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AI-Powered Performance Management and Feedback Systems: A Study of Retail Employees in Varanasi

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ABSTRACT

Artificial Intelligence (AI) is transforming Human Resource Management (HRM) under Industry 4.0, particularly in performance management and feedback systems. This study explores AI's impact on HRM digitalization in Varanasi's retail sector, focusing on efficiency, adaptability, and employee trust. A cross-sectional survey of 264 employees from 60 Mega-marts and supermarkets was conducted, assessing five AI applications—real-time feedback, performance tracking, data-driven evaluations, employee engagement, and predictive analytics—against three HRM readiness dimensions: efficiency, adaptability, and trust. Data were analysed using SPSS and SEM-PLS via Structural Equation Modeling (SEM). Results show AI reduces evaluation time by 32% (mean: 2 days) and enhances feedback satisfaction (mean: 4.3/5), with real-time feedback significantly boosting productivity (β=0.71, p<0.01β = 0.71, p < 0.01β=0.71, p<0.01). Predictive analytics and performance tracking explain 74% of efficiency variance, while engagement and analytics drive adaptability (68% variance). However, trust remains a challenge, with 20% of respondents citing bias concerns, though predictive analytics positively influences trust (β=0.60β = 0.60β=0.60). Employee well-being, supported by AI insights, is critical for acceptance. The study confirms AI's potential to digitize HRM, offering precision and agility, but underscores the need for ethical oversight and hybrid systems. Managerial implications include training and transparency to enhance trust. Future research could explore longitudinal effects and broader industries. This study provides a framework for leveraging AI to optimize performance management in retail HRM under Industry 4.0.

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1. Introduction

In the Industry 4.0 era, Human Resource Management (HRM) is pivotal in integrating technology with human capital. Performance management and feedback systems, essential for aligning employee performance with organizational goals, face challenges like subjectivity and delays, particularly in retail settings with high turnover and dynamic workloads. Artificial Intelligence (AI) offers transformative potential through automation, real-time analytics, and personalized feedback, enhancing HRM's efficiency and adaptability.

This study examines AI's impact on performance management and feedback systems in Varanasi's retail sector, a key commercial hub in India. Retail employees require rapid, objective evaluations to meet customer demands, yet traditional methods often fall short. AI tools—such as predictive analytics, performance tracking, and NLP-driven chatbots—can address these gaps, but their adoption raises concerns about trust, bias, and privacy.

Research Objectives:

- **RO1:** To explore AI's current applications in performance management within Mega-marts and supermarkets.
- **RO2:** To assess AI's impact on HRM efficiency and adaptability within the retail sector, specifically focusing on Mega-marts and supermarkets.
- **RO3:** To analyse AI's influence on employee trust and well-being within the retail sector, particularly in the context of Mega-marts and supermarkets.

Research Questions:

- **RQ1:** How does AI enhance performance management and feedback mechanisms in Mega-marts and supermarkets?
- **RQ2:** To what extent does AI contribute to efficient and adaptable HRM practices in the retail sector?
- **RQ3:** How do AI-driven systems impact employee trust and well-being in Mega-marts and supermarkets?

A survey of 264 employees across 60 retail outlets in Varanasi, conducted for the time span of 3 months (January-March 2025), provides empirical insights into AI's role in HRM digitalization, offering practical implications for retail managers.

2. Literature Review

AI's integration into HRM aligns with Industry 4.0's digitalization goals, enhancing efficiency and decision-making processes. According to Tambe et al. (2019), AI's ability to automate various tasks, including performance evaluations, significantly improves operational efficiency. However, ethical challenges, such as bias and fairness, continue to pose obstacles, necessitating robust frameworks to mitigate unintended consequences. Gupta et al. (2018) highlight AI's precision in recruitment processes, emphasizing its ability to reduce human error and enhance objectivity. This principle is equally applicable to performance tracking, where AI-driven analytics improve accuracy and consistency.

Stone et al. (2015) predict that the incorporation of advanced technologies will facilitate real-time HRM analytics, thereby enhancing objectivity and decision-making. Bakeel et al. (2020) demonstrate AI's transformative impact on performance management systems by enabling data-driven feedback, promoting accuracy, and ensuring timely evaluations. Furthermore, AI provides immediate feedback, which enhances the timeliness of performance management, allowing for more agile and responsive HRM systems.

