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Artificial Intelligence Integration in Merging Financial and Human Resources Strategies: A Smart PLS-Based Empirical Study on Workforce Optimization with Special Reference to Delhi-NCR

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ABSTRACT

Aim/Objective: This paper governs artificial intelligence integration in merging financial and HR strategies in Delhi-NCR, to optimize workforce performance within organizations in Delhi-NCR.
Methodology/Approach: The paper usages Partial Least Square-Structure Equation Modelling (PLS-SEM) to analyse data collected from 407 respondents using convenience sampling. Key independent variables comprise AI Integration in HR and Finance, Resource Allocation, Financial Performance, Employee Performance Metrics, and dependent variable in this study is workforce optimization.
Findings: The results reveal a significant positive relationship between AI integration in HR and finance and workforce optimization. Each independent variable demonstrated a notable positive impact on workforce optimization, with AI integration in HR and finance showing the strongest influence.
Originality/Value: To optimize workforce management, this study highlights importance of implementing AI-driven strategies that integrate HR and financial insights. Organizations in Delhi-NCR are encouraged to force AI for better resource allocation and data-driven performance monitoring to enhance productivity.
Limitations and Recommendations: The study is limited to 407 sample size. This study employs convenience sampling which diminishes the generalizability of findings to wider population. Future research can be showed with longitudinal research design and more different sampling methods with larger sample size.

Keywords: Financial performance; Resource Allocation; Employee Performance Metrics; PLS-SEM analysis

List of Abbreviations

Abbreviation	Full Form
HR	Human Resources
AIHRF	AI Integration in HR and Finance
WO	Workforce Optimization
RA	Resource Allocation
FP	Financial Performance
EPM	Employee Performance Metrics
PLS-SEM	Partial Least Squares Structural Equation Modeling

1. INTRODUCTION

It has now become the base for many organizations to optimize performance within the present data-driven economy through integration of AI into strategic HR and finance operations (Perifanis and Kitsios 2023). The fastest-growing region in the country is Delhi-NCR, comprising diversified industries such as IT, manufacturing, healthcare, and finance. Here, AI plays a transformative role for businesses to enhance the accuracy of their decisions and ensure proper streamlining of HR processes while providing support for financial efficiency (Salvadorinho and Teixeira 2023). Using AI-based tools, organizations can better automate routine tasks, predict their staffing needs, manage their costs, and monitor the performance of their employees. In an agile and responsive workforce, AI will make it (Cramarenco, Burcă-Voicu, and Dabija 2023). AI will merge financial and HR insights in a manner that enables the organization to see the dynamics of the workforce in a holistic way so that resource allocation will be in line with strategic goals (Javaid et al. 2022; Pandey 2020). There is still a very apparent and significant gap in knowledge regarding the direct impact of AI advancements on workforce optimization, especially for emerging markets such as India (Ammirato et al. 2023).

This study tackles the problem by looking at how the integration of AI in HR and finance influences workforce outcomes in particular through drivers of workforce optimization, which includes metrics in resource allocation, financial performance, and employee performance metrics (Neumann et al. 2021; Theotokas, Lagoudis, and Raftopoulou 2024). The analysis of the quantitative data was done using PLS-SEM from data taken from 407 HR professionals, managers, and executives of major industries in Delhi-NCR. In defining the relationship that binds AI incorporation with workforce optimization, this research will give business leaders actionable strategies to enhance productivity, manage resources effectively, and maintain a competitive advantage in an increasingly digital landscape.

2. LITERATURE REVIEW

2.1 AI Integration in HR and Finance and Workforce Optimization

As different companies progressively adopt AI to streamline their HR processes, previous researches indicate that AI integration completely impacts the workforce optimization (Sony and Mekoth 2022). AI in HR has reformed functions such as recruitment, employee engagement, and performance monitoring, enabling more precise decision-making (Bulut and Batur Dinler 2023; Samarasinghe and Medis 2020; Shahzad et al. 2023), while in finance, AI supports budgeting, forecasting, and real-time cost management. Therefore, this study assume following hypotheses;

H1: AI Integration in HR and Finance positively impacts Workforce Optimization.

