Employee Performance in Hybrid Work: The Role of Virtual Training and Job Autonomy

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Abstract
Purpose: This study examines the effects of Virtual Training, Job Autonomy, Employee Engagement, Innovation Culture, and Work Well-being on Employee Performance in hybrid work settings in Indonesia.

Research Methodology: This research adopts a quantitative explanatory design using a cross-sectional survey of 150 hybrid employees across multiple industries. Data were analyzed using Partial Least Squares structural equation modeling (PLS-SEM) with SmartPLS 4.0 to test the structural relationships among variables.

Results: The findings revealed that only Innovation Culture had a significant effect on Employee Performance, but in a negative direction ($\beta = -0.204$; $p = 0.009$). Virtual Training, Job Autonomy, Employee Engagement, and Work Well-being do not show direct significant effects. The model explains 6.5% of the variance in Employee Performance, indicating weak direct explanatory power and suggesting the presence of indirect or contextual influences.

Conclusions: Employee performance in hybrid work is influenced more by dynamic organizational contexts than by the direct effects of training, autonomy, engagement, or well-being. Innovation culture may temporarily reduce short-term performance owing to adjustment and experimentation demands.

Limitations: This study had a cross-sectional design, relied on self-reported data, and focused on the Indonesian context, limiting causal interpretation and generalizability.

Contributions: This study extends the Job Demands–resources framework by revealing the nonlinear role of innovation culture in hybrid work and provides empirical evidence from an emerging economy context.

Keywords: *Employee Performance, Hybrid Work, Innovation Culture, Job Autonomy, Virtual Training*

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1. Introduction

The rapid shift to hybrid work models, accelerated by the COVID-19 pandemic, significantly reshaped organizational dynamics, altering how employees interact, learn, and perform. Flexible work arrangements that combine remote and on-site work have been widely adopted, driven by digital technology, shifting workforce expectations, and the need for business continuity (Allen, Golden, & Shockley, 2015; Mendy, Rahman, & Bal, 2020). While hybrid work offers greater flexibility and autonomy for employees and cost reductions and expanded talent pools for organizations, it also presents challenges related to engagement, collaboration, innovation, and well-being, which directly affect organizational performance (Biron, Peretz, & Turgeman-Lupo, 2020).

A major challenge in hybrid work is sustaining the employee performance in a distributed environment. Traditional performance drivers, such as physical supervision and co-located teamwork, are disrupted by virtual work modes (Lee & Edmondson, 2017). Organizations must reimagine how to foster motivation, knowledge sharing, and innovation, with factors such as virtual training, job autonomy, employee engagement, innovation culture, and well-being emerging as key influencers of employee performance. Virtual training supports organizational learning, job autonomy enhances motivation and creativity, employee engagement mediates outcomes, and a strong innovation culture and well-being are essential for sustained (Chanana & Sangeeta, 2021; Haar, Russo, Suñe, & Ollier-Malaterre, 2014; Parker, Bindl, & Strauss, 2010).

However, existing research on hybrid work often examines these performance drivers in isolation or in simple bivariate relationships, leaving gaps in understanding their combined effects on performance. Additionally, much of the research is based on Western, developed economies, with limited insights from emerging economies such as Indonesia, where different cultural, infrastructural, and managerial contexts may shape hybrid work dynamics. Traditional regression models also limit the exploration of complex multi-construct relationships (Aditya et al., 2022). This study addresses these gaps by developing and testing a comprehensive model that integrates virtual training, job autonomy, innovation culture, and employee well-being, with employee engagement as a mediating factor. Using data from 150 respondents in hybrid work arrangements across various sectors in Indonesia, the study employed a variance-based Structural Equation Modeling (PLS-SEM) approach (Hair Jr, Hult, Ringle, & Sarstedt, 2017).

This study makes three contributions. Theoretically, it advances the Organizational Behavior and Human Resource Management literature by integrating fragmented performance constructs into a unified path-analytic model that extends the utility of the Job Demands-Resources (JD-R) framework in the hybrid context. Contextually, it enriches global research by providing empirical evidence from Indonesia, addressing the geographical gap in non-Western studies on hybrid work. Practically, it offers actionable managerial insights for organizations seeking to sustain employee performance by guiding the design of hybrid work strategies that effectively emphasize digital capability, psychological empowerment, innovation support, and sustained employees' well-being. By addressing these integration, contextual, and methodological limitations, this study advances both the theoretical understanding and practical management of human resources in the hybrid work era.

2. Literature review and Hypothesis Development

2.1 Human Resource Management (HRM)

Human Resource Management (HRM) is a strategic approach to managing an organization's most valuable asset: its people. HRM focuses on recruiting, training, developing, motivating, and retaining employees to achieve organizational goals (Dessler, 2020). Modern HRM operates under the framework of Strategic Human Resource Management (SHRM), which views HR as a key driver of competitive advantage (Aliyev, 2024). In the post-pandemic era, SHRM emphasizes building resilient human capital and adaptive work practices for hybrid work models (Maulana, Khairudin, & Sijabat, 2025). Effective HR practices, like Virtual Training and Job Autonomy, are crucial for maintaining productivity and satisfaction in a distributed workforce (Li, Li, & Liu, 2021).