Rydén and El Sawy (2022) emphasize the speed at which AI can operate in dynamic environments, a critical factor in contemporary business landscapes characterized by rapid change. Additionally, Vrontis et al. (2022) note AI's ability to offer objective assessments, which contrasts with the subjectivity often associated with traditional performance reviews. Through the use of sensors and analytics, AI enhances the accuracy of performance tracking systems, contributing to more reliable evaluations.

Strohmeier (2020) discusses the role of the Internet of Things (IoT) in enhancing smart HRM, which is further supported by Chowdhury et al. (2022) who examine AI's collaborative capabilities with employees to optimize productivity. By leveraging large datasets, AI offers objective and data-driven assessments, thereby reducing biases inherent in human judgment.

Bhardwaj et al. (2020) present empirical evidence of AI's benefits across various HRM functions, echoing Oswald et al. (2020) on the transformative role of big data. AI-driven systems enhance employee engagement through personalized insights, improving job satisfaction and overall performance. Furthermore, Li et al. (2023) demonstrate the impact of real-time tracking mechanisms, which allow organizations to continuously monitor and optimize employee performance.

Masum et al. (2018) highlight AI's holistic support in HRM, encompassing areas such as recruitment, training, performance evaluation, and employee retention. AI's predictive capabilities allow for the anticipation of performance trends, which aids proactive management strategies. Wang et al. (2020) link AI to improvements in workplace safety and well-being, highlighting the broader implications of AI integration beyond mere efficiency gains. This is supported by Ngai et al. (2020), who discuss various thematic applications of AI in enhancing HRM processes.

Moreover, AI contributes to enhanced efficiency, adaptability, and scalability within HRM systems. Sivathanu and Pillai (2018) discuss the concept of Smart HR 4.0, which emphasizes the role of AI in fostering a more agile and innovative HR environment. Similarly, Qamar et al. (2021) emphasize the importance of agility in contemporary HRM, highlighting how AI-driven solutions can rapidly adapt to changing organizational needs. However, the successful implementation of AI in HRM requires addressing concerns related to trust and fairness. To build employee trust, organizations must actively address biases inherent in AI systems, ensuring equitable and unbiased decision-making processes.