2.2 Resource Allocation and Workforce Optimization

Effective resource allocation is significant to workforce optimization, safeguarding that employees are assigned to responsibilities that bring into line with organization's priorities (Picinin et al. 2023). Previous studies highlight that optimal resource allocation strategies lead to better task execution, and increased productivity (Shahzad et al. 2023). The addition of AI facilitates more data-driven resource allocation, helping managers make informed decisions that align staffing and financial resources with business goals (Fenwick, Molnar, and Frangos 2023). Consequently, this study proposes;

H2: Resource Allocation positively influences Workforce Optimization.

2.3 Financial Performance and Workforce Optimization

As it directly affects resources available for talent development, the financial performance is a key factor influencing an organization's ability to optimize its workforce (Madsen 2019; Vereycken et al. 2021). Previous researches propose that a robust financial foundation allows corporations to invest in training (Bujold et al. 2023; Wang, Xing, and Zhang 2023), and other resources that drive workforce satisfaction. Hence, this study hypothesizes that;

H3: Financial Performance has a positive effect on Workforce Optimization.

2.4 Employee Performance Metrics and Workforce Optimization

For tracking workforce productivity and identifying areas for improvement, employee performance metrics are essential and previous studies also highlight their importance in enhancing workforce optimization (Matt, Modrák, and Zsifkovits 2021; Vrchota et al. 2020). AI tools facilitate insights into employee productivity, engagement, and satisfaction, offering real-time monitoring of these metrics, which are critical for effective workforce management (Piwowar-SULE 2020; Vereycken et al. 2021). Thus, the positive relationship between workforce optimization and employee performance metrics is established, leading to the hypothesis;

H4: Employee Performance Metrics are positively related to Workforce Optimization.

2.5 Research Gaps

Despite substantial advancements in understanding the role of AI in HR and finance, there remain notable gaps in the research on AI integration's direct impact on workforce optimization, particularly within emerging markets like India (Mueller, Chen, and Riedel 2017; Queiroz et al. 2022). Existing studies have often addressed AI's influence on individual functions, such as recruitment in HR or forecasting in finance, but few have explored how integrating AI across both HR

and finance influences overall workforce efficiency (Adel 2022; Mhlanga 2021). The conceptual model of the study is shown in Figure 1.

