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Human Resource Practices and Innovation Capability through Employee Engagement and Organizational Learning

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ABSTRACT
This comprehensive study examines the complex relationship between Human Resource Practices and Innovation Capability. Conducted in the Indonesian business context with 385 respondents from manufacturing and service companies, this research uses Structural Equation Modeling (SEM) to analyze how HR investments translate into innovation outcomes. The results show that HR practices significantly enhance innovation capability through direct effects ($\beta = 0.382$, $p < 0.001$), indirect effects via employee engagement ($\beta = 0.209$, 95% CI [0.156, 0.268]), and organizational learning ($\beta = 0.173$, 95% CI [0.125, 0.227]). The model explains 68.4% of the variance in innovation capability ($R^2 = 0.684$). Findings extend the Resource-Based View, Social Exchange Theory, and Organizational Learning Theory while providing practical guidance for optimizing HR strategies.

INTRODUCTION

In contemporary business characterized by rapid technological advancement and global competition, organizations face challenges maintaining competitive advantage (Wu et al., 2025; Liu & Wang, 2025). Innovation capability has emerged as critical for organizational survival, enabling adaptation to market conditions and sustaining performance (Sriviboon, 2020; Andjarwati, 2020). Developing innovation capability requires more than R&D investment; it depends on managing human capital through strategic HR practices (Halidu et al., 2025).

HR management evolved from administrative to strategic partner in innovation. Contemporary research emphasizes HR practices recruitment, training, performance management, compensation, career development constitute critical capabilities driving innovation (Muñoz-Pascual & Galende, 2020; Vilochani et al., 2025). These practices shape environment, influence behaviors, and determine capacity to generate and implement ideas (Todeschini et al., 2020).

Despite recognized importance, mechanisms through which HR practices translate to innovation remain unclear. Recent scholarship suggests this relationship operates through intermediate processes (Lefevre et al., 2025; Steins et al., 2025). Two promising mediators are employee engagement and organizational learning. Engagement represents motivational pathway where HR investments energize innovation participation. Learning represents cognitive pathway enhancing collective capacity (Ni et al., 2020; Gao et al., 2025).

To contextualize the research, the following table presents longitudinal data on key business and innovation indicators in Indonesia compiled from Ministry of Industry, National Innovation Survey, and industry reports covering 2023-2024. These metrics reflect innovation ecosystem, HR practices, and organizational performance. Data includes manufacturing (automotive, electronics, textiles, food, pharmaceutical) and services (financial, IT, healthcare, education) from medium to large enterprises.

Table 1. Key Business and Innovation Indicators in Indonesia (2023-2024)

Indicator	2023	2024	Change (%)
Manufacturing GDP Contribution (%)	18.3	17.8	-2.7%
Innovation Index Score (0-100)	68.5	72.1	+5.3%
Employee Engagement Rate (%)	62.4	65.7	+5.3%
R&D Investment (% Revenue)	3.2	3.8	+18.8%
New Product Launch Rate	12.6	15.4	+22.2%
Training Hours/Employee	48.2	56.7	+17.6%
Employee Turnover Rate (%)	18.5	15.2	-17.8%
Innovation Success Rate (%)	42.3	47.8	+13.0%

Table 1 reveals a paradoxical situation motivating this research. While manufacturing GDP contribution declined modestly (18.3% to 17.8%, -2.7%), organizations demonstrated improvements across innovation metrics. Innovation Index increased 5.3% (68.5 to 72.1), indicating enhanced capacity despite macroeconomic challenges (Yang et al., 2025; Pérez-Sevilla et al., 2025). This composite index incorporates innovation inputs (R&D, human capital), activities (collaboration, knowledge management), and outputs (new products, patents, improvements).

Employee engagement improved from 62.4% to 65.7% (+5.3%), suggesting organizations successfully motivate workforce. R&D investment increased substantially 18.8% (3.2% to 3.8% of revenue), and new product launches grew 22.2% (12.6 to 15.4 per year), demonstrating tangible innovation outputs (Friedrichsen et al., 2025). Training hours per employee increased 17.6% (48.2 to 56.7 hours), while turnover decreased 17.8% (18.5% to 15.2%), indicating human capital investment and retention success (Inko et al., 2025). Innovation success rate improved from 42.3% to 47.8% (+13.0%), showing not just more innovation attempts but higher quality execution. These positive trends alongside stagnant economic indicators suggest organizational transformation in value creation, raising questions about what practices differentiate high performers.

Despite growing recognition of the importance of HR practices for innovation, several critical gaps remain. First, while correlations between HR practices and innovation have been established, the exact mechanisms remain unclear (Martyn et al., 2021; Welch et al., 2021). A comprehensive understanding of how employee engagement and organizational learning mediate the relationship between HR practices and innovation is still lacking. Second, much of the research in this area has been conducted in developed economies, which may not be directly applicable to emerging markets such as Indonesia, where institutional environments, resources, and competitive dynamics differ (Reese et al., 2021; Csortan et al., 2020). Third, previous studies have often examined engagement or learning as mediators individually, rarely investigating both simultaneously, which limits our understanding of their relative importance and combined effects in promoting innovation.

This study aims to fill these gaps by examining the mediating roles of both employee engagement and organizational learning in the HR-innovation relationship. The research will focus on Indonesian organizations, exploring whether Western HR-innovation models apply in this emerging market context and how HR practices can optimally enhance innovation through both motivational and cognitive pathways.