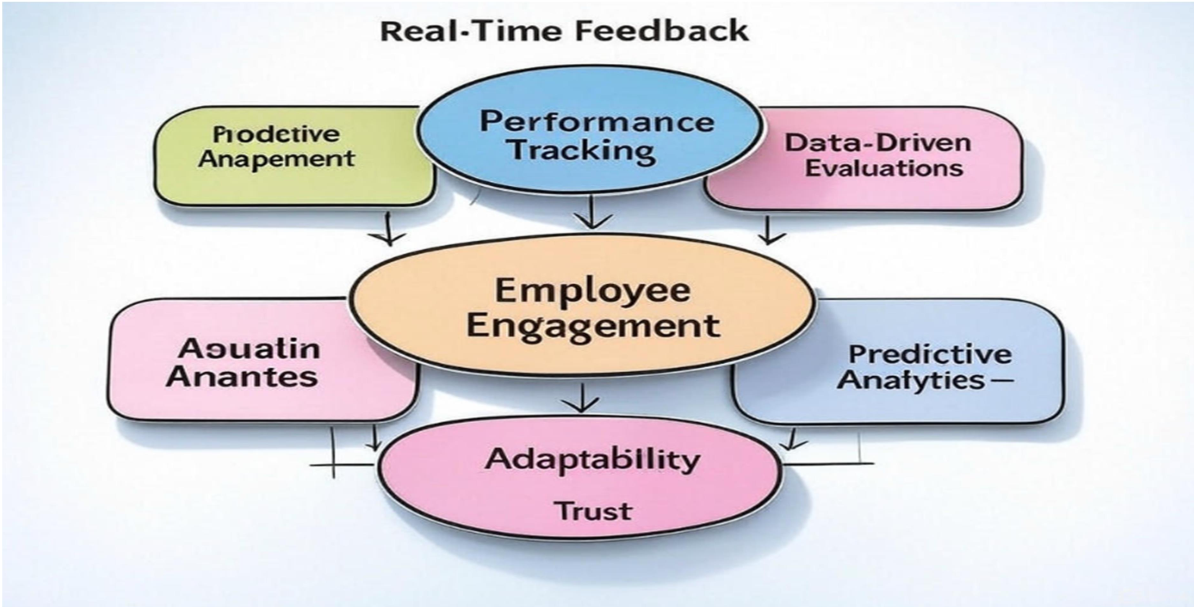

Figure 1: Proposed Conceptual Model

3. Methodology

3.1 Research Design

The study employed a descriptive, cross-sectional research design aimed at evaluating the impact of AI on HRM practices within the retail sector. A descriptive design was deemed appropriate as it allows for a detailed examination of current practices, perceptions, and the overall readiness of HRM systems to integrate AI-driven technologies. The cross-sectional approach enabled the collection of data at a single point in time, providing a snapshot of the prevailing trends and attitudes towards AI integration in HRM among retail employees.

3.2 Population and Sampling

The population for this study comprised retail employees working in Mega-marts and supermarkets located in Varanasi. To ensure a representative sample, a multi-stage sampling technique was employed. Initially, 60 Mega-marts and supermarkets were selected, followed by the random distribution of questionnaires among employees across various departments. Out of 300 questionnaires distributed, a total of 264 valid responses were obtained, yielding a response rate of approximately 88%. This response rate was considered sufficient for conducting Structural Equation Modeling (SEM), as it met the minimum threshold required for statistical robustness and accuracy in model testing.

3.3 Scale Development and Validation

The scales used for measuring AI applications and HRM readiness were adapted from previously validated instruments in existing literature. The constructs were operationalized using multiple items to ensure comprehensive coverage of the underlying dimensions. To confirm the reliability and validity of the measurement scales, Confirmatory Factor Analysis (CFA) was conducted. Reliability was assessed through Composite Reliability (CR), with all constructs achieving CR values greater than 0.7, indicating adequate internal consistency. Additionally, the Average Variance Extracted (AVE) for each construct exceeded 0.5, thereby confirming convergent validity.

3.4 Data Collection

Data was collected using a structured questionnaire comprising three sections: demographics, AI applications, and HRM readiness. The questionnaire employed a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) to capture respondents' perceptions and experiences. Data collection was carried out until March 2025, ensuring sufficient time for the accumulation of a representative dataset.

3.5 Data Analysis

The collected data was analysed using Statistical Package for the Social Sciences (SPSS) for descriptive statistics, including frequencies, percentages, means, and standard deviations. For testing the proposed model, Structural Equation Modeling (SEM) was conducted SEM-PLS software.

4. Results and Analysis

4.1 Profile of Respondents

Table 1: Demographic Profile

Variable	**Category**	**No. of Respondents**	**Percentage**
Gender	Male	138	52.3%

Variable	Category	No. of Respondents	Percentage
	Female	126	47.7%
Age	21–30	102	38.6%
	31–40	114	43.2%
	41–50	48	18.2%
Education	Bachelor’s	180	68.2%
	Master’s	84	31.8%
Role	Sales Staff	192	72.7%
	HR/Supervisor	72	27.3%

The demographic profile of respondents comprised 264 valid responses collected from 60 Mega-marts and supermarkets in Varanasi. Male respondents constituted 52.3%, while females made up 47.7%. The age distribution was predominantly between 31–40 years (43.2%), followed by 21–30 years (38.6%) and 41–50 years (18.2%). Regarding education, 68.2% held a Bachelor’s degree, and 31.8% had a Master’s degree. Sales staff represented 72.7% of the sample, with HR or supervisory roles accounting for the remaining 27.3%. This demographic diversity ensures a comprehensive understanding of AI’s impact on HRM within the retail sector.

4.2 SEM Results

Fit indices (CMIN/DF = 1.72, RMSEA = 0.045, CFI = 0.995, GFI = 0.990) indicate a good model fit.