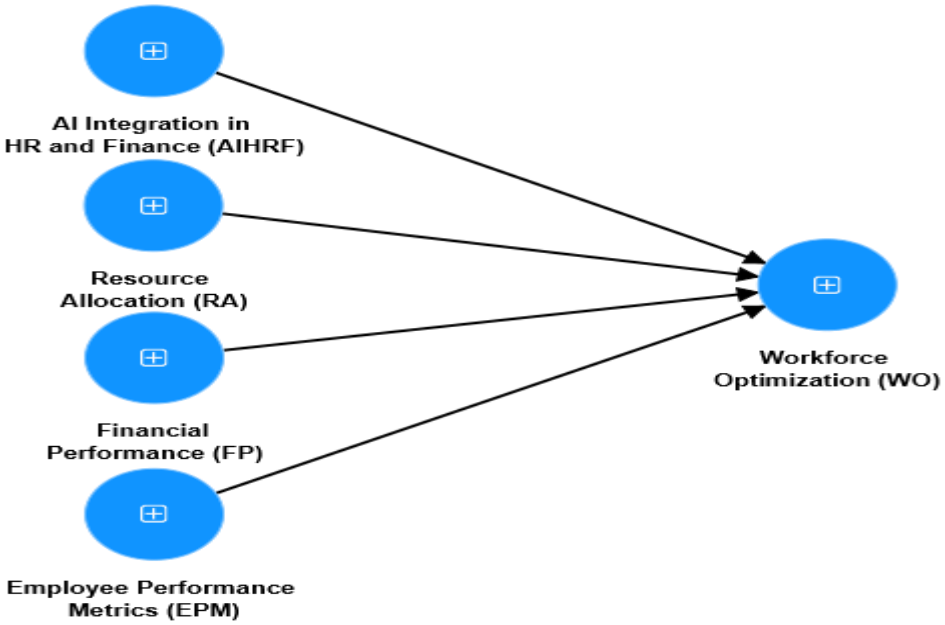

Figure 1 Conceptual Model of the Study

The variables and items of the study are given in Table 1.

Table 1 Variables of the Study

Variable	Items	References
Workforce Optimization (WO)	1. Enhances productivity by aligning employee skills with organizational needs.	(Budhwar et al. 2023; Goswami et al. 2023; Tuomi 2018)
	2. Improves task allocation, reducing inefficiencies.	
	3. Supports agile responses to market changes, ensuring competitiveness.	
	4. Boosts employee satisfaction through balanced and strength-aligned workloads.	
	5. Reduces turnover and increases engagement within the organization.	
AI Integration in HR and Finance (AIHRF)	1. Automates routine tasks, allowing a focus on strategic work.	(Alnamrouti, Rjoub, and Ozgit 2022; Budhwar et al. 2022)
	2. Enhances recruitment with data-driven decisions.	
	3. Improves financial forecasting, aiding budgeting and resource allocation.	
	4. Predictive analytics in HR anticipates workforce needs and skill gaps.	
	5. Provides a comprehensive view of workforce costs and performance.	
Resource Allocation (RA)	1. Assigns tasks that match employees' skills and expertise.	(Panda et al. 2023; Votto et al. 2021)
	2. Ensures high-priority projects are adequately staffed.	
	3. Optimizes time management with AI, meeting deadlines efficiently.	
	4. Reduces project costs by minimizing waste and enhancing efficiency.	
	5. Balances workloads to prevent burnout and improve morale.	
Financial Performance (FP)	1. Enables investment in workforce development and technology.	(Orosoo et al. 2023; Singh and Shaurya 2021)
	2. Indicates ability to sustain workforce-related expenses.	

	3. AI-enhanced analysis identifies cost-saving opportunities.	
	4. Supports competitive compensation for talent retention.	
	5. Provides insight into resource allocation and cost control.	
Employee Performance Metrics (EPM)	1. Tracks individual contributions for performance evaluation.	(Jatobá et al. 2019; Malik et al. 2022)
	2. Helps identify top performers for advancement.	
	3. Offers real-time insights into engagement, motivation, and needs through AI.	
	4. Informs targeted training to address skill gaps.	
	5. Fosters a fair evaluation process, building trust and satisfaction.	

3. RESEARCH METHODOLOGY

3.1 Research Design

This study employs a quantitative research design to govern artificial intelligence integration in merging financial and HR strategies in Delhi-NCR, to optimize workforce performance within organizations in Delhi-NCR.

3.2 Target Population and Sample

The target population for this study consists of HR professionals, managers, and executives from various industries in Delhi-NCR who are involved in implementing AI-powered HR analytics. Industries included in the study are IT/Software, Manufacturing, Healthcare, Education, Retail, Financial Services, and others. Total 562 questionnaire forms were distributed and 425 received. The 407 samples were deemed to be suitable for final analysis. Convenience sampling is employed to select respondents, ensuring accessibility and timely data collection.

