Influence of Artificial Intelligence on Employee Performance in Banking Industry-An Indian Perspective

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Abstract. An important development in the banking industry is the incorporation of Artificial Intelligence (AI) into HRM procedures, which is meant to improve efficiency and judgment. In order to offer critical insights for a successful implementation, this study explores bank employees' perspectives and intentions regarding the deployment of artificial intelligence in HRM. Data was collected through surveys from employees and HR specialists at eight carefully chosen banks in India, using a mixed-methods technique. The analysis was driven by the Unified Theory of Acceptance and Utilization of Technology (UTAUT) paradigm, which placed emphasis on elements such as competitive pressure, effort expectancy, performance expectancy, and enabling conditions. The findings show that although there is a significant intentionality to use AI, there are other contextual elements that also affect actual utilization. Important conclusions highlight the role that competitive pressures, performance advantages, and supportive settings play in increasing AI adoption. Creating favorable environments, offering specialized training, and highlighting the advantages of AI are some techniques to increase its acceptance. This discussion is further enhanced by addressing ethical and demographic aspects, which suggests a comprehensive approach to AI integration in banking HRM. This study adds to our theoretical knowledge of AI deployment in HRM as well as its practical consequences, especially in dynamic and culturally varied domains like the Indian banking sector.

Keywords: Artificial Intelligence, HR Management, Banking Industry, Employee Perception, Technology Adoption

1. Introduction

One significant development in the industry over the past few years has been the incorporation of AI into HRM initiatives. AI's ability to replicate human cognition and automate regular activities may have a positive impact on decision-making, human resource procedures, and overall corporate effectiveness[1]. This study aims to provide businesses with valuable insights into workers' views, concerns, and expectations

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around AI adoption, which will help them successfully integrate AI-driven HRM practices[2].

The ultimate purpose of the study is to improve decision-making about the effective integration of AI technology into HRM practices for HR practitioners, organizational executives, and policymakers in the banking sector. AI is starting to play a bigger role in the workplace, influencing how companies operate and make decisions[3]

AI in HRM offers a number of possible benefits, such as increased productivity, improved decision-making, and improved employee experiences. One of the main advantages of integrating AI into HRM is the capacity to efficiently fill unfilled positions[4]. AI may automate a variety of tasks, including hiring, reviewing applicants, and setting up initial interviews. Artificial intelligence (AI) algorithms that search through applicant databases, review applications, and assess candidates based on their qualifications, experience, and talents may speed up the hiring process. HR is benefiting from AI in another way: better application evaluation[5]. Artificial intelligence (AI) facilitates and improves automated evaluation processes, including video interviews and online exams. Employing artificial intelligence (AI) to examine video interviews enables a more impartial evaluation of candidates' nonverbal cues, facial expressions, and communication skills. AI-powered online tests can assess a candidate's technical proficiency, cognitive ability, and personality traits, providing valuable information to support the selection process. AI's capacity to customize each worker's experience increases employee satisfaction and engagement [3]. Chatbots, artificial intelligence (AI) driven virtual assistants, support employees in real time with inquiries, onboarding, training, and evaluations of their work and progress.

1.1 Problem Statement

The present research topic, pertaining to the Indian banking sector's adoption of Artificial Intelligence (AI) in Human Resource Management (HRM) practices, has not yet been explored. As such it meets an important gap in existing literature. There are many papers in current literature on AI's application to different industries, but there is no lack of case-by-case research that focuses explicitly and solely on the banking market. The particular problems and prospects of AI in HRM, as applied to an industry that is very labor-intensive like banking, which has close relations with customers due its high degree of openness between human beings. In addition, current research on AI tends to focus mainly on the technical and operational aspects. There is a lack of knowledge about its use from the standpoint of human beings and organizations. This is particularly important in a dynamic and multifaceted industry like India, where both banking practices as well the adoption of technology vary greatly from global patterns. And workforce development standards are not always consistent with universal norms either. Moreover, the thesis also highlights a distinction in terms of AI adoption between private and public sector banks that may often be ignored in studies on technology's spread. In focusing on this small field, the research not only enriches typical academic discussions about AI in HRM, but also provides pragmatic value to banking practitioners and policy makers in India itself or similar emerging economies. As a result, this research gap represents an extraordinary chance to take the top advanced technology and human resources in such a critical area for analysis so as to produce both theoretical and practical pillars of wisdom.

