additionally, it identifies gaps in the existing literature regarding the application of digital HR technology in developing economies and emphasizes the need for longitudinal studies to assess long-term impacts on employee well-being and organizational culture. This paper contributes to the understanding of how technology integration in HRM can enhance organizational performance and sustainability in a dynamic business environment.

This study examines the key drivers and impacts of technological adoption in HRM to improve business outcomes. Using survey data from 200 respondents, a set of targeted questions was developed to facilitate data interpretation and analysis. The collected data were analyzed using SPSS software to derive actionable insights. The literature review was conducted using ProQuest and Emerald Insight, which provide extensive resources across management, business, and social sciences, offering tools for tracking citations and accessing relevant publications.

1. INTRODUCTION

In the evolving field of Human Resources (HR), the adaptation of technology refers to the adjustment of HR processes, strategies, and systems to effectively integrate and leverage new technological tools. This adaptation is essential for increasing operational efficiency, supporting data-driven decision-making, and enhancing employee experience (Bondarouk & Brewster, 2016; Strohmeier, 2020).

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1.1 Key Aspects of Technology Adaptation in HR:

Software Integration: Implementing systems such as Human Resource Information Systems (HRIS), Applicant Tracking Systems (ATS), and Learning Management Systems (LMS) allows for the automation of repetitive HR tasks like payroll processing and application tracking. According to Strohmeier and Parry (2014) such systems help to streamline HR processes and free up HR professionals for more strategic responsibilities. Process Improvement: Technology-driven tools, including artificial intelligence (AI) and analytics, are transforming core HR processes, enabling improvements in recruitment, onboarding, performance management, and employee engagement. For instance, data-driven recruitment processes allow companies to analyze a larger pool of candidates quickly, thereby reducing hiring time and improving fit (Chughtai & Buckley, 2013). Data-Driven Decision-Making: People analytics, a key feature of modern HR technology, supports strategic HR decisions. By analyzing real-time data, HR departments can optimize workforce planning, identify skill gaps, and implement targeted training programs. Davenport et al. (2010) highlight that data-driven HR departments can make better-informed decisions that support overall organizational objectives. Enhancing Employee Experience: Self-service portals, mobile applications, and engagement platforms empower employees and improve their experience within the company. Studies show that technology-enabled self-service tools enhance employee satisfaction by fostering transparency and providing easy access to information (Marler & Boudreau, 2017). Change Management: Adapting to new technologies requires effective change management strategies, including training, communication, and continuous support for HR staff and employees. Kotter (1996) change management model is often applied in HR to ensure a smooth technology transition and reduce resistance, highlighting the importance of involving employees early in the adoption process.

The adaptation of technology in HR delivers numerous benefits, such as improved recruitment and onboarding processes, streamlined employee data management, increased efficiency, and enhanced productivity (Marler & Fisher, 2013). Data analytics fosters better decision-making by enabling HR professionals to use insights from real-time data, aligning with organizational goals (Davenport et al., 2010). Additionally, technology in HR improves employee engagement and experience, as shown by the adoption of digital tools that allow for a more transparent and accessible work environment (Chughtai & Buckley, 2013). Compliance, scalability, and cost savings are also notable advantages that contribute to the long-term sustainability and growth of organizations (Bondarouk et al., 2016).

2. LITERATURE REVIEW

Rubel et al. (2023) underscore the role of High Involvement HRM (HIHRM) practices—such as employee participation, empowerment, information sharing, and recognition—in fostering innovation within organizations. These practices build a culture of engagement, enhancing both radical and incremental innovation. Additionally, employee creativity and technical adaptability serve as moderating factors between HIHRM and innovation performance, making HRM strategies vital for driving technological advancements and maintaining competitive advantage.

