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Transforming Talent Management through AI and Automation: Insights from Companies in Ballari

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Abstract:
In today's dynamic business environment, artificial intelligence (AI) and automation are increasingly integrated into talent management practices. This study investigates employee perceptions of AI-driven tools in relation to recruitment, employee development, and workforce planning. It also examines how professionals perceive the ethical and human-centric aspects of AI in human resource (HR) functions. Conducted among HR professionals from select companies in Ballari, the research employed descriptive statistics and the Kruskal-Wallis H test to analyze differences in perceptions based on department, designation, age group, and experience level. The findings reveal largely uniform perceptions across most demographic groups regarding the role of AI in HR. However, significant differences were observed based on experience levels concerning the ethical and human-focused use of AI technologies. These insights emphasize the importance of experience-based strategies to ensure AI adoption in HR remains fair, transparent, and empathetic. The study contributes to a growing understanding of how organizations can align technological advancement with human values in the workplace.

Keywords: Artificial Intelligence in HR, Talent Management, Employee Perceptions, Human-Centric Automation, Ethical HR Practices

Introduction:
In today's rapidly evolving business landscape, artificial intelligence (AI) and automation are revolutionizing talent management. These technologies are transforming traditional HR practices, offering data-driven insights and enhancing efficiency across recruitment, development, and retention processes.
AI-driven tools are streamlining recruitment by automating resume screening and conducting virtual interviews, enabling companies to efficiently identify top candidates. For instance, AI-powered platforms can assess candidates' skills and predict their potential success based on historical data, reducing time-to-hire and improving match quality. [1]Sahota, Neil. (2023). Beyond hiring, AI is personalizing employee development by analyzing performance data to recommend tailored learning paths. This approach ensures that training aligns with individual career goals and organizational needs, fostering continuous growth and adaptability. [2]HONO Ai. (2023).
Performance management is also undergoing a transformation, with AI enabling real-time monitoring and feedback. By analyzing various data sources, AI provides insights into productivity and engagement, allowing for timely interventions and support. Hono Ai. (2023)

Moreover, AI is enhancing employee engagement by detecting patterns in feedback and performance metrics, helping HR teams proactively address potential issues and improve retention. [3]SHL. (2023**).**
As organizations continue to integrate AI and automation into their talent management strategies, it's crucial to balance technological advancements with the human touch. Ensuring transparency, fairness, and empathy in AI applications will be key to building trust and fostering a positive workplace culture.
By embracing these innovations thoughtfully, businesses can create agile, inclusive, and future-ready workforces poised to thrive in the digital age.

Need of the study:

In the face of ongoing challenges such as skill shortages, workforce diversity, and rising employee expectations, organizations are increasingly turning to emerging technologies like AI and automation. However, how HR professionals perceive the role of these technologies in recruitment, employee development, and engagement remains underexplored. As organizations strive to implement data-driven and fair HR practices, understanding employee perceptions of AI's relevance, fairness, and ethical use is crucial for informed adoption. This study aims to fill that gap by exploring how HR professionals perceive AI's role in shaping future-ready, people-centric talent management.

Limitations of the Study:

- Limited to a specific sample (HR professionals only).
- Self-reported data may include bias.
- Rapidly evolving AI landscape may affect generalizability over time.

Statement of the problem:

There is a growing disconnect between traditional talent management practices and the evolving demands of modern workplaces. Organizations today face significant challenges such as talent shortages, inefficiencies, and increasing employee expectations. While AI and automation are often promoted as solutions, many companies lack clarity about how these technologies are perceived by HR professionals — especially regarding their ethical use, potential for job displacement, and compatibility with existing systems. This study seeks to explore the perceptions of HR professionals about the role of AI and automation in talent management, with a focus on understanding concerns, opportunities, and variations in viewpoints across different organizational roles and experience levels.

Objectives:

1. To compare employee perceptions of how AI and automation support recruitment, employee development, and workforce planning across different departments, designations, and age groups.
2. To assess differences in employee perceptions regarding human-centric and ethical dimensions of AI in HR across levels of experience and job roles.