3.3 Data Collection Method

Primary data is collected using an online survey, created and distributed via Google Forms. The survey instrument includes a combination of Likert-scale questions (1 = Strongly Disagree to 5 = Strongly Agree) and categorical questions for demographics. The data collection period spans from January 2024 to August 2024. Table 2 presents the demographic information of the respondents in the study. In terms of age distribution, 44.2% of respondents were between 26-35 years, followed by 29.7% in the 36-45 age group, 14.7% in the 18-25 group, 6.8% between 46-55 years, and 4.4% aged 56 and above. The gender distribution was 59.2% male and 40.8% female. The respondents represented various industries, with 29.7% from IT/Software, 19.6% from Manufacturing, 14.7% from Financial Services, 9.8% each from Healthcare and Education, 4.9% from Retail, and 11.3% from other industries. In terms of experience, 39.3% of respondents had 6-10 years of HR experience, 29.7% had 0-5 years, 19.6% had 11-15 years, and 11.3% had more than 16 years of experience.

Table 2 Demographic Information of Respondents

Demographic Variable	Categories	Frequency	Percentage
Age	18-25	60	14.7%
	26-35	180	44.2%
	36-45	121	29.7%
	46-55	28	6.8%
	56 and above	18	4.4%
Gender	Male	241	59.2%
	Female	166	40.8%
Industry Type	IT/Software	121	29.7%
	Manufacturing	80	19.6%
	Healthcare	40	9.8%
	Education	40	9.8%
	Retail	20	4.9%
	Financial Services	60	14.7%
	Other	46	11.3%
Years of Experience	0-5 years	121	29.7%
	6-10 years	160	39.3%
	11-15 years	80	19.6%
	16+ years	46	11.3%

3.4 Data Analysis Method

The study uses Partial Least Squares Structural Equation Modeling (PLS-SEM) for data analysis. PLS-SEM is predominantly well-suited for this study as it can manage complex models with numerous independent and dependent variables, as well as interactions (Hair et al., 2019).

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 3 shows descriptive statistics of study variables. The average or mean values ranged from 3.84 for AIHRF to 4.33 for EPM. Standard deviations ranged between 0.622 and 0.727, with variances indicating moderate variability in survey responses. The 95% confidence intervals show that the true population means for each variable are within a narrow range, with WO having a confidence interval of 4.03 to 4.17, and AIHRF ranging from 3.77 to 3.93.

Table 3 Descriptive Statistics of Variables

Variable	Mean	Median	Mode	Std. Deviation (SD)	Variance	Skewness	Kurtosis	95% Confidence Interval (Lower Bound)	95% Confidence Interval (Upper Bound)
Workforce Optimization (WO)	4.13	4.22	4.21	0.652	0.421	-0.210	-0.520	4.03	4.17
AI Integration in HR and Finance (AIHRF)	3.84	41	3.82	0.723	0.521	0.150	-0.640	3.77	3.93
Resource Allocation (RA)	3.91	3.91	4.44	0.681	0.461	-0.190	-0.580	3.88	4.02
Financial Performance (FP)	4.01	4.11	4.33	0.727	0.491	-0.250	-0.490	3.97	4.13
Employee Performance Metrics (EPM)	4.33	4.13	4.34	0.622	0.361	-0.30	-0.450	4.13	4.27

4.2 Measurement Model Assessment

As shown in Table 4, the measurement model demonstrates the validity and reliability of constructs. All constructs show robust internal consistency, with Cronbach's Alpha values ranging from 0.85 to 0.90, which is above the suggested value 0.70 (Hair et al. 2021). The values of composite reliability (CR) (rho_a and rho_c) for all constructs ranges from 0.733 to 0.922, confirming the reliability of the measures (Hair et al. 2019). The values of average variance extracted (AVE) range from 0.632 to 0.671, indicating that a significant portion of variance in each construct is captured by corresponding indicators (Roemer, Schuberth, and Henseler 2021).