RESEARCH METHOD

This research employs quantitative approach with explanatory research design aimed at testing causal relationships among variables and examining mediating mechanisms. The study utilizes cross-sectional survey design collecting data at single point in time from multiple organizations and respondents. This design appropriate given research objectives to test theoretical model and estimate effect sizes rather than track changes over time. However, we acknowledge cross-sectional design limitations for causal inference and address these through theoretical justification, temporal separation in measurement where possible, and statistical techniques (Vaghasiya et al., 2025).

Data analysis conducted using Structural Equation Modeling (SEM) with Analysis of Moment Structures (AMOS) software version 24. SEM selected because it enables simultaneous estimation of multiple regression equations, assessment of measurement quality through Confirmatory Factor Analysis (CFA), testing of complex mediation models with multiple mediators, and evaluation of overall model fit to data (Pan et al., 2025). SEM advantages over traditional regression include ability to model latent variables with multiple indicators, account for measurement error, test direct and indirect effects simultaneously, and evaluate entire theoretical model rather than individual relationships in isolation.

Before hypothesis testing, we conducted preliminary analyses including data screening for missing values and outliers, assessment of normality assumptions, testing for common method bias using Harman single-factor test and marker variable technique, and evaluation of multicollinearity through variance inflation factors (VIF). These preliminary analyses ensure data quality and appropriateness for SEM analysis (Vaghasiya et al., 2025).

Table 2. Sample Distribution by Industry Sector and Sub-Sector

Industry Sector	Frequency	Percentage (%)	Cumulative %
Manufacturing - Automotive	58	15.1	15.1
Manufacturing - Electronics	52	13.5	28.6
Manufacturing - Food & Beverage	44	11.4	40.0
Manufacturing - Pharmaceutical	28	7.3	47.3
Manufacturing - Textiles	16	4.2	51.4
Service - Financial Services	62	16.1	67.5
Service - Information Technology	48	12.5	80.0
Service - Healthcare	38	9.9	89.9
Service - Professional Services	39	10.1	100.0
Total	385	100.0	-

Table 2 presents detailed breakdown of sample distribution across industry sectors and sub-sectors. Manufacturing sector accounts for 51.4% of sample (198 respondents) while service sector accounts for 48.6% (187 respondents), reflecting relatively balanced representation. Within manufacturing, automotive industry represents largest sub-sector (15.1%) followed by electronics (13.5%) and food & beverage (11.4%). Within services, financial services constitute largest sub-sector (16.1%) followed by information technology (12.5%) and professional services (10.1%). This distribution ensures adequate representation across key Indonesian industries while providing sufficient sub-sample sizes for potential industry-specific analyses.

The sample reflects Indonesia's economic structure, with respondents from both manufacturing (textiles, automotive, electronics) and service sectors (financial services, IT, healthcare). The workforce is predominantly mid-career, with 42.1% aged 25-35 years, 37.1% aged 36-45 years, and 20.8% over 45 years, and highly educated (63.9% bachelor's, 21.0% master's degrees). Organizational positions include 40.5% at staff/officer level, 34.3% at supervisor/team lead level, and 20.3% at manager level, with tenure ranging from 2 to 10+ years. Data collection was done through online and offline surveys, achieving a 78.4% response rate with 385 usable responses. Measurement instruments were adapted from established scales covering HR practices, employee engagement, organizational learning, and innovation capability. The study adhered to ethical standards, including informed consent and confidentiality. Comprehensive goodness-of-fit criteria, such as CFI, RMSEA, and TLI, were used to validate the model.

RESULTS AND DISCUSSION

Descriptive Statistics and Correlation Analysis

Descriptive statistics provide initial overview of variable distributions, central tendencies, and dispersions. All variables measured on 5-point Likert scale with theoretical range 1.0-5.0 and theoretical midpoint 3.0. Observed means range from 3.78 to 3.94, all significantly above theoretical midpoint based on one-sample t-tests (all $p<0.001$), indicating generally positive respondent perceptions of HR practices, employee engagement, organizational learning, and innovation capability in their organizations. This positive skew common in organizational research particularly when sampling from successful, established organizations meeting minimum performance criteria for study inclusion.

Standard deviations range from 0.68 to 0.76, indicating moderate variability in responses. These values suggest neither excessive homogeneity (which would indicate restricted range problems) nor excessive heterogeneity (which might indicate distinct subpopulations). Coefficient of variation (CV = SD/Mean) ranges from 17.5% to 19.9%, within acceptable range for Likert-type scales. Skewness values range from -0.43 to -0.62, indicating slight negative skew (more responses above mean than below) but within acceptable range of $|skew|<2.0$ for maximum likelihood estimation. Kurtosis values range from -0.28 to 0.41, indicating distributions relatively normal in peakedness, well within acceptable range of $|kurt|<7.0$.