Jani et al. (2023) explore the evolution of digital HR technology, noting a shift from basic administrative functions to advanced systems incorporating AI, ML, SaaS, and AR/VR. Effective digital HR transformation enhances business outcomes by positioning HR as a strategic partner and change agent, although challenges in integration and capability persist. Do et al. (2016) discuss the importance of HR flexibility—adaptable skills, behaviors, and practices—in helping organizations respond to changing environments. High-tech firms, in particular, benefit from flexible HR policies that encourage risk-taking and experimentation, promoting process and product innovation.

Shirish and Batuekueno (2021) examine user resistance to IT adoption in HR, focusing on factors like perceived value, self-efficacy, and switching costs. Their study shows that these elements significantly impact user behavior during technology transitions, especially in HR and IT departments. Afaishat et al. (2024) highlight how digital strategy adoption bolsters competitive advantage through enhanced service quality, operational efficiency, and cost management. Employee satisfaction moderates this relationship, as satisfied employees are more likely to embrace digital tools, contributing to organizational success—findings confirmed in the Jordanian banking sector.

Yadav et al. (2024) examine how digitalization in HR, particularly within the Indian IT sector, aligns digital tools with structured HR policies. These policies mediate the effectiveness of digital tools, improving talent planning and management outcomes. Mishrif and Khan (2023) emphasize the critical role of technology adoption for SMEs' resilience and competitive advantage, particularly during crises. Industry 4.0 technologies, such as AI and IoT, are essential for SME survival and growth, though limited resources and sector-specific challenges affect implementation success.

Islam et al. (2024) note that AI in recruitment remains underexplored in developing contexts, where factors like performance expectancy and enabling conditions affect adoption. Challenges include technological infrastructure gaps and varying attitudes towards AI. Jeganathan et al. (2022) explore blockchain's potential to revolutionize HR processes by enhancing transparency and reducing fraud, although regulatory and integration challenges remain.

Owusu-Ansah and Nyarko (2015) argue that IT adoption in recruitment is transformative, yielding cost savings, process efficiency, and enhanced communication. A hybrid approach combining e-recruitment and traditional methods allows HR to transition from administrative to strategic roles. Duan et al. (2024) highlight that technological affordances, such as AI and collaboration platforms, improve communication, collaboration, and decision-making in digital work environments. However, their findings may be context-specific and not universally applicable.

Hamid (2022) finds that employee technology readiness enhances adaptive performance and productivity. Job meaningfulness strengthens this effect, while proactive personalities further improve adaptability.

Al-Faouri et al. (2024) examine how technological advancements and Smart HRM (SHRM) practices drive organizational innovation. SHRM integrates technology into HR practices, boosting talent management and aligning with strategic goals. Kumi et al. (2024) demonstrate that technology readiness significantly impacts career adaptability and job performance. Career adaptability mediates the relationship between technology readiness and adaptive behaviors.

Badghish and Soomro (2024) use the Technology-Organization-Environment (TOE) framework to show how AI adoption in SMEs enhances operational and economic performance, though impacts vary by firm size and sector. Agarwal (2023) emphasizes that organizational readiness, perceived benefits, and technical expertise are pivotal for effective AI adoption in HRM. Models like Task–Organization–Environment and Task–Technology Fit elucidate AI’s alignment with HR tasks, enhancing efficiency and employee experiences.

Tanantong and Wongras (2024) use a modified UTAUT model to investigate AI adoption in Thai recruitment processes, identifying perceived value, effort expectancy, autonomy, and social influence as key adoption drivers.

Jierasup and Leelasantitham (2024) find that HR chatbot adoption depends on ease of use, peer feedback, and perceived risk. Successful implementation requires organizational development, policy support, and technology integration. Wenting et al. (2024) underscore AI’s transformative role in HRM, especially in data-driven decision-making across workforce planning, engagement, and talent acquisition. Regulatory and legal factors must be considered for effective implementation.

Espina-Romero et al. (2024) show that digital transformation fosters collaborative, data-driven cultures, enhancing operational performance and supporting sustainable practices through improved transparency and communication.