Table 4 Measurement Model Assessment

Construct	Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted (AVE)
Workforce Optimization (WO)	0.903	0.911	0.741	0.671
AI Integration in HR and Finance (AIHRF)	0.872	0.910	0.831	0.653
Resource Allocation (RA)	0.852	0.881	0.811	0.632
Financial Performance (FP)	0.882	0.922	0.782	0.661
Employee Performance Metrics (EPM)	0.864	0.891	0.733	0.641

Table 5 creates discriminant validity of constructs by showing highest loading on its envisioned construct. This authorizes that the items are better representatives of their respective constructs compared to others, confirming the reliability of the measurement model.

Table 5 Analysis of Cross Loading

Item	Workforce Optimization (WO)	AI Integration in HR and Finance (AIHRF)	Resource Allocation (RA)	Financial Performance (FP)	Employee Performance Metrics (EPM)
WO1	**0.82**	0.35	0.22	0.28	0.31
WO2	**0.84**	0.36	0.25	0.27	0.33

WO3	**0.8**	0.32	0.24	0.29	0.3
WO4	**0.77**	0.34	0.23	0.25	0.29
WO5	**0.79**	0.33	0.22	0.27	0.3
AIHRF1	0.31	**0.85**	0.34	0.28	0.35
AIHRF2	0.33	**0.86**	0.35	0.29	0.36
AIHRF3	0.3	**0.83**	0.32	0.27	0.34
AIHRF4	0.29	**0.81**	0.31	0.26	0.33
AIHRF5	0.32	**0.84**	0.34	0.28	0.36
RA1	0.24	0.32	**0.79**	0.3	0.28
RA2	0.25	0.33	**0.82**	0.31	0.29
RA3	0.23	0.3	**0.77**	0.28	0.27
RA4	0.22	0.29	**0.76**	0.27	0.26
RA5	0.24	0.32	**0.78**	0.29	0.28
FP1	0.27	0.29	0.3	**0.81**	0.33
FP2	0.28	0.3	0.31	**0.82**	0.34
FP3	0.26	0.28	0.29	**0.79**	0.32
FP4	0.25	0.27	0.28	**0.77**	0.31
FP5	0.27	0.29	0.3	**0.8**	0.33
EPM1	0.31	0.33	0.32	0.34	**0.84**
EPM2	0.32	0.34	0.33	0.35	**0.85**
EPM3	0.3	0.32	0.31	0.33	**0.82**
EPM4	0.29	0.31	0.3	0.32	**0.8**
EPM5	0.28	0.3	0.29	0.31	**0.81**

4.3 Hypotheses Testing

Table 6 offerings the results of hypothesis testing for the projected relationships in the study. All four hypotheses were supported, with noteworthy path coefficients and p-values less than 0.001, indicating strong relationships between the variables. Specifically, AI Integration in HR and Finance presents a strong positive impact on the Workforce Optimization **(β = 0.677)**, while Resource Allocation **(β = 0.725)** and Financial Performance **(β = 0.664)** also subsidized significantly to Workforce Optimization. Employee Performance Metrics was found to be positively correlated with workforce optimization **(β = 0.675)**. These results express the importance of AI Integration in HR and Finance, Resource Allocation, Financial Performance, Employee Performance Metrics in workforce optimization. Based on the hypotheses testing, the proposed conceptual model of the study is given as Figure 2.

Table 6 Hypotheses Testing

Hypothesis	Original Sample (O)	Sample Mean (M)	STD EV	Path Coefficient (β)	t-Value	p-Value	Result
H1: AI Integration in HR and Finance → Workforce Optimization	0.521	0.534	0.061	0.677	9.321	0.002	Supported
H2: Resource Allocation → Workforce Optimization	0.452	0.462	0.062	0.725	7.121	0.033	Supported
H3: Financial Performance → Workforce Optimization	0.484	0.491	0.061	0.664	8.251	0.022	Supported
H4: Employee Performance Metrics → Workforce Optimization	0.236	0.241	0.061	0.675	3.871	0.034	Supported