1.1 Research Objectives

Research Questions
RQ1 How is employee performance affected by the adoption of artificial intelligence?
RQ2: How acceptability in AI adoption in HRM practices can be enhanced?

1. To study the impact of Artificial Intelligence adoption on Employees Performance.
2. To make suggestions to enhance the acceptability in AI adoption in HRM practices

1.2 Significance of the Study

To effectively capitalize on the opportunities of the digital economy, small businesses need to understand how to enhance the adoption of e-commerce methods. The current study holds significant importance for several reasons. Firstly, by identifying the barriers related to digital literacy and consumer engagement, it can assist in the development of targeted interventions and support programs by the government and professional organisations aimed at empowering small retailers with the necessary skills and knowledge for successful e-commerce adoption [10]. Secondly, the insights gained from this research can help small retailers optimize their e-commerce strategies to achieve increased market reach, improve competitiveness, and enhance customer satisfaction. With this, it supports the more generic aim of establishing a more eclectic digital economy in which smaller companies can flourish alongside larger enterprises. The study's ultimate goal is to offer valuable knowledge for e-commerce platforms, business owners, and regulators so they may formulate plans that would assist small retail businesses in India's digital marketplace prosper sustainably.

2. Literature Review

How employees feel about AI has a big impact on how successfully HRM implements and adopts technology [1]. Since it directly affects employees' attitudes, actions, and acceptance of AI-driven initiatives, the perception of AI's presence and impact on HRM practices is crucial to comprehend [6].
The way AI is employed in human resource management is heavily influenced by the attitudes of employees toward the technology in general (Garg et al., 2018). These viewpoints are shaped in part by their encounters with AI technology, their conceptions of its potential, and their expectations regarding its potential impact on their jobs and employment security [7]. There are several reasons to be optimistic about AI, including its ability to deliver tailored training and education, enhance decision-making via data analysis, and expedite administrative procedures [8]. Workers can focus on higher-value projects when AI automates repetitive administrative tasks [8].
Another critical factor is how much employees trust AI in HRM and how open and honest they are about its use. For workers to rely on AI systems' recommendations and

outcomes, they must have confidence in them [9]. Employee perception of AI algorithms is significantly influenced by their level of transparency. Workers might be dubious of AI's recommendations and reluctant to put them into practice if there are unclear explanations of how AI systems arrive at their judgments [10]. Transparent AI systems that provide clear explanations of how they arrive at specific decisions can help to foster trust among employees and increase confidence in the adoption of AI in HRM [11]. Human resources departments must also clear up any misconceptions or concerns that employees may have by being open and honest with them regarding the benefits and reasoning for implementing AI [12].

Employee sentiments are impacted by how AI is included and presented in HRM processes. By involving workers in the adoption process and asking for their feedback, employers can increase employee buy-in and enthusiasm in AI-driven projects [13]. Workers should be given the necessary training and support to understand and effectively use AI technologies in order to motivate them to use AI in their daily work (Khatri et al., 2020). Human resources departments should stress that AI is designed to amplify and supplement existing human skills rather than replace them. Workers are more likely to see AI as a boon than a danger if the technology is presented to them as a helpful tool that improves productivity and precision [14].

[2] stated that next-generation human resource management (HRM) is characterized by the deployment of sophisticated HR analytics and artificial intelligence (AI) to deliver individualized HR solutions, and personalized HRM is a subset of high-performance work practices (HPWPs) executed at the individual level. Human resource management (HRM) programme and practices that are tailored to the specific needs of each employee are the subject of this theoretical article. Researchers contend that HRM that is tailored to each individual employee is a distinct competitive advantage for a company over time and provides extra positive performance impacts beyond those of other HPWPs. Researchers use theories of individual differences and person-organization fit to describe how customized HRM improves business outcomes including employee output, morale, adaptability, and financial returns on HR expenditures. Researchers further argue that business strategy mediates the connection between HRM and productivity within an organization. Expanding on the work-displacing AI idea, researchers argue that the adoption of AI is favourably (negatively) connected to the mechanical and analytical intelligence necessary for personalized HRM activities. Finally, researchers discuss the ramifications and demonstrate how cutting-edge HR analytics and AI may ease the shift to individualized HRM

2.1 Theoretical Framework

The quantitative research model adopted in carrying out this study was the development of a conceptual model. Methodical collection of data pertaining to the several concepts contained in this model formed the basis for it. We used a particularly well-designed questionnaire to collect data. The concepts that needed testing were on the Likert scale as designed. UTAUT Model Technology adoption and use can be better understood and predicted with the help of UTAUT model. It is used to examine whether an individual has intentionality about giving in, embracing, or using technology. The UTAUT paradigm created by Venkatesh in 2003 attempts to encompass and expand upon the current modes of thought surrounding how people embrace new technologies.