The integration of technology within Human Resource Management (HRM) has emerged as a pivotal factor in fostering innovation, efficiency, and competitive advantage across various sectors. High Involvement HRM practices, digital tools, and advanced technologies such as AI, blockchain, and collaboration platforms are transforming HR's role from administrative support to a strategic partner within organizations. Research shows that digital transformation in HRM not only streamlines recruitment, performance management, and talent planning but also enhances employee engagement, decision-making, and adaptability. Moreover, the adoption of technology in HRM is influenced by several moderating factors, including employee readiness, organizational support, perceived value, and technological infrastructure. High-tech firms, SMEs, and organizations in developing contexts each face unique challenges and enablers in technology adoption, highlighting the need for context-specific strategies to optimize HRM practices. Studies underscore the role of flexible HR policies and an adaptability-oriented culture in supporting both product and process innovation, which is crucial for organizations aiming to stay competitive in rapidly evolving markets. Overall, as HR departments increasingly leverage digital HR technologies, strategic HRM practices, and data-driven tools, they are better positioned to enhance organizational performance, foster sustainable growth, and respond to dynamic business environments. Future research could further investigate sector-specific applications, the long-term effects of emerging technologies, and the ways in which HRM can drive innovation through strategic digitalization.

Despite the substantial advancements in digital HRM practices and the integration of technology in organizational settings, several research gaps remain that warrant further exploration. Firstly, much of the current literature focuses on digital HR technology in developed economies, leaving a significant gap in understanding its application and challenges within developing countries. Emerging economies face unique infrastructure limitations, cultural differences, and varying attitudes toward technology, all of which can affect the successful implementation of digital HRM tools. Secondly, while studies have examined the impacts of specific technologies like AI, blockchain, and HR analytics, there is limited research on how these technologies collectively shape strategic decision-making and contribute to holistic HR transformation. The interplay between these tools and traditional HR practices, as well as the potential risks and limitations, are underexplored areas that could provide insights into creating a balanced digital-physical HR ecosystem.

Another gap exists in understanding the role of employee adaptability and technology readiness in different organizational contexts, such as SMEs versus large corporations. Most research has focused on the broader impact of technology on organizational outcomes, overlooking how individual differences in technology acceptance influence overall HR performance and innovation. Finally, while digital tools are recognized for enhancing efficiency and data-driven decision-making, there is a need for more longitudinal studies to assess the long-term effects of these technologies on employee well-being, job satisfaction, and organizational culture. The lack of empirical evidence on these dimensions limits our understanding of the sustainable impact of digital transformation in HRM. Addressing these gaps could significantly enrich HRM strategies and inform more inclusive, adaptable, and context-sensitive approaches to digital transformation in HR.

3. METHODOLOGY

This study employed a quantitative research design utilizing a structured online questionnaire to assess the relationship between demographic factors (gender, age, and education level) and the adaptation of HR technology among 200 respondents selected through convenience sampling. Descriptive statistics summarized the demographic characteristics, revealing a predominance of female participants and a significant representation of younger individuals. Chi-square tests of independence were conducted to evaluate the influence of demographic factors on technology adaptation, with results indicating significant relationships for gender and education level ($p < 0.05$), while age showed no significant effect. Additionally, Kaiser-Meyer-Olkin (KMO) measures and Bartlett's test of sphericity were performed to confirm sampling adequacy for further analysis. Principal Component Analysis (PCA) was utilized to identify underlying factors influencing HR technology adaptation, with Varimax rotation facilitating interpretation of the results. Ethical considerations, including informed consent and confidentiality, were upheld throughout the study, although limitations such as response bias were acknowledged.

3.1 Descriptive statistics

The collected data were grouped based on the demographical characteristics of the individuals like, Age of the respondents, gender of the respondents and education level of the respondents. The table 1 shows the respondents summary.