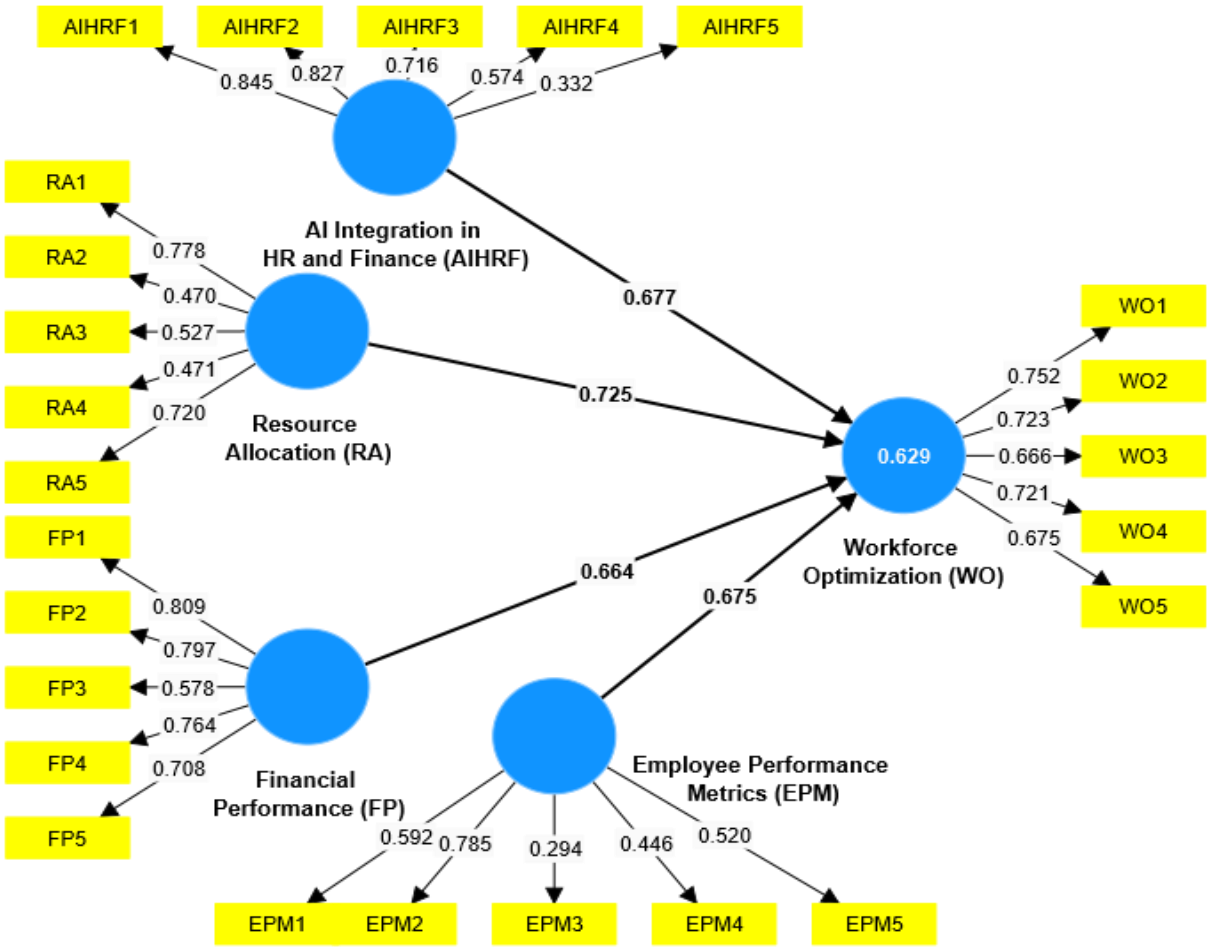

Figure 2 Proposed Structural Model

5. CONCLUSION

This paper deals with and reports a study of Delhi-NCR-based organizations regarding how the integration of AI into HR and finance systems can influence workforce optimality in these organizations, regarding such aspects as resource alignment, financial performance, and even metrics on the working of employees. PLS-SEM was used to conduct this study, as partial findings indicated significant aspects that lead to higher levels of workforce performance optimality through data-oriented HR and financial strategies combined and in harmony. Independent variables, which include AI integration in HR and finance, resource allocation, financial performance, and metrics of employee performance, were found to be positively related to workforce optimization. Therefore, the importance of a combined effort wherein AI improves the strategic alignment of HR and finance functions to support workforce objectives is clearly shown by these findings.