2.2 Hypothesis Development

2.2.1. PERFORMANCE EXPECTANCY (PE)

H01: Performance Expectancy would not significantly influence Banking Industry to use AI in HRM Practices.

H11: Performance Expectancy would significantly influence Banking Industry to use AI in HRM Practices.

2.2.2. EFFORT EXPECTANCY (EE)

H02: Effort Expectancy would not significantly influence Banking Industry to use AI in HRM Practices.

H12: Effort Expectancy would significantly influence Banking Industry to use AI in HRM Practices

2.2.3. COMPETITIVE PRESSURE (CP)

H03: Competitive Pressure would not significantly influence Banking Industry to use AI in HRM Practices.

H13: Competitive Pressure would significantly influence Banking Industry to use AI in HRM Practices

2.2.4. FACILITATING CONDITION (FC)

H04: Facilitating Condition would not significantly influence User behavior to use AI in HRM Practices.

H14: Effort Expectancy would significantly influence User behavior to use AI in HRM Practices

2.2.5. BEHAVIOUR INTENTION (BI)

H05: Banking Industry would not significantly influence User behavior to use AI in HRM Practices.

H15: Effort Expectancy would significantly influence User behavior to use AI in HRM Practices.

3. Research Methodology

The methodology of this current research work is meticulously designed to examine the variables affecting the behaviour intention of employees while adopting artificial intelligence. Additionally, this study investigates how employee performance influence the use of AI. This section outlines the methods used for data collecting, analysis, sampling strategy, and research design in the study.

3.1 Research Design

The aim of the study was to estimate the strength and direction of these associations. Smart PLS 4 software was used for quantitative data analysis. The utilization of a mixed-methods research methodology in this study facilitated a thorough examination of the implementation of artificial intelligence in human resource management practices within the banking industry. This research approach incorporates an exploratory phase to gather insights and a descriptive phase to quantify these findings, providing a comprehensive understanding of employees' perspectives and intentions toward the use of AI in HRM. Integrating quantitative data enriches the analysis by providing more comprehensive insights and improves the overall validity of the study's conclusions

3.2 Sample

There are 43 working commercial banks in all according to the Indian government; and they maintain a fixed standard rate of bank charges upon which no one has imposed restrictions so that businesses seeking more lenient terms simply go elsewhere for their banking services. At the same time sample units are selected to demonstrate use of AI by 4 private commercial banks and 4 public sector banks.

Table 1. Number of employees of 8 Banks Selected for the Study

S.NO	Bank Name	Total Number of Employees(Up till March,2022)	Percentage of Employees (Per Bank)	Number of respondents from each bank (SAMPLE SIZE=400)
1	State Bank Of India	2,44,250	29	116
2	Hdfc Bank	1,41,579	16.85	68
3	Icici Bank	1,05,844	12.6	50
4	Canara Bank	86,919	10.34	42
5	Axis Bank	85,815	10.21	41
6	Bank Of Baroda	79,173	9.42	38
7	Kotak Mahindra Bank	66,000	7.85	31
8	Central Bank Of India	30,289	3.61	14
		TOTAL=8,39,869		

Source: Author's Compilation

3.3 Data Collection Methods

In order to analyze the employee's perception and their intention to adopt AI with HR function in their organizations, a method of surveying is used to collect data from employees and HR Professionals of the Banking Industry with good knowledge of AI and HR functions.
This study is of the quantitative type and is based on two significant variables: artificial intelligence and adoption intentions. In order to achieve the research's conclusions, secondary data is also used.

4. Data Analysis

The PLS-SEM analysis was applied with the use of the Smart PLS software, a leading tool for PLS-SEM analysis in business research. The analysis proceeded in the following manner:

- **Measurement Model Assessment**: In this initial step the reliability, along with the validity of the constructs within the survey were calculated. Techniques such as Coefficient alpha for consistency, AVE measure for convergent validity, and the Heterotrait-Monotrait ratio criterion for discriminant validity were employed to assess the measurement model's adequacy.

  Structural Model Assessment: In this phase, the hypothesized relationships between various factors impacting digital literacy, consumer engagement, and e-commerce adoption were examined. Path coefficients were calculated to determine the strength and significance of these relationships, and the model's inferences and explanatory power was evaluated through the statistical measure of R^2 for the dependent variables.