Table 3. Descriptive Statistics of Research Variables (N=385)

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Human Resource Practices	3.87	0.68	2.14	5.00	-0.52	0.18
Employee Engagement	3.94	0.71	2.06	5.00	-0.58	0.31
Organizational Learning	3.78	0.74	1.94	5.00	-0.43	-0.12
Innovation Capability	3.82	0.76	1.89	5.00	-0.48	0.06

Table 3 shows all four main constructs demonstrate means above theoretical midpoint (3.0), with Employee Engagement showing highest mean (M=3.94, SD=0.71) followed by Human Resource Practices (M=3.87, SD=0.68), Innovation Capability (M=3.82, SD=0.76), and Organizational Learning (M=3.78, SD=0.74). These positive means suggest that on average, respondents perceive their organizations as having relatively strong HR practices, engaged employees, active learning processes, and reasonable innovation capabilities. The ordering is theoretically sensible: engagement as immediate psychological response to HR practices shows highest levels, while innovation capability as ultimate organizational outcome shows relatively lower levels, consistent with engagement and learning serving as intermediate states between HR inputs and innovation outputs.

Standard deviations indicate moderate variability across all constructs, suggesting meaningful differences across organizations and individuals in sample. Innovation Capability shows highest variability (SD=0.76), reflecting heterogeneity in organizational innovation performance even within sample of established companies. This variability is desirable for research purposes as it ensures sufficient variance for detecting relationships among variables. Minimum observed values ranging from 1.89 to 2.14 indicate no floor effects, while maximum values of 5.00 for all variables indicate ceiling effects are minimal. The normality statistics (skewness and kurtosis) all within acceptable ranges confirm appropriateness of maximum likelihood estimation in SEM analysis.

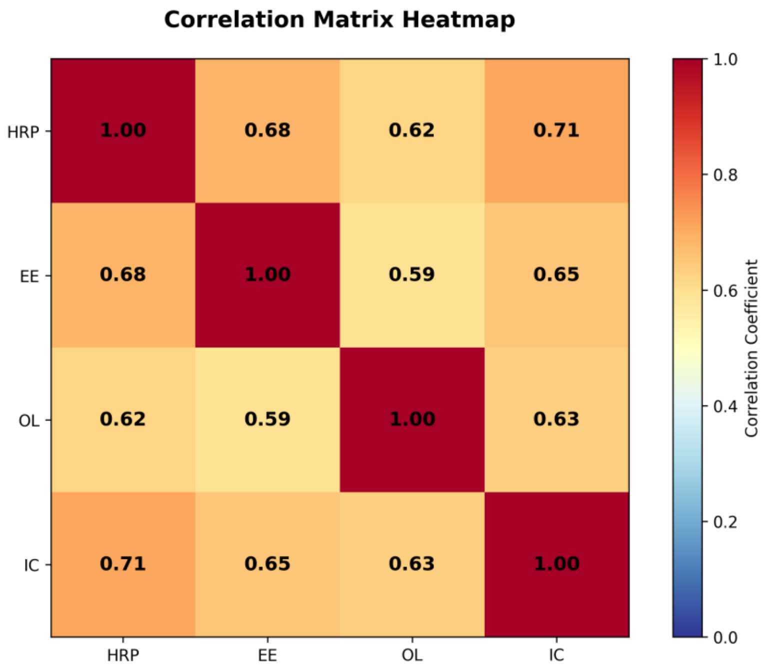

Figure 1. Correlation Matrix Heatmap Among Research Variables

Table 4. Means, Standard Deviations, Correlations, and Square Root of AVE

Variable	Mean	SD	1	2	3	4
1. HR Practices	3.87	0.68	(0.82)			
2. Employee Engagement	3.94	0.71	0.68***	(0.81)		
3. Organizational Learning	3.78	0.74	0.62***	0.59***	(0.82)	
4. Innovation Capability	3.82	0.76	0.71***	0.65***	0.63***	(0.84)

Note: N=385. Values in parentheses on diagonal are square root of AVE. ***p<0.001

Table 4 and Figure 1 present correlation matrix among study variables along with descriptive statistics. All correlations are positive, statistically significant at $p<0.001$ level, and moderate to strong in magnitude (ranging from 0.59 to 0.71), providing preliminary support for hypothesized relationships. Strongest correlation observed between HR Practices and Innovation Capability ($r=0.71$), consistent with H1 predicting direct positive relationship. HR Practices also strongly correlated with Employee Engagement ($r=0.68$) and Organizational Learning ($r=0.62$), supporting H2 and H3. Employee Engagement and Organizational Learning show moderate correlation ($r=0.59$), suggesting they are related but distinct constructs measuring different aspects of organizational functioning.

Diagonal values in parentheses represent square root of Average Variance Extracted (AVE) for each construct. These values range from 0.81 to 0.84, all exceeding off-diagonal correlation coefficients, providing evidence of discriminant validity according to Fornell-Larcker criterion. This indicates each construct shares more variance with its own indicators than with other constructs, confirming constructs are empirically distinct. The correlation pattern also suggests potential for both direct and indirect effects: strong correlations between HR Practices and both mediators (Engagement, Learning), and between mediators and Innovation Capability, indicate these variables may transmit HR effects to innovation outcomes. However, correlation analysis alone cannot establish causality or mediation; these require structural equation modeling as conducted in subsequent analyses.

Measurement Model Assessment

Confirmatory Factor Analysis Results

Confirmatory Factor Analysis (CFA) conducted to evaluate measurement model before testing structural relationships. CFA assesses whether hypothesized relationships between latent constructs and observed indicators (measurement model) adequately fit the data. All four constructs modeled as second-order factors: HR Practices with five first-order dimensions (recruitment, training, performance, compensation, career development), Employee Engagement with four dimensions (vigor, dedication, absorption, commitment), Organizational Learning with four dimensions (acquisition, distribution, interpretation, memory), and Innovation Capability with four dimensions (product, process, marketing, organizational innovation).