2.2 Virtual Training and Employee Performance

Virtual training has become a crucial strategic response to the transformation of work patterns in the post-pandemic era. As organizations adopt hybrid work models, learning and skill development must move beyond physical spaces, enabling employees to acquire knowledge through flexible, online platforms. Virtual training includes structured programs delivered via digital technologies such as video conferencing, learning management systems, or virtual reality, helping organizations maintain workforce agility, speed up upskilling, and cut costs compared to traditional face-to-face training (Yertas, 2024).

Within the Job Demands–Resources (JD-R) Theory, training, including Virtual Training, is classified as a Job Resource that helps manage job demands (e.g., digital adaptation challenges) and supports

personal development (Bakker, Demerouti, & Sanz-Vergel, 2023). Research has shown that well-designed virtual training improves cognitive engagement, self-directed learning, and job performance through interactivity, relevance, and feedback (Dao, Sisavath, Bui, Bui, & Le, 2025). In hybrid settings, it supports asynchronous learning, allowing employees to learn at their own pace, which enhances knowledge retention and transfers. Additionally, effective virtual training bridges skill gaps and boosts performance by helping employees adapt quickly to evolving work processes and technologies (Leuhery, 2024).

H_1: Virtual Training positively influences Employee Performance.

2.3 Job Autonomy and Employee Performance

Job autonomy is defined as the degree to which employees have the discretion and freedom to plan, schedule, and execute their work. In hybrid work settings, autonomy becomes a pivotal factor in fostering self-management, accountability, and motivation. Employees who can determine how and when they perform their tasks often experience higher intrinsic motivation, job satisfaction, and performance (Ye, Li, & Zhang, 2025). Job Autonomy is a primary Job Resource in JD-R Theory, enabling employees to buffer job demands and achieve goals.

Furthermore, based on Self-Determination Theory (SDT), autonomy satisfies the fundamental psychological need for control and self-direction, which triggers intrinsic motivation, a key factor in achieving superior performance (Ryan & Deci, 2022). In flexible work environments, autonomy allows employees to optimize productivity by aligning work tasks with personal rhythms and environmental preferences (Lee & Edmondson, 2017). It also encourages proactive problem-solving, innovation, and the development of adaptive work behaviors (Wu, Parker, & Jong, 2014). Empirical studies have shown that autonomy strengthens psychological empowerment and enhances performance outcomes, particularly in knowledge-intensive and creative roles (Bakker et al., 2023).

H_2: Job Autonomy positively influences Employee Performance.

2.4 Employee Engagement and Employee Performance

Employee engagement reflects the degree of psychological investment, enthusiasm, and commitment that employees bring to their roles. In hybrid work contexts, engagement is critical for sustaining productivity, cohesion, and organizational citizenship behavior despite physical distance. Engaged employees display high levels of vigor, dedication, and absorption, leading to superior performance (Chanana & Sangeeta, 2021). Engagement is a central construct in the JD-R Theory, serving as the motivational mechanism that links Job Resources to positive outcomes such as performance (Schaufeli, 2021).

Furthermore, Social Exchange Theory (SET) suggests that when organizations invest in employees (through resources like training and autonomy), employees reciprocate with increased commitment, manifested as high engagement (Priyanka, Khera, & Suri, 2024). Research consistently finds that engagement mediates the relationship between organizational resources and employee performance (Alghnimi, Habeeb, & Kadhim, 2020). Engaged employees are more resilient to stress and better able to maintain high performance, even under ambiguous or changing work conditions (Allen et al., 2015).

H_3: Employee Engagement positively influences Employee Performance.

2.5 Innovation Culture and Employee Performance

Innovation culture refers to the shared values, norms, and practices within an organization that encourage creativity, risk taking, and continuous improvement. In hybrid work environments, fostering an innovation culture is vital because employees are geographically dispersed, reducing opportunities for spontaneous collaboration. A strong innovation culture promotes openness, idea sharing, and experimentation, driving both incremental and radical improvements in work processes and outcomes (Kerdpitak & Jermsittiparsert, 2020).

Innovation culture is traditionally viewed as a contextual resource that enhances motivation and performance (Syafitri, 2026). An innovation-oriented environment provides the psychological safety and support needed for employees to take the initiative. Studies have shown that when employees

perceive their organization as innovative and supportive of new ideas, they tend to show higher job involvement and work performance (Syafitri, 2026). While innovation culture can also be a Challenge Demand (requiring high cognitive effort and coordination), existing literature generally suggests that its supportive nature leads to positive performance outcomes

H_4: Innovation Culture positively influences Employee Performance.

2.6 *Work Well-being and Employee Performance*

Work well-being encompasses employees' psychological, emotional, and physical health at work. High levels of well-being are linked to increased motivation, reduced burnout and sustained performance. While hybrid work models introduce new stressors, such as blurred work