4.1 Results

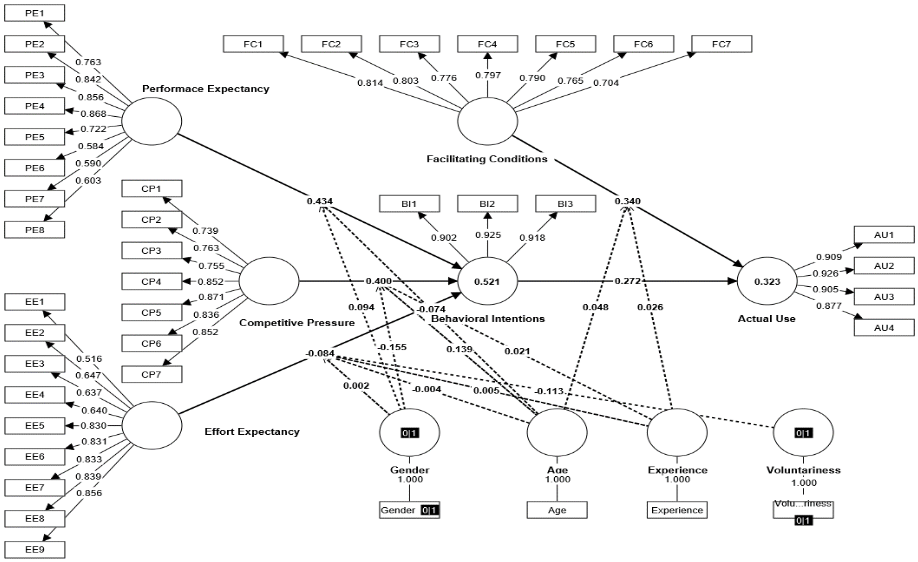

Figure 1.
PLS Algorithm on Conceptual Model
Source: UTAUT Model (Venkatesh et al., 2003)
Source: Author's Compilation

The PLS Algorithm analysis on the conceptual model reveals that performance expectancy positively influences behavioral intention regarding AI use in HR management in the banking industry, with a beta value of 0.434. This indicates that employees' expectations of improved performance enhance their behavioral intentions, further facilitating actual AI use. Competitive pressure also positively impacts behavioral intention (beta = 0.094), suggesting that increased competition encourages AI adoption. Conversely, effort expectancy negatively affects behavioral intention (beta = -0.084), implying that higher effort requirements deter AI usage. Facilitating conditions positively influence actual AI use (beta = 0.340), indicating that supportive conditions in HR departments enhance AI implementation. Age does not significantly moderate AI use, as shown by low T values and high P values. Gender, age, experience, and voluntariness interactions show minimal impact on behavioral intentions, except for a notable link between age and competitive pressure, suggesting older workers' intentions are influenced by competition stress. Lastly, voluntariness strongly correlates with behavioral intentions, indicating that when employees feel they have a choice, they are more likely to use AI. However, voluntariness does not significantly impact effort expectancy or change behavioral plans.

Table 2: **Construct reliability and validity**

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
"Actual Use"	0.926	0.928	0.947	0.818
"Behavioral-Intentions"	0.903	0.903	0.939	0.838
"Competitive Pressure"	0.913	0.917	0.931	0.658
"Effort Expectancy"	0.905	0.981	0.917	0.557
"Facilitating Conditions"	0.899	0.914	0.915	0.607
"Performance-Expectancy"	0.877	0.9	0.903	0.544

Source: Researcher's Calculation

Table presents reliability and validity metrics, showcasing strong internal consistency with Cronbach's alpha values ranging from 0.877 to 0.926 for constructs like Actual Use, Behavioral Intentions, and others. Moreover, composite reliability—which is determined by rho_a and rho_c—confirms dependability; values for Actual Use are higher than 0.9. Values of Average Variance Extracted (AVE), more than 0.5 for every construct, indicate that the latent constructs account for a significant amount of variation. These findings support the robustness of the model and point to valid and trustworthy evaluation instruments for researching AI adoption in banking HRM.