Table1. Demographic distribution of respondents

Demographic characteristics		No of Respondents	Percentage
Gender	Male	59	29.5%
	Female	141	70.5%
Age	18-25	108	54%
	26-30	84	42%
	31-35	6	3%
	36-40	1	0.5%
	41+	1	0.5%
Education Level	Doctorate	10	5%
	Post Graduate	149	74.5%
	Under Graduate	6	3%
	Graduate	35	17.5%

There are significantly more female respondents (141) than male respondents (59), indicating a predominance of females in this sample. Females constitute 70.5% of the total respondents, while males make up only 29.5%. This suggests that the survey or study may have a bias towards female perspectives.

The majority of respondents fall within the 18-25 age range, comprising 54% of the total sample (108 respondents). This indicates that the survey has a strong representation of younger individuals. The next largest group is the 26-30 age range, which accounts for 42% (84 respondents). Together, these two age groups represent a significant 96% of the respondents, highlighting a focus on younger adults.

The majority of respondents hold a postgraduate degree, accounting for 74.5% (149 respondents). This suggests that the survey primarily includes individuals with advanced education, which could influence their perspectives and responses. The second-largest group is those with a graduate degree, making up 17.5% (35 respondents).

3.2 Validation of the scale

Through the structured questionnaires data were collected, these questionaries' were validated through the Exploratory factor analysis and once again it is confirmed by conducting Confirmatory factor analysis.

3.3 Sample adequacy test

KMO and Bartlett's test is conducted to check the data is sufficient to conduct the EFA and CFA.The test statistics is shown in the table 2.

Table 2. KMO and Bartlett's Test statistics

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.906
Bartlett's Test of Sphericity	Approx. Chi-Square	1999.038
	df	171
	Sig.	.000

The KMO Measure of Sampling Adequacy is 0.906, indicating excellent suitability for factor analysis. Bartlett's Test of Sphericity shows a Chi-Square value of 1999.038 with a significance level of 0.000, suggesting that the variables are sufficiently correlated. A KMO value above 0.9 and a significant Bartlett's Test both support conducting factor analysis. Together, these results confirm that the data is appropriate for uncovering underlying factors.

3.4 Exploratory Factor analysis:

To reduce the number of items and the dimensions EFA were conducted, the table 3 shows the total variance explained during the EFA analysis.

Table 3. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.536	39.664	39.664	7.536	39.664	39.664	5.514	29.021	29.021
2	1.761	9.269	48.933	1.761	9.269	48.933	2.276	11.980	41.001
3	1.164	6.126	55.060	1.164	6.126	55.060	1.783	9.384	50.385
4	1.123	5.910	60.970	1.123	5.910	60.970	1.648	8.672	59.057
5	1.002	5.272	66.242	1.002	5.272	66.242	1.365	7.184	66.242
6	.896	4.718	70.960						
7	.796	4.191	75.151						
8	.703	3.699	78.850						
9	.613	3.224	82.074						
10	.584	3.071	85.145						
11	.557	2.932	88.077						
12	.490	2.577	90.654						
13	.419	2.207	92.862						
14	.410	2.155	95.017						
15	.315	1.657	96.674						
16	.182	.956	97.630						
17	.172	.905	98.535						
18	.167	.878	99.413						
19	.112	.587	100.000						
Extraction Method: Principal Component Analysis.									

The Total Variance Explained table from the PCA shows that the first component accounts for 39.664% of the variance, and the first five components together explain 66.242%. This indicates that a significant amount of the data's variability can be captured by just a few components. After rotation, the first two components still provide meaningful insights. Overall, the results suggest a strong underlying factor structure, allowing for a more simplified analysis by focusing on these key components.

Table 4. Rotated Component Matrix

	Component				
	1	2	3	4	5
Q12	.884				
Q1	.858				
Q16	.829				
Q11	.829				
Q4	.824				
Q13	.814				
Q10	.786				
Q14		.702			

Q17		.670			
Q20		.670			
Q9			.619		
Q6			.600		
Q8			.599		
Q7			.573		
Q25				.823	
Q24				.551	
Q23				.539	
Q5					.792
Q19					.597
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 7 iterations.					