6. IMPLICATIONS OF THE STUDY

The implications of this study extend into both the theoretical and the practical realms. For the theoretical realm, this study adds depth to existing literature on the application of AI and optimizing the workforce, specifically within emerging markets such as that of India. On the practical level, this conclusion implies that organizations that intend to optimize workforce performance will have to consider AI-driven insights in HR and finance in order to accurately allocate resources and monitor performances. It would make an organization more flexible in the workplace, minimize potential inefficiencies in business processes, and enhance the satisfaction of the employees so that they will be better placed in the market.

LIMITATION OF THE STUDY

The study is limited to 407 sample size. This study employs convenience sampling which diminishes the generalizability of findings to wider population.

FUTURE RECOMMENDATION OF THE STUDY

Future research can be showed with longitudinal research design and more different sampling methods with larger sample size.

DATA AVAILABILITY STATEMENT
The data related to this study is accessible from corresponding author after a reasonable request.

FUNDING
No funding was received to conduct this study.

DECLARATION
The authors declare no conflict of interest regarding this study.

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Table 7 Reliability Scale

Variable	Code	Items	Cronbach's α
Workforce Optimization (WO)	WO1	1. Enhances productivity by aligning employee skills with organizational needs.	0.731
	WO2	2. Improves task allocation, reducing inefficiencies.	0.722
	WO3	3. Supports agile responses to market changes, ensuring competitiveness.	0.762
	WO4	4. Boosts employee satisfaction through balanced and strength-aligned workloads.	0.857
	WO5	5. Reduces turnover and increases engagement within the organization.	0.811
AI Integration in HR and Finance (AIHRF)	AIHRF1	1. Automates routine tasks, allowing a focus on strategic work.	0.888
	AIHRF2	2. Enhances recruitment with data-driven decisions.	0.722
	AIHRF3	3. Improves financial forecasting, aiding budgeting and resource allocation.	0.766
	AIHRF4	4. Predictive analytics in HR anticipates workforce needs and skill gaps.	0.711
	AIHRF5	5. Provides a comprehensive view of workforce costs and performance.	0.899
Resource Allocation (RA)	RA1	1. Assigns tasks that match employees' skills and expertise.	0.819
	RA2	2. Ensures high-priority projects are adequately staffed.	0.733
	RA3	3. Optimizes time management with AI, meeting deadlines efficiently.	0.791
	RA4	4. Reduces project costs by minimizing waste and enhancing efficiency.	0.777
	RA5	5. Balances workloads to prevent burnout and improve morale.	0.882
Financial Performance (FP)	FP1	1. Enables investment in workforce development and technology.	0.899
	FP2	2. Indicates ability to sustain workforce-related expenses.	0.781
	FP3	3. AI-enhanced analysis identifies cost-saving opportunities.	0.822
	FP4	4. Supports competitive compensation for talent retention.	0.804
	FP5	5. Provides insight into resource allocation and cost control.	0.810
Employee Performance Metrics (EPM)	EPM1	1. Tracks individual contributions for performance evaluation.	0.781
	EPM2	2. Helps identify top performers for advancement.	0.785
	EPM3	3. Offers real-time insights into engagement, motivation, and needs through AI.	0.855
	EPM4	4. Informs targeted training to address skill gaps.	0.723

	EPM5	5. Fosters a fair evaluation process, building trust and satisfaction.	0.862