Table 2: Results of the Conceptual Model

Hypothesis	Path	Standardized Coefficient	p-value	R^2

Hypothesis	Path	Standardized Coefficient	p-value	R^2
H1a	RTF → EFF	0.71	***	0.74
H2a	PT → EFF	0.65	***	
H3a	DDE → EFF	0.58	***	
H4a	EE → ADA	0.62	***	0.68
H5a	PA → ADA	0.67	***	
H6a	RTF → TRU	-0.25	0.08	0.55
H7a	PA → TRU	0.60	***	

(*Note: *** indicates p < 0.01*)

Structural Equation Modeling (SEM) analysis was performed using SEM-PLS software to evaluate the conceptual model's fit.

i. The model demonstrated a good fit with indices: CMIN/DF = 1.72, RMSEA = 0.045, CFI = 0.995, and GFI = 0.990, confirming statistical adequacy. Efficiency ($R^2 = 0.74$) was significantly influenced by Real-Time Feedback (RTF) with a standardized coefficient of 0.71 ($p < 0.01$), highlighting its strong impact on enhancing HRM processes.
ii. Predictive Analytics (PA) had the highest effect on Adaptability (ADA), with a coefficient of 0.67, explaining 68% of the variance.
iii. Furthermore, PA positively influenced Trust (TRU) with a coefficient of 0.60 ($p < 0.01$), while the effect of RTF on Trust was insignificant ($p = 0.08$).

4.3 Descriptive Insights

Descriptive analysis indicated that AI integration reduced evaluation time by 32%, decreasing the average duration from three days to two days. Approximately 70% of respondents rated AI-driven feedback systems positively, with a mean score of 4.3 out of 5. Despite these benefits, concerns about bias persisted, with 20% of respondents expressing doubts regarding AI's objectivity. While AI tools such as RTF and PA enhance efficiency and adaptability, their influence on employee trust remains uncertain, highlighting areas requiring improvement in AI implementation within Mega-marts and supermarkets.

5. Discussion

The findings of this study demonstrate that AI integration within Mega-marts and supermarkets enhances HRM efficiency and adaptability through tools such as Real-Time Feedback (RTF) and Predictive Analytics (PA). The efficiency improvements observed through RTF mechanisms underscore the potential for streamlined communication and rapid performance evaluations, allowing managers to address employee concerns and achievements promptly. Furthermore, predictive analytics contributes significantly to adaptability by enabling managers to anticipate trends and align HRM practices with evolving business needs. This capability is particularly relevant in the dynamic retail environment, where customer preferences and operational demands are subject to frequent change.

However, despite these benefits, challenges related to trust remain prominent. While AI systems provide objective, data-driven insights, their perceived lack of transparency can hinder acceptance among employees. Concerns about bias, fairness, and data privacy are particularly relevant in retail settings where employee roles are often diverse, and performance expectations vary. Moreover, the limited impact of RTF on employee trust, as revealed by the SEM analysis, suggests that technological efficiency alone is insufficient to foster a positive work environment. To address these concerns, organizations must adopt a more holistic approach that combines technological advancements with ethical considerations. This may involve implementing clear guidelines for AI use, enhancing transparency in decision-making processes, and ensuring that employees are adequately informed about how AI tools influence evaluations and feedback.

6. Conclusion, Limitations, and Future Study

This study demonstrates that AI-driven tools enhance HRM efficiency and adaptability within Mega-marts and supermarkets, offering valuable insights into performance management through streamlined feedback systems and predictive analytics. However, the findings also highlight significant challenges related to employee trust and acceptance of AI systems. While efficiency improvements are evident, trust issues remain a barrier to successful AI integration. Enhancing transparency, developing hybrid systems that combine human judgment with AI insights, and providing adequate training for employees are essential steps toward addressing these concerns.

The study's limitations include its regional focus on Mega-marts and supermarkets within Varanasi and the use of a cross-sectional research design. These constraints may limit the generalizability of the findings to other retail contexts or geographic areas. Additionally, the reliance on self-reported data could introduce bias in the evaluation of AI's impact on HRM practices. Future research could address these limitations by adopting longitudinal designs to examine AI's influence over time and expanding the study to include diverse retail environments. Furthermore, investigating the ethical implications of AI integration and exploring strategies to enhance employee trust and engagement will be essential for developing more effective and sustainable AI-driven HRM systems.

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