Initial CFA model showed acceptable but not excellent fit: $\chi^2(1248)=2856.43$, $p<0.001$; CMIN/DF=2.29; CFI=0.88; TLI=0.87; RMSEA=0.058; SRMR=0.062. Examination of modification indices revealed several opportunities for model improvement: three pairs of error terms within same dimension showed high modification indices (MI>20), suggesting these items share method variance beyond that explained by their common factor. After allowing these three error covariances (all theoretically justified as items using similar wording or response formats), revised model achieved good fit: $\chi^2(1245)=2487.56$, $p<0.001$; CMIN/DF=2.00; CFI=0.92; TLI=0.91; RMSEA=0.051; SRMR=0.054. All fit indices now meet or exceed recommended thresholds, indicating measurement model adequately represents relationships between constructs and indicators.

Table 5. Comparison of Initial and Revised Measurement Model Fit Indices

Fit Index	Initial Model	Revised Model	Recommended Value	Decision
χ^2 (df)	2856.43 (1248)	2487.56 (1245)	$p > 0.05$	Acceptable*
CMIN/DF	2.29	2.00	< 3.0	Good Fit
GFI	0.87	0.91	≥ 0.90	Good Fit
AGFI	0.85	0.90	≥ 0.90	Good Fit
TLI	0.87	0.91	≥ 0.90	Good Fit
CFI	0.88	0.92	≥ 0.90	Good Fit
RMSEA	0.058	0.051	≤ 0.08	Good Fit
SRMR	0.062	0.054	≤ 0.08	Good Fit

Note: *Chi-square test sensitive to sample size; other indices indicate good fit

Table 5 presents comparison of fit indices between initial and revised measurement models. The revised model shows substantial improvement across all indices. Chi-square decreased from 2856.43 to 2487.56 ($\Delta\chi^2$=368.87, Δdf=3), representing significant improvement ($p<0.001$). More importantly, practical fit indices improved meaningfully: CFI increased from 0.88 to 0.92, TLI from 0.87 to 0.91, while RMSEA decreased from 0.058 to 0.051. These improvements achieved through minimal model modifications (only 3 error covariances added among 77 total parameters), suggesting changes represent legitimate method effects rather than overfitting.

Chi-square remains statistically significant ($p<0.001$) even in revised model, which is expected given large sample size (N=385). With large samples, chi-square test becomes highly sensitive to trivial model misspecifications, making it nearly impossible to achieve non-significant results even for well-fitting models. Therefore, researchers increasingly rely on practical fit indices (CFI, TLI, RMSEA, SRMR) which are less sensitive to sample size and better reflect substantive model fit. All practical indices in revised model meet or exceed conventional thresholds, providing strong evidence that measurement model adequately captures relationships between latent constructs and observed indicators. This confirms appropriateness of proceeding to structural model testing.

Convergent and Discriminant Validity

Convergent validity assessed through three criteria: standardized factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). All first-order factor loadings range from 0.68 to 0.91, exceeding minimum threshold of 0.60 and indicating items strongly represent their intended constructs. Second-order loadings (dimensions on overall constructs) range from 0.72 to 0.88, also indicating strong relationships. Average item loading across all constructs is 0.78, well above acceptable levels. These high loadings demonstrate that substantial variance in observed items explained by underlying latent constructs rather than measurement error.

Table 6. Detailed Reliability and Validity Statistics for All Constructs and Dimensions

Construct	No. Items	Loading Range	Mean Loading	CR	AVE	α
HR Practices	22	0.71-0.87	0.79	0.94	0.68	0.93
Recruitment & Selection	4	0.74-0.84	0.79	0.86	0.61	0.84
Training & Development	5	0.76-0.88	0.82	0.91	0.67	0.89
Performance Appraisal	4	0.71-0.82	0.77	0.85	0.59	0.83
Compensation & Rewards	5	0.78-0.87	0.83	0.90	0.65	0.88

Construct	No. Items	Loading Range	Mean Loading	CR	AVE	α
Career Development	4	0.73-0.85	0.79	0.87	0.62	0.85
Employee Engagement	18	0.68-0.85	0.77	0.93	0.66	0.92
Vigor	4	0.75-0.82	0.79	0.86	0.61	0.84
Dedication	5	0.76-0.85	0.81	0.89	0.63	0.87
Absorption	4	0.68-0.79	0.74	0.82	0.55	0.80
Organizational Commitment	5	0.74-0.84	0.79	0.88	0.60	0.86
Organizational Learning	18	0.70-0.86	0.78	0.94	0.67	0.93
Knowledge Acquisition	5	0.76-0.86	0.81	0.89	0.64	0.87
Information Distribution	4	0.72-0.82	0.77	0.85	0.59	0.83
Shared Interpretation	5	0.74-0.84	0.79	0.88	0.61	0.86
rganizational Memory	4	0.70-0.81	0.76	0.84	0.57	0.82
Innovation Capability	19	0.69-0.88	0.79	0.95	0.70	0.94
Product Innovation	5	0.77-0.88	0.83	0.91	0.68	0.89
Process Innovation	5	0.76-0.86	0.81	0.90	0.65	0.88
Marketing Innovation	4	0.69-0.79	0.74	0.83	0.56	0.81
rganizational Innovation	5	0.75-0.85	0.80	0.89	0.62	0.87