Table:3 **Fornell and Larcker Criterion**

	AU	**Age**	**BI**	**CP**	**EE**	**Experience**	**FC**	**Gender**	**PE**
AU	0.905								
Age	-0.04	1							
BI	0.504	-0.02	0.915						
CP	0.59	-0.02	0.525	0.811					
EE	-0.02	0.07	-0.15	0.02	0.746				
Experience	-0.01	-0.12	-0.04	-0.07	-0	1			
FC	0.528	-0.02	0.668	0.719	-0.04	-0.044	0.78		
Gender	0.031	-0.08	0.001	0.025	-0.03	0.043	0.01	1	

PE	0.511	-0.03	0.634	0.463	-0.03	0.011	0.59	-0.024	0.74

The Fornell and Larcker criteria is shown in Table 3; it is necessary for evaluating the discriminant validity of the model's latent constructs. This criterion looks at the correlations between each construct and all others, as well as the square root of the average variance extracted (AVE) for that construct. model looks to have strong discriminant validity according to the Fornell and Larcker criteria. The latent constructs on AI adoption in employess performance in the banking industry seem to be unique from one another, since the square roots of the AVE for each construct are often larger than the correlations with other constructions.

Table 4: **Hypothesis Testing**

	Original sample (O)	**M**	**(STDEV)**	**T Value**	**P values**
Age -> “Actual Use”	-0.03	-0.03	0.041	0.729	0.466
Age -> “Behavioral-Intentions”	0.008	0.009	0.036	0.215	0.829
“Behavioral-Intentions” -> “Actual Use”	0.272	0.268	0.07	3.912	0
“Competitive Pressure” -> “Behavioral-Intentions”	0.4	0.393	0.091	4.387	0
“Effort Expectancy” -> “Behavioral-Intentions”	-0.084	-0.092	0.106	0.793	0.428
Experience -> “Actual Use”	0.013	0.013	0.04	0.316	0.752
Experience -> “Behavioral-Intentions”	-0.02	-0.021	0.034	0.591	0.555

"Facilitating Conditions" -> "Actual Use"	0.34	0.348	0.062	5.47	0
Gender -> "Behavioral-Intentions"	0.042	0.043	0.082	0.513	0.608
"Performance-Expectancy" -> "Behavioral-Intentions"	0.434	0.446	0.1	4.354	0
Voluntariness -> "Behavioral-Intentions"	0.136	0.133	0.069	1.976	0.048
Gender x "Performance-Expectancy" -> "Behavioral-Intentions"	0.094	0.081	0.118	0.797	0.425
Gender x "Competitive Pressure" -> "Behavioral-Intentions"	-0.155	-0.145	0.108	1.431	0.153
Gender x "Effort Expectancy" -> "Behavioral-Intentions"	0.002	0	0.108	0.016	0.987
Age x "Effort Expectancy" -> "Behavioral-Intentions"	-0.004	-0.004	0.043	0.102	0.919

Age x "Competitive Pressure" -> "Behavioral-Intentions"	0.139	0.139	0.049	2.817	0.005
Age x "Performance-Expectancy" -> "Behavioral-Intentions"	-0.074	-0.074	0.053	1.397	0.162
Age x "Facilitating Conditions" -> "Actual Use"	0.048	0.048	0.046	1.051	0.293
Experience x "Effort Expectancy" -> "Behavioral-Intentions"	0.005	0.008	0.039	0.129	0.897
Experience x "Competitive Pressure" -> "Behavioral-Intentions"	0.021	0.021	0.034	0.601	0.548
Experience x "Facilitating Conditions" -> "Actual Use"	0.026	0.025	0.046	0.559	0.576
Voluntariness x "Effort Expectancy" -> "Behavioral-Intentions"	-0.113	-0.103	0.092	1.229	0.219

Source: Researcher's Calculation

Statistical analysis indicates several key findings in the model. According to Table 4 Age has no significant impact on actual usage or planned behaviors, as shown by T statistics of 0.729 and 0.215, and p-values of 0.466 and 0.829, respectively. Behavioral intentions significantly influence actual usage (T = 3.912, p = 0). Competitive pressure also significantly impacts future behavior (T = 4.387, p = 0).