The Rotated Component Matrix indicates strong loadings for items Q12 (0.884), Q1 (0.858), and Q16 (0.829) on Component 1, suggesting a strong association with a specific underlying construct (Table 4). Components 2 and 5 also display distinct groupings, with items like Q14 and Q25 indicating different aspects of the data. Moderate loadings for Q9, Q6, and Q8 on Component 3 highlight the complexity of relationships among the variables. Overall, the stable factor structure, confirmed by convergence in 7 iterations, reveals multiple underlying constructs within the dataset, which can be further analysed for deeper insights (Table 4).

The extracted five factors were named based on the relevance of the measurable items, it is shown in the table 5, they are:

1. Perceptions of HR Technology Adaptation and Effectiveness
2. Impact of Educational and Geographic Factors on HR Technology Adaptation.
3. Assessment of HR Technology Implementation and Support.
4. Assessment of HR Technology Implementation and Support.

3.5 Impact of HR Technology on Cost Efficiency and Employee Experience

The measurable impacts are depicted on table 5.

Table 5. Measurable items

Questions	Questions	Components
Q12	Do you believe your age affects your ability to adapt to HR technology?	Perceptions of HR Technology Adaptation and Effectiveness
Q1	Does your organization adapt HR technology to align with long-term strategic goals?	
Q16	In your view, does access to training on HR technology differ by age group in your organization?	
Q11	Do you agree that HR technology improved the accuracy and reliability of employee data in an effective manner?	
Q4	Do you find it easier to access HR services like payroll and leave management through technology?	
Q13	In your opinion, does gender influence the use of HR technology in your organization?	
Q10	Do you agree that the HR tools like HRIS,ATS,LMS, and performance management tools improves the effectiveness of your organization?	
Q14	How well do you feel that your educational background impacted your ability to adapt HR technology?	"Impact of Educational and Geographic Factors on HR Technology Adaptation."
Q17	Do u feel that Employees in urban locations are more comfortable using HR technology than those of rural areas?	
Q20	How has HR technology influenced your ability to manage your career development like training and performance tracking?	
Q9	How good is the current training and support provided for learning new technology in your organization?	"Assessment of HR Technology Implementation and Support."
Q6	How manageable is the time spent on routine HR tasks like payroll and attendance tracking after technology adaptation?	
Q8	How manageable is the risk of errors in compliance and reporting since the adoption of HR technology?	
Q7	How would you rate the effectiveness of HR technology in your organization?	
Q25	How likely are you to recommend the HR technology used in your organization to new employees?	Assessment of HR Technology Implementation and Support.
Q24	To what extent does HR technology provide you with transparency about your benefits, compensation and rewards?	

Questions	Questions	Components
Q23	How do you rate the HR technology implementation has improved employee engagement and satisfaction?	
Q5	How frequently do cost savings drive your decision to implement HR technology?	"Impact of HR Technology on Cost Efficiency and Employee Experience.
Q19	How would you rate the overall impact of HR technology on your employee experience?	

3.6 Confirmatory factor analysis

To verify the extracted five dimensions and the 19 items confirmatory factor analysis was done using SPSS Amos software, the figure 1 show the confirmed measurement model.