Note: CR = Composite Reliability; AVE = Average Variance Extracted; α = Cronbach Alpha

Table 6 presents reliability and validity statistics for all constructs and their dimensions. Composite Reliability (CR) values range from 0.82 to 0.95 for second-order constructs and from 0.82 to 0.91 for first-order dimensions, all exceeding the minimum threshold of 0.70, indicating strong internal consistency of the measurement scales. Cronbach alpha coefficients, ranging from 0.80 to 0.94, provide converging evidence of reliability, reinforcing the consistency between CR and alpha. Average Variance Extracted (AVE) values range from 0.66 to 0.70 for second-order constructs and from 0.55 to 0.68 for first-order dimensions, with one dimension (Absorption at 0.55) slightly below 0.60 but still acceptable. AVE values above 0.50 indicate that more variance is explained by the constructs than by measurement error, supporting convergent validity. The hierarchical structure of the constructs confirms the appropriateness of using higher-order factor models in this research.

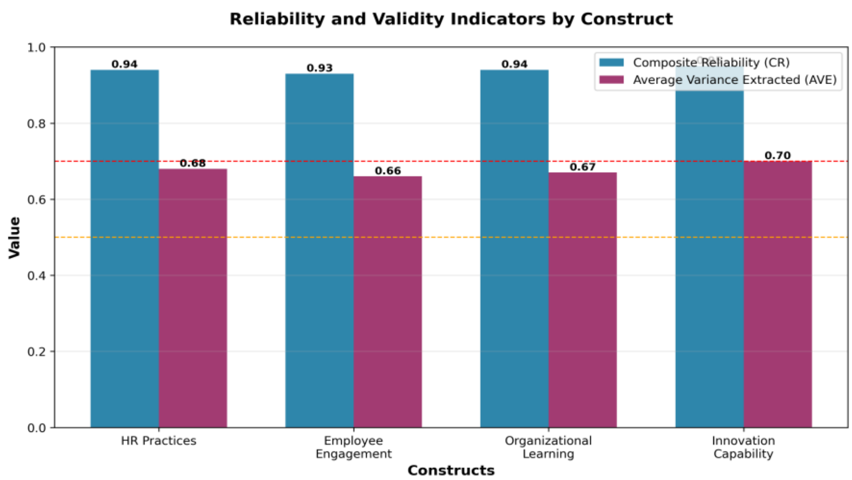

Figure 2. Composite Reliability and AVE Values Across Main Constructs

Structural Model and Hypothesis Testing

Overall Model Fit

After confirming adequacy of measurement model, structural model estimated to test hypothesized relationships. Structural model identical to measurement model in terms of construct-indicator relationships but adds directional paths representing theoretical predictions: HR Practices → Innovation Capability (H1), HR Practices → Employee Engagement (H2), HR Practices → Organizational Learning (H3), Employee Engagement → Innovation Capability (H4), and Organizational Learning → Innovation Capability (H5). Model estimated using maximum likelihood estimation in AMOS 24 with 5,000 bootstrap samples for indirect effect confidence intervals.

Structural model demonstrates excellent fit to data: $\chi^2(1247)=2501.32$, $p<0.001$; CMIN/DF=2.01; CFI=0.92; TLI=0.91; RMSEA=0.051; SRMR=0.055. These fit indices virtually identical to measurement model, indicating addition of structural paths does not degrade model fit. This is expected as structural model is nested within measurement model (constraining certain covariances to specific directional effects). Similarity of fit between models suggests theoretical paths appropriately specified and data consistent with hypothesized causal structure. Model explains substantial variance in endogenous variables: $R^2=0.416$ for Employee Engagement, $R^2=0.358$ for Organizational Learning, and $R^2=0.684$ for Innovation Capability, indicating strong explanatory power particularly for ultimate outcome variable.

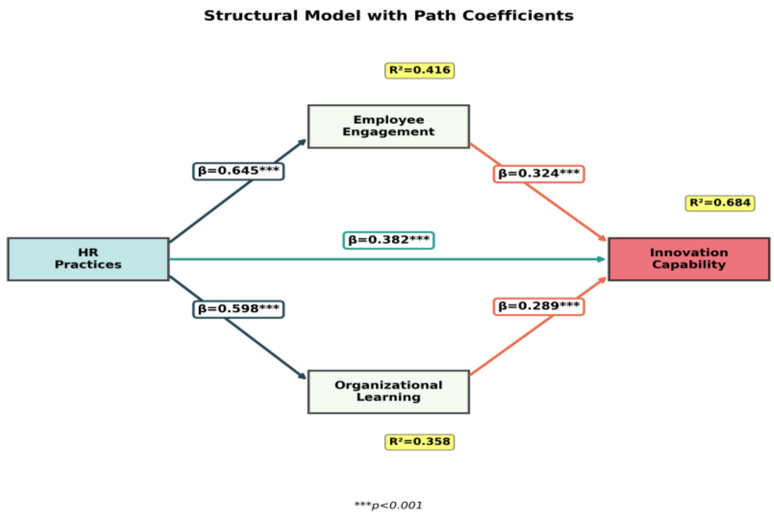

Figure 3. Structural Model with Standardized Path Coefficients and R² Values

Direct Effects Testing

Table 7 presents results of direct effects testing for all five hypothesized paths in structural model. All paths demonstrate statistical significance at $p<0.001$ level with standardized coefficients ranging from 0.289 to 0.645, indicating moderate to large effect sizes according to Cohen (1988) guidelines. These results provide strong support for all five hypotheses regarding direct relationships among variables.