However, effort expectancy does not significantly affect behavioral intentions (T = 0.793, p = 0.428). Experience does not significantly influence actual usage or future behavior, indicated by T statistics of 0.316 and 0.591, and p-values of 0.752 and 0.555, respectively. Facilitating conditions significantly enhance actual usage (T = 5.47, p = 0). Gender does not significantly predict future behavior (T = 0.513, p = 0.608). Performance expectancy significantly influences behavioral intentions (T = 4.354, p = 0). Voluntariness also has a significant positive impact on behavioral intentions (T = 1.976, p = 0.048). Interaction terms such as gender x performance expectation and gender x competitive pressure are not significant, with T statistics of 0.797 and 1.431, and p-values of 0.425 and 0.153, respectively. The interaction of age and competitive pressure significantly impacts behavioral intentions (T = 2.817, p = 0.005). Other interactions, like age x facilitating conditions and experience x effort expectation, are not significant. The key predictors of actual usage and behavioral intentions include behavioral intentions, competitive pressure, facilitating conditions, performance expectancy, voluntariness, and the interaction between age and competitive pressure. These results support the model's hypotheses and highlight areas for potential refinement

4.2 Interpretation and Discussion of Results

The results highlight a stronger link between predictors and intentions to use AI than actual use, suggesting that while the model captures employees' plans well, real-world usage is affected by additional factors. The gap between intentions and actual use underscores the need for supportive environments, ease of use, and group acceptance to bridge this gap. Key findings show that facilitating conditions (HTMT = 0.52), performance expectancy (HTMT = 0.55), and competitive pressure (HTMT = 0.64) are critical for AI adoption. Although effort expectancy has a low HTMT value (0.06) with Actual Use, indicating that perceived effort alone doesn't deter AI usage, demographic factors like age and gender play a slight role, particularly when combined with other factors like competitive pressure.

The intricacy of AI adoption in HRM is highlighted by the fact that, overall, the model only partially captures real AI usage while explaining a sizable fraction of employees' intents. It is crucial to emphasize the usefulness of AI integration, offer training, and guarantee organizational support. Several tactics can be used to increase banks' acceptance of AI in HR procedures. Establishing favorable circumstances is essential, which includes giving employees the tools, guidance, and support they need to incorporate AI technologies into their regular jobs. By exhibiting AI's efficacy and disseminating success stories within the company, highlighting its performance advantages helps promote adoption.

Utilization can be further encouraged by addressing competitive pressures and presenting AI as a tool for preserving and boosting competitiveness. Although not a significant obstacle, effort expectation should nonetheless be reduced by providing accessible AI training courses that increase proficiency over time. Inclusivity is ensured by customizing training to different employee demographics, such as younger workers who may adjust faster and older workers who would require a more gradual approach.

To sum up, a thorough strategy for integrating AI into HR should take into account procedural, technological, and human factors. AI adoption and utilization in banking HR procedures can be improved by including staff members, establishing clear goals, providing incentives, and creating an atmosphere of ongoing learning and moral application.

In summary, the study depicts a complex interplay of factors that contribute to the adoption of e-commerce, highlighting the importance of technological readiness, customer orientation, market orientation, and particularly the utilization of social media and the environmental impact generated by the facilitating conditions. It elucidates the significant mediating aspect of digital literacy and customer engagement in influencing the contribution of these factors. In the current study's context, digital literacy is not about just having knowledge about digital tools, but the ability to harness it well for commercial purpose. Integrating SEO's, drop shipping, fraud prevention, personalised engines, and augment reality into the everyday business of small business owners, substantially enhancing the experience of the consumers and generating sales.

5. Conclusion

In conclusion, a number of critical elements are necessary for the effective integration of AI into HR management in Indian banks. Enough funding must be set aside to create reliable AI systems. In-depth training courses designed to meet the various needs of bank employees are necessary to guarantee that AI technologies are widely used and that users are proficient in their use. It is critical to uphold fairness and openness in AI activities by strictly adhering to ethical rules in order to preserve trust with both customers and staff. Moreover, tailoring AI solutions to the particular difficulties and demands faced by Indian banks will maximize their efficacy. Protecting sensitive HR data requires giving data security and privacy safeguards top priority. AI initiatives must be regularly monitored and evaluated in order to pinpoint areas in need of development and guarantee that they are in line with corporate goals.

6. Future Research

Subsequent investigations ought to concentrate on ongoing or extended studies to monitor the changing application of AI throughout time. It is essential to comprehend how it affects productivity, job happiness, career advancement, and worker well-being. To overcome barriers, more research into the issues surrounding AI application, such as data protection, system integration, and change management, is required. Optimizing the efficacy of particular AI-based HRM techniques and technologies, like hiring programs and predictive analytics, also requires close examination. A closer look is necessary at the ethical issues surrounding the use of AI in hiring and performance review processes. It is recommended that researchers investigate methods for augmenting staff involvement and AI literacy in order to streamline transitions and optimize the advantages of AI implementation. Cross-cultural comparisons and regulatory compliance monitoring can yield important insights into global AI adoption trends and cultural impacts.

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