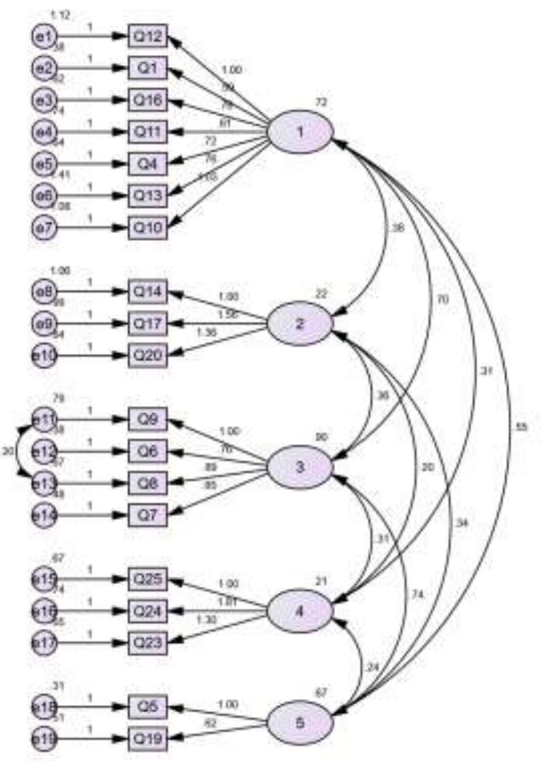

Figure 1. Measurement model

Table 6. Model Fit Summary

CMIN					
Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	49	257.709	141	.000	1.828
Saturated model	190	.000	0		
Independence model	19	1019.500	171	.000	5.962

RMR, GFI				
Model	RMR	GFI	AGFI	PGFI
Default model	.089	.808	.742	.600
Saturated model	.000	1.000		
Independence model	.421	.300	.222	.270

Baseline Comparisons					
Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.747	.693	.867	.833	.862
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

RMSEA				
Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.084	.067	.100	.001
Independence model	.205	.193	.217	.000

The Chi-square statistic is reported as CMIN = 257.709 with degrees of freedom (DF) = 141 and a p-value of P = .000. A significant p-value indicates that the model significantly deviates from the observed data, suggesting a poor fit (Byrne, 2016). However, the CMIN/DF ratio of 1.828 is less than the commonly accepted threshold of 3.0, indicating a relatively acceptable fit (Kline, 2015). This model has a CMIN (Table 6) of 0, which indicates it perfectly reproduces the data, a condition generally expected in saturated models (Schumacker & Lomax, 2010).

This model's CMIN = 1019.500 suggests a very poor fit, with a CMIN/DF of 5.962, indicating that it significantly deviates from the data (Kline, 2015).

The RMR value of .089 is above the ideal threshold of .05, indicating that there is room for improvement in the model fit. The GFI value of .808 suggests a moderate fit; values above .90 are generally considered indicative of a good fit (Hu & Bentler, 1999). This model shows very poor fit, with an RMR of .421 and a GFI of .300, both indicating significant discrepancies from the observed data (Kline, 2015). The Normed Fit Index (NFI = .747) and the Comparative Fit Index (CFI = .862) both fall below the recommended cutoff of .90, indicating a less than optimal fit (Bentler, 1990). Although these values are not ideal, they suggest some level of adequacy in the model. Both NFI and CFI are 1.000, which indicates perfect fit, although this is typical in saturated models (Schumacker & Lomax, 2010).The values of 0 for all fit indices highlight a severe lack of fit, indicating that the model does not adequately capture the relationships in the data. The RMSEA is reported as .084, with a 90% confidence interval of .067 to .100 and a p-close value of .001. RMSEA values below .05 indicate good fit, while values up to .08 are considered acceptable (Hu & Bentler, 1999). Thus, an RMSEA of .084 suggests a reasonable but not optimal fit. The low p-close value indicates that the model does not fit well (Browne & Cudeck, 1993).

An RMSEA of .205 clearly indicates a poor fit, far exceeding the acceptable threshold (Kline, 2015).
The default model demonstrates some strengths, particularly with the CMIN/DF ratio, suggesting a moderate fit despite the significant Chi-square result. This indicates a need for potential revisions to improve the model's fit. The perfect fit of the saturated model is typical but not practical for real-world applications due to the risk of overfitting (Schumacker & Lomax, 2010). The independence model results reflect a significant lack of fit, demonstrating that the relationships among variables are not being captured.