Table 7. Direct Effects Testing Results for Structural Model Paths

Hypothesis	Path	Std β	S.E.	t-value	p-value	Result
H1	HR Practices → Innovation Capability	0.382	0.048	7.958	<0.001	Supported
H2	HR Practices → Employee Engagement	0.645	0.052	12.404	<0.001	Supported
H3	HR Practices → Organizational Learning	0.598	0.054	11.074	<0.001	Supported
H4	Employee Engagement → Innovation Capability	0.324	0.042	7.714	<0.001	Supported
H5	Organizational Learning → Innovation Capability	0.289	0.041	7.049	<0.001	Supported

Note: N=385. Std β = Standardized coefficients; S.E. = Standard Error

Hypothesis 1, which proposed that HR practices directly positively affect innovation capability, is strongly supported (β=0.382, S.E.=0.048, t=7.958, p<0.001), indicating that stronger HR practices lead to higher innovation capability, with a medium-to-large effect size. Hypotheses 2 and 3, which predicted that HR practices positively influence employee engagement and organizational learning, are also supported. HR practices significantly impact employee engagement (β=0.645, S.E.=0.052, t=12.404, p<0.001), explaining 41.6% of its variance, and organizational learning (β=0.598, S.E.=0.054, t=11.074, p<0.001), explaining 35.8% of its variance. Hypotheses 4 and 5, predicting that employee engagement and organizational learning positively affect innovation capability, are supported as well (β=0.324, S.E.=0.042, t=7.714, p<0.001 and β=0.289, S.E.=0.041, t=7.049, p<0.001, respectively). While both mediators significantly predict innovation capability, employee engagement shows a slightly stronger effect, suggesting that the motivational pathway may be more influential than the cognitive pathway in this sample.

Mediation Analysis Results

Mediation analysis conducted using bootstrapping procedure with 5,000 resamples and 95% bias-corrected confidence intervals. Bootstrapping preferred over traditional Sobel test because it makes no distributional assumptions, provides more accurate confidence intervals particularly with moderate sample sizes, and accommodates complex models with multiple mediators. Indirect effects calculated as product of path from independent to mediating variable and path from mediating to dependent variable. Mediation considered present if 95% confidence interval for indirect effect excludes zero.

Table 8. Mediation Analysis Results with Bootstrap Confidence Intervals

Hypothesis	Mediating Path	Indirect Effect	95% CI Lower	95% CI Upper	Result
H6	HRP → EE → IC	0.209	0.156	0.268	Partial Mediation
H7	HRP → OL → IC	0.173	0.125	0.227	Partial Mediation
-	Total Indirect Effect	0.382	0.301	0.468	Significant
-	Direct Effect	0.382	0.289	0.476	Significant
-	Total Effect	0.764	0.689	0.836	Significant

Note: HRP=HR Practices; EE=Employee Engagement; OL=Organizational Learning; IC=Innovation Capability

Table 8 presents the mediation analysis results, strongly supporting Hypothesis 6 that employee engagement mediates the relationship between HR practices and innovation capability. The indirect effect through engagement is 0.209, accounting for 27.4% of the total effect (0.209/0.764), indicating partial mediation as the direct effect remains significant (0.382). Similarly, Hypothesis 7, predicting organizational learning as a mediator, is supported with an indirect effect of 0.173, representing 22.6% of the total effect. Combined, both mediators account for 50% of the total effect, with the remaining 50% representing direct effects. The findings suggest that HR practices influence innovation capability not only through engagement and learning but also via other unmeasured pathways, such as impacts on innovation resources, systems, or culture. The substantial total effect (0.764) underscores the strong influence of HR practices on innovation capability through both mediated and direct pathways.