Hypotheses:

1. Objective 1:

H0: There is no significant difference in perceptions of AI and automation across departments/designations/age groups.

H1: There is a significant difference in perceptions of AI and automation across departments/designations/age groups.
2. Objective 2:
H0: There is no significant difference in perceptions of human-centric and ethical AI practices across experience levels and job roles.
H1: There is a significant difference in perceptions of human-centric and ethical AI practices across experience levels and job roles.

Factors:

Perception Variables (IV)	Dependent Variable	Suv-Vaiables	References
Department, Designation, Age group, Experience	AI and Automation Adoption	AI-Integration, Automation, Tech-Application, Digitalization	[4]Marler, J. H., & Boudreau, J. W.(2017)
	Data-Driven HRM	Data-Decision-Making, Personalization, Workforce-Analytics, Emerging-Technologies	[5]Levenson, A.(2018)
	Talent Strategy and Agility	Talent-Planning, Performance-Management, Agility, Adaptability	[6]Bondarouk, T., &Brewster, C.(2016)
	Human-Centric and Ethical Practices	Ethics, Employer-Branding, Innovation, Upskilling	[7]Daugherty, P. R., & Wilson, H. J.(2018)
	AI and Automation Impact	Development, Efficiency, Effectiveness, Adoption	[8]Huang, M.-H., & Rust, R. T.2021
	Data-Driven HRM	Data-Decision-Making, Personalization, Workforce-Analytics, Emerging-Technologies	Levenson, A.(2018)
	Talent Management Outcomes	Acquisition, Retention, Continuity, Readiness	[9]Collings, D. G., & Mellahi, K.2009
	Human and Ethical Dimensions	Perception, Ethics-Outcomes, Competitiveness, Sustainability	Daugherty, P. R., & Wilson, H. J.2018

Research Methodology:

1. **Type: Descriptive and Exploratory Research**

- Descriptive: To assess the current status and impact of AI and automation in HR practices.

- Exploratory: To identify potential human-centric strategies and ethical considerations in adopting AI.

2. Research Approach:

A Mixed Method Approach was used to provide both breadth and depth of understanding.

- Quantitative data were collected using structured questionnaires designed to measure perceptions on a 5-point Likert scale.
- Qualitative data were obtained through semi-structured interviews to gain deeper insights into ethical concerns, emotional responses, and the perceived alignment between AI adoption and human values in HR.

3. Population and Sample:

- Population: The study targeted HR professionals, talent managers, and decision-makers from organizations across various industries, particularly those with exposure to or involvement in AI-driven HR practices.
- Sampling Technique: Purposive sampling was employed to select respondents with relevant experience or knowledge of AI in HRM.
- Sample Size: Quantitative survey: 100 respondents, Qualitative interviews: 8–10 participants

4. Data Collection Methods:

A. Primary Data:

- Quantitative Tool: A structured questionnaire comprising Likert-scale items focusing on perceptions of AI in recruitment efficiency, employee development, planning, fairness, and ethical issues.
- Qualitative Tool: Semi-structured interviews exploring participants' personal experiences, challenges, and recommendations related to AI and automation in HR.

B. Secondary Data:

Relevant academic journals, industry white papers, and published reports (e.g., SHRM, McKinsey, Forbes, HONO AI) were reviewed to support the theoretical foundation and context of the study.

5. Data Analysis Techniques:

- Descriptive Statistics were used to summarize and analyze overall perception levels regarding AI and automation in HR functions.
- Kruskal-Wallis H Test, a non-parametric method, was employed to examine whether perceptions significantly differ across demographic variables such as department, designation, age group, and years of experience.

Data Analysis & Interpretation:

A. Descriptive Statistics:

Descriptive statistics were computed to assess the overall perceptions of employees toward AI and automation in talent management. The results (N = 100) showed high mean scores across all dimensions, indicating a generally positive perception.

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
AAA_AVG	100	4	5	4.45	.274
DDH_AVG	100	4	5	4.36	.366
TSA_AVG	100	4	5	4.46	.374

HCEP_AVG	100	4	5	4.48	.370
AAI_AVG	100	4	5	4.63	.367
DDHO_AVG	100	4	5	4.65	.402
TMO_AVG	100	4	5	4.57	.331
HED_AVG	100	4	5	4.58	.372
Valid N (listwise)	100				

Therefore, these high mean values suggest that employees generally agree AI and automation contribute positively across HR areas.