3.7 Relationship between HR technology adaptation anddemographic factor of the respondents

To explore the relationship between HR Technology adaptation and demographical factor Chi Square test was conducted, test statistics were represented in the table 7.
H_0: Demographical factor of the respondents will not influence on the Technology adaptation in HR
H_1: Demographical factor of the respondents will influence on the Technology adaptation in HR

Table 7. Relationship between HR technology adaptation anddemographic factor

Demographical Factor	Status		Chi Square Output	Significance
Gender	Strongly Agree	72	Chi-Sq = 7.389, DF = 3, P-Value =0.050	5%
	Agree	41		
	Neutral	37		
	Disagree	33		
	Strongly Disagree	16		
Age	Strongly Agree	32	Chi-Sq = 0.896, DF = 3, P-Value =0.826	NS
	Agree	34		
	Neutral	35		
	Disagree	26		
	Strongly Disagree	32		
Education Level	Strongly Agree	26	Chi-Sq = 2.875, DF = 3, P-Value =0.011	5%
	Agree	34		
	Neutral	45		
	Disagree	32		
	Strongly Disagree	26		

The Chi-square analysis reveals that both gender and education level significantly influence technology adaptation in HR, as indicated by a p-value less than 0.05. This suggests that we should reject the null hypothesis and accept the alternative hypothesis. In contrast, the p-value for age is greater than 0.05, leading us to accept the null hypothesis, indicating that the age of respondents does not significantly affect technology adaptation in HR.

4. RESULTS

The survey revealed a significant gender imbalance, with 70.5% of respondents being female (141 out of 200), compared to 29.5% male (59 respondents). The age distribution highlighted a predominance of younger respondents, with 54% aged 18-25 (108 respondents) and 42% aged 26-30 (84 respondents), together comprising 96% of the total sample. Most participants held postgraduate degrees (74.5%**,** 149 respondents), suggesting that the sample reflects a highly educated demographic, potentially influencing perceptions about HR technology.
The Chi-square analysis assessed the relationship between demographic factors and technology adaptation in HR:

- **Gender**: The results indicate a significant influence of gender on technology adaptation, with a Chi-square value of 7.389 and a p-value of 0.050**.** This suggests a rejection of the null hypothesis (H0) and supports the alternative hypothesis (H1).
- **Age**: The Chi-square value was 0.896 with a p-value of 0.826**,** indicating no significant relationship between age and technology adaptation. Thus, we accept the null hypothesis (H0).
- **Education Level**: The analysis revealed a significant relationship with a Chi-square value of 2.875 and a p-value of 0.011**.** Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), affirming that education level significantly influences technology adaptation.

5. DISCUSSION

The findings underscore the critical role of demographic factors in influencing HR technology adaptation. The strong representation of females in the sample aligns with previous studies indicating that women are often more engaged with digital HR tools (Marler & Boudreau, 2017). The significant impact of education on technology adaptation highlights the necessity of designing training programs tailored to different educational backgrounds to enhance technology utilization in HR processes.

The KMO and Bartlett's tests confirmed the appropriateness of the dataset for factor analysis, supporting the notion that the items used were sufficiently correlated to explore underlying factors. The results from PCA indicated that HR technology adaptation is influenced by perceptions of its effectiveness, educational background, and organizational support. This resonates with the literature emphasizing that successful digital transformation in HRM hinges on employee perceptions and readiness (Davenport et al., 2010; Jani et al., 2023).

The model fit summary reflects a complex relationship between the variables, where some fit indices suggest adequacy, while others indicate room for improvement. This disparity highlights the need for further refinement of the HR technology adaptation model to ensure that it captures the intricate dynamics present within organizations.

In conclusion, as organizations increasingly adopt technology in HR, understanding the demographic influences and ensuring that appropriate support mechanisms are in place becomes crucial. Future research should explore the role of technology readiness across different sectors, with a particular focus on developing economies and the interplay between emerging technologies and traditional HR practices. This will not only enrich the existing literature but also inform HR strategies that promote inclusivity and adaptability in technology adoption.

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