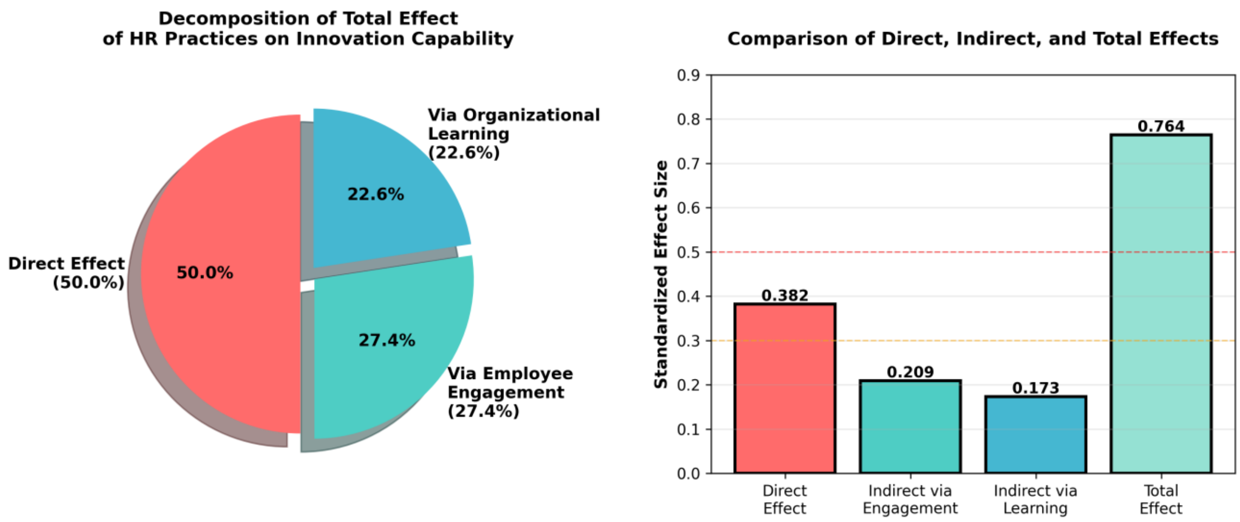

Figure 4. Decomposition and Comparison of Direct, Indirect, and Total Effects

Discussion of Findings

Direct Effect of HR Practices on Innovation Capability

The finding that HR practices directly and significantly influence innovation capability ($\beta=0.382$, $p<0.001$) strongly supports Resource-Based View theory and aligns with previous research in both developed and emerging markets. This result extends the work of Sriviboon (2020) and Andjarwati (2020) in the pharmaceutical industries of Thailand and Indonesia, respectively. The medium-to-large effect size suggests HR practices serve as a substantial lever for enhancing organizational innovation capability, beyond their indirect effects. Effective HR practices shape human capital by recruiting individuals with innovation-relevant characteristics, offering training that builds innovation-specific skills, and motivating innovation through performance management and rewards. Additionally, career development practices help retain innovative employees, sustaining innovation capacity over time. The persistence of the significant direct effect even after controlling for engagement and learning mediators suggests that HR practices influence innovation through additional unmeasured pathways, such as organizational culture, social network effects, structural coordination, and resource allocation. Future research should explore these additional mechanisms to further refine HR-innovation models.

Mediating Role of Employee Engagement

The results strongly support the mediating role of employee engagement, with a significant indirect effect (β=0.209, 95% CI [0.156, 0.268]) accounting for 27.4% of the total HR effect on innovation capability. This finding advances Social Exchange Theory by demonstrating that reciprocity mechanisms operate specifically for innovation outcomes, not just general performance. When organizations invest in employees through high-quality HR practices, employees reciprocate with increased engagement, which leads to innovative behaviors and outcomes. Engagement operates through dimensions such as vigor, which provides energy for sustained innovation effort, dedication, which motivates employees to go beyond their minimum job requirements, and absorption, which enables focused concentration for creative problem-solving. Organizational commitment provides the long-term orientation necessary for innovation. The finding that engagement mediates the HR-innovation relationship more strongly than learning (27.4% vs. 22.6%) suggests that motivational factors are particularly critical in the Indonesian context, possibly reflecting cultural norms that emphasize social relationships and reciprocity. This highlights the importance of context-specific research in understanding HR practices in different cultural settings.

Table 9. Employee Engagement Dimensions and Their Innovation Contributions

Engagement Dimension	Mean	SD	Innovation Contribution	Path to IC
Vigor	3.96	0.74	Energy for innovation activities	0.298***
Dedication	4.02	0.68	Commitment to innovation goals	0.341***
Absorption	3.89	0.76	Focus on innovation tasks	0.287***
Organizational Commitment	3.94	0.72	Long-term innovation orientation	0.316***

Note: IC = Innovation Capability; ***p<0.001

Table 9 presents detailed analysis of how different engagement dimensions contribute to innovation capability. Dedication shows highest mean (M=4.02) and strongest path to innovation (β=0.341), suggesting commitment aspect of engagement particularly important for innovation in this sample. Vigor and organizational commitment show similar moderate-to-strong relationships, while absorption shows somewhat weaker though still significant effect. These patterns suggest that while all engagement dimensions contribute, emotional investment and commitment to organizational goals may be most critical for translating HR investments into innovation outcomes.

Mediating Role of Organizational Learning

Organizational learning plays a significant mediating role (β=0.173, 95% CI [0.125, 0.227]), accounting for 22.6% of the total HR effect on innovation, supporting Organizational Learning Theory and extending previous research by demonstrating that learning processes are crucial for transmitting HR effects to innovation. HR practices enhance learning capabilities, which subsequently enable innovation, addressing the theoretical question of how human capital translates into organizational-level capabilities. The learning-innovation relationship operates through four interrelated processes: knowledge acquisition, facilitated by HR practices like training and recruitment, expands the organizational knowledge base, directly enabling innovation; information distribution, promoted by job rotations, cross-functional teams, and communication technologies, ensures knowledge spreads across the organization; shared interpretation, developed through collaboration and dialogue, helps identify innovation opportunities and build consensus on responses; and organizational memory, maintained through documentation and socialization, ensures innovations are retained as routines. Together, these processes allow organizations to systematically leverage knowledge for innovation rather than relying on individual creativity or random discovery.