B. Inferential Statistics:

Inferential statistics were applied to determine whether there are statistically significant differences in HR professionals' perceptions of AI and automation across various demographic groups. Specifically, the Kruskal-Wallis H test, a non-parametric test is used to compare perception scores based on variables such as department, designation, age group, and years of experience. This approach helps identify patterns in how different segments of respondents perceive the role, fairness, and human-centricity of AI in talent management.

1. AI and Automation Adoption-Department:

Ranks			
	Department	N	Mean Rank
AAA_AVG	HR	19	11.68
	Recruitment & Training	1	15.50
	Training & development	3	15.67
	HR Operations & Administration	1	15.50
	Total	24	

Test Statistics[a,b]	
	AAA_AVG
Chi-Square	1.371
df	3
Asymp. Sig.	.712
a. Kruskal Wallis Test	
b. Grouping Variable: Department	

Interpretation:

A Kruskal-Wallis H test revealed no statistically significant difference in AI & Automation Adoption scores across different departments, $\chi^2(3) = 1.37$, $p = .712$. This suggests that employee perceptions of AI adoption are consistent across departments.

2. Data-Driven HRM- Designation:

Ranks

	Designation	N	Mean Rank
DDH_AVG	Asst.Manager	23	50.48
	Hr C0-ordinator	2	60.50
	T&D Officer	2	60.50
	Manager	20	47.63
	HR Manager	2	20.00
	Compensation & benifits analyst	1	20.00
	Seniour HR Manager	11	57.23
	Operations Executive	3	53.50
	HR Business Partner	1	60.50
	HR Assistant	6	43.42
	Finance Executive	17	41.94
	Syaytem Administrator	1	20.00
	ASO	6	68.83
	AFO	1	20.00
	Accountant	1	60.50
	Total	97	

Test Statistics[a,b]

	DDH_AVG
Chi-Square	12.582
df	14
Asymp. Sig.	.560
a. Kruskal Wallis Test	
b. Grouping Variable: Designation	

Interpretation:

A Kruskal-Wallis test indicated no significant differences in Data-Driven HRM perceptions across designations, $\chi^2(14) = 12.58$, $p = .560$. Thus, perceptions of how data-driven practices are used in HR are similar across job roles.

3. Talent Strategy and Agility-Age group:

Ranks

	Age group	N	Mean Rank
TSA_AVG	18-25	2	3.50
	25-35	40	51.60
	35-45	48	50.58
	45& above	10	55.10
	Total	100	

Test Statistics[a,b]	
	TSA_AVG
Chi-Square	5.796
df	3
Asymp. Sig.	.122
a. Kruskal Wallis Test	
b. Grouping Variable: Age group	

Interpretation:
The Kruskal-Wallis H test showed no significant differences in Talent Strategy and Agility scores among age groups, $\chi^2(3) = 5.80$, $p = .122$. This result implies that age does not significantly influence employees' perceptions of talent agility and planning supported by AI.

4. Human-Centric and Ethical Practices-Experience:

Ranks			
	Experience	N	Mean Rank
HCEP_AVG	2-5	4	15.50
	6-10	19	61.03
	10&above	77	49.72
	Total	100	

Test Statistics[a,b]	
	HCEP_AVG
Chi-Square	8.886
df	2
Asymp. Sig.	.012
a. Kruskal Wallis Test	
b. Grouping Variable: Experience	

Interpretation:
A Kruskal-Wallis test showed a significant difference in perceptions of human-centric ethical AI practices based on experience level, $\chi^2(2) = 8.89$, $p = .012$. Employees with 6–10 years of experience reported higher mean ranks, indicating they perceive greater integration of human values in AI-based HR practices.

5. AI and Automation Impact- Department:

Ranks			
	Department	N	Mean Rank
AAI_AVG	HR	19	35.84
	Recruitment & Training	1	5.50
	Training & development	3	24.83

	HR Operations & Administration	1	21.00
	HR Compliance & Policy	2	55.50
	Marketing	1	21.00
	Compensation & Benefits	2	34.50
	Organizational Development	1	55.50
	Operations / Production Department	1	55.50
	Finance	17	26.65
	Marketing	4	31.13
	IT	12	38.42
	Marketing & Sales	2	45.00
	Supply & Logistic	1	55.50
	Total	67	

Test Statistics[a,b]	
	AAI_AVGDV
Chi-Square	14.772
df	13
Asymp. Sig.	.322
a. Kruskal Wallis Test	
b. Grouping Variable: Department	

Interpretation:

The Kruskal-Wallis test found no significant difference in perceived AI impact across departments, $\chi^2(13) = 14.77$, $p = .322$. This indicates that departments generally share similar views on the effectiveness of AI and automation in HR functions.

6. Data-Driven HR Outcomes- Designations:

Ranks			
	Designation	N	Mean Rank
DDHO_AVG	Asst.Manager	23	48.76
	Hr C0-ordinator	2	29.25
	T&D Officer	2	43.50
	Manager	20	46.08
	HR Manager	2	24.50
	Compensation & benifits analyst	1	34.00
	Seniour HR Manager	11	41.73
	Operations Executive	3	63.83
	HR Business Partner	1	74.00
	HR Assistant	6	52.33

	Finance Executive	17	60.41
	System Administrator	1	74.00
	ASO	6	37.42
	AFO	1	43.50
	Accountant	1	74.00
	Total	97	

Test Statistics[a,b]	
	DDHO_AVGDV
Chi-Square	12.513
df	14
Asymp. Sig.	.565
a. Kruskal Wallis Test	
b. Grouping Variable: Designation	

Interpretation:

No significant differences were observed in Data-Driven HR Outcomes across different designations, $\chi^2(14) = 12.51$, $p = .565$. This suggests job role does not significantly affect how employees view the outcomes of AI-driven HR decisions.

7. Talent Management Outcomes-Age Group:

Ranks			
	Age group	N	Mean Rank
TMO_AVG	18-25	2	8.00
	25-35	40	59.33
	35-45	48	44.19
	45& above	10	54.00
	Total	100	

Test Statistics[a,b]	
	DDHO_AVGDV
Chi-Square	.924
df	3
Asymp. Sig.	.820
a. Kruskal Wallis Test	
b. Grouping Variable: Designation	

Interpretation:

There was no significant difference in Talent Management Outcomes across age groups, $\chi^2(3) = 0.92$, $p = .820$. This indicates similar perceptions of AI's role in supporting talent acquisition, retention, and readiness across all age groups.

8. Human and Ethical Dimensions-Experience:

Ranks			
	Experience	N	Mean Rank
HED_AVG	2-5	4	72.00
	6-10	19	65.37
	10&above	77	45.71
	Total	100	

Test Statistics[a,b]	
	HED_AVGDV
Chi-Square	9.796
df	2
Asymp. Sig.	.007
a. Kruskal Wallis Test	
b. Grouping Variable: Experience	

Interpretation:

The Kruskal-Wallis H test revealed a significant difference in Human & Ethical Dimension scores based on experience, $\chi^2(2) = 9.80$, $p = .007$. Employees with less experience (2–5 years and 6–10 years) reported **higher scores** than those with over 10 years of experience, suggesting younger professionals view AI-driven HR as more ethically aligned and human-focused.

Hypotheses Decision:

1. **Hypothesis 1 (Objective 1):**
   Since none of the differences are statistically significant ($p > .05$), we fail to reject the null hypothesis (H0)**.**
   Result**:** There is no significant difference in employees' perceptions of AI and automation across departments, designations, or age groups**.**
2. **Hypothesis 2 (Objective 2):**
   Since both p-values are less than .05, we reject the null hypothesis (H0).
   Result: There is a significant difference in how employees with different experience levels perceive human-centric and ethical practices in AI-driven HR systems.

Findings:

A. Descriptive Findings:

- ✓ All variables (e.g., AI adoption, data-driven HR, talent strategy, ethical practices) had mean scores above 4.3, indicating high agreement among employees.
- ✓ The highest mean was observed for AI & Automation Impact ($M = 4.63$) and Data-Driven HR Outcomes ($M = 4.65$)**,** showing strong employee confidence in AI's effectiveness.

B. Inferential Statistics:

3. AI Adoption Across Departments: No significant difference found. Employees across various departments perceive AI adoption similarly. ($\chi^2(3) = 1.37$, $p = .712$)
4. Data-Driven HRM Across Designations: No significant difference. ($\chi^2(14) = 12.58$, $p = .560$). Job title does not influence perception of data-driven HR practices.

5. Talent Strategy and Agility Across Age Groups: No significant variation. ($\chi^2(3) = 5.80$, $p = .122$). All age groups view talent agility supported by AI in a similar way.
6. Human-Centric Ethical Practices Across Experience: Significant difference found. ($\chi^2(2) = 8.89$, $p = .012$). Employees with 6–10 years of experience perceive human values in AI usage more positively than others.
7. AI Impact Across Departments: No significant difference. ($\chi^2(13) = 14.77$, $p = .322$). Perceptions of AI's impact on HR are consistent across departments.
8. Data-Driven HR Outcomes Across Designations: No significant difference. ($\chi^2(14) = 12.51$, $p = .565$). Designation does not affect how employees view AI-driven HR outcomes.
9. Talent Management Outcomes Across Age Groups: No significant difference. ($\chi^2(3) = 0.92$, $p = .820$). Age is not a major factor in evaluating talent management effectiveness through AI.
10. Human & Ethical Dimensions Across Experience: Significant difference observed. ($\chi^2(2) = 9.80$, $p = .007$). Employees with less experience (2–10 years) see AI in HR as more ethical and human-friendly than highly experienced staff.

Conclusion:

1. Employees across all roles and demographics generally perceive AI and automation positively in HR functions.
2. Experience level plays a role in shaping views on human-centric and ethical practices in AI-driven HR systems.
3. There are no significant differences in AI perceptions based on department, designation, or age group, indicating a uniform organizational acceptance of AI-enabled HR functions.
4. The findings support the importance of integrating AI with human values, especially in training mid-career employees to align with AI tools.
5. These insights can help HR departments customize AI integration strategies to be more inclusive and ethical.

Suggestions:

1. Design Experience-Based AI Training:

a. Since perceptions of ethical AI vary by experience, offer customized workshops: For mid-level employees (6–10 years), enhance their role as AI champions. For senior employees (10+ years), address trust issues or resistance by emphasizing transparency, control, and human oversight in AI systems.

2. Promote Human-Centric AI Policies:

a. Establish ethical AI usage guidelines in HR processes. Reinforce AI as a support tool, not a decision-maker — this can improve acceptance across all experience levels.

3. Strengthen Feedback Mechanisms:

a. Encourage employees to share feedback on AI-based tools used in recruitment, performance reviews, and training. Use that feedback to improve AI tools and maintain a people-first approach.

4. Uniform Awareness Across Departments:

a. Although department-wise differences were not significant, keep promoting inter-departmental AI knowledge sharing through: Cross-functional HR-AI panels & Shared success stories in recruitment or onboarding automation.

5. Leverage Positive Perception of AI Impact:

a. The high mean scores across AI-related variables indicate strong acceptance. Use this momentum to expand AI usage in:
Succession planning
Skills gap analysis
Personalized learning and development (L&D) paths

6. Avoid One-Size-Fits-All Tools:

a. While AI adoption was consistent, individual needs still exist. Deploy adaptive AI tools that can adjust recommendations or decision-making logic based on role, experience level, or individual preferences.

7. Periodic Evaluation of AI Ethics in HR:

a. Since ethical perceptions shift by experience, form an AI Ethics Review Committee within HR to: Audit tools for fairness, bias, and transparency. Involve employees from various experience levels

6. Highlight Human Oversight

a. Promote the message that AI supports but does not replace human judgment. This helps build trust among senior and experienced employees, who may fear dehumanization or loss of control.

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