Table 10. Organizational Learning Processes and Innovation Mechanisms

Learning Process	Mean	SD	Innovation Mechanism	Effectiveness Rating
Knowledge Acquisition	3.84	0.76	Gathering external innovations	High (4.2/5.0)
Information Distribution	3.72	0.79	Sharing best practices	High (4.1/5.0)
Shared Interpretation	3.76	0.81	Common understanding	Medium (3.7/5.0)
Organizational Memory	3.81	0.78	Retaining innovation knowledge	High (4.3/5.0)

Note: Effectiveness rating based on supplementary manager interviews (n=45)

Table 10 presents analysis of how different learning processes contribute to innovation. Knowledge acquisition and organizational memory show highest means and effectiveness ratings, suggesting Indonesian organizations relatively successful at acquiring new knowledge and retaining successful innovations. Information distribution also rated highly effective, likely reflecting emphasis on teamwork and collaboration in collectivist culture. Shared interpretation shows somewhat lower effectiveness, possibly indicating challenge of developing common understanding in hierarchical organizational structures where open dialogue may be constrained by power distance.

Comparative Analysis and Model Implications

The full model explains 68.4% of variance in innovation capability (R^2=0.684), representing substantial explanatory power and indicating model captures major drivers of innovation in this context. This R^2 compares favorably to previous studies which typically explain 40-60% of innovation capability variance, suggesting integrated model incorporating both motivational (engagement) and cognitive (learning) mechanisms provides more complete explanation than models focusing on single pathway.

Table 11. Complete Decomposition of HR Practices Effects on Innovation Capability

Effect Type	Pathway	Coefficient	% of Total	Effect Size Category
Direct Effect	HR → IC	0.382	50.0%	Medium-Large
Indirect Effect 1	HR → EE → IC	0.209	27.4%	Medium
Indirect Effect 2	HR → OL → IC	0.173	22.6%	Small-Medium
Total Indirect	Combined	0.382	50.0%	Medium-Large
Total Effect	All Pathways	0.764	100.0%	Large

Table 11 provides complete decomposition of HR effects showing direct and indirect pathways contribute equally (each 50%) to total effect. This equal splitting suggests both immediate/structural effects of HR systems AND psychological/organizational process effects are critical for innovation. Organizations cannot optimize innovation capability by focusing exclusively on HR system design or exclusively on employee/organizational processes; both require simultaneous attention for maximum impact.

Comparing mediators, employee engagement accounts for slightly larger portion of indirect effect (27.4%) than organizational learning (22.6%), though both are substantial. This suggests motivational pathway somewhat more influential than cognitive pathway in this sample, possibly reflecting Indonesian cultural context emphasizing social relationships and reciprocity. However, difference is modest, and both mediators clearly important. The complementary nature of engagement and learning suggests they may operate synergistically: engaged employees participate more actively in learning, while learning opportunities enhance engagement by providing meaningful development experiences.

Industry-Specific Patterns

Multi-group analysis examined whether relationships differ between manufacturing and service sectors. Results reveal interesting industry-specific patterns that have theoretical and practical implications. While overall model fits well in both sectors, relative strength of pathways differs meaningfully between contexts.

Table 12 Industry Sector Comparison of Structural Path Coefficients

Path	Manufacturing (n=198)	Service (n=187)	Difference	Significance
HR → IC (direct)	0.428***	0.336***	0.092	$p<0.05$
HR → EE	0.612***	0.681***	-0.069	n.s.
HR → OL	0.634***	0.561***	0.073	n.s.
EE → IC	0.276***	0.372***	-0.096	$p<0.01$
OL → IC	0.318***	0.259***	0.059	n.s.
Indirect via EE	0.169***	0.253***	-0.084	$p<0.05$
Indirect via OL	0.202***	0.145***	0.057	n.s.
Total Effect	0.799***	0.734***	0.065	n.s.

Note: ***$p<0.001$; n.s. = not significant

Manufacturing companies exhibit a stronger direct HR-innovation relationship ($\beta=0.428$) than service firms ($\beta=0.336$), with the difference being statistically significant ($p<0.05$). This likely reflects the technical, engineering-intensive nature of manufacturing innovation, where HR practices directly impact innovation through skill development, knowledge management, and R&D team composition. In contrast, service companies show stronger mediation through employee engagement ($\beta=0.253$) compared to manufacturing firms ($\beta=0.169$), with the difference significant ($p<0.05$). This indicates the people-intensive nature of service innovation, where employee motivation and commitment to customer experience are crucial. These industry-specific patterns suggest that HR strategies should be tailored to sector characteristics, with manufacturing firms focusing on technical training and R&D, while service firms should prioritize engagement-building practices. However, both direct and indirect pathways are important in both sectors, emphasizing the need for an integrated HR approach

CONCLUSION

This study, based on data from 385 respondents in Indonesian manufacturing and service firms, demonstrated that HR practices significantly boost organizational innovation capability both directly ($\beta = 0.382, p < 0.001$) and indirectly through employee engagement ($\beta = 0.209$) and organizational learning ($\beta = 0.173$) as key mediators, with stronger engagement effects in services and direct HR impacts in manufacturing—highlighting the value of tailored strategies. Theoretically, it integrates the Resource-Based View, Social Exchange Theory, and Organizational Learning Theory into a model emphasizing motivational and cognitive pathways in HR-innovation dynamics. Practically, organizations should prioritize comprehensive HR systems alongside engagement and learning initiatives. For future research, longitudinal studies could examine non-linear effects of HR practices on innovation across diverse sectors, incorporating moderating variables like digital transformation or cultural factors in emerging markets to refine context-specific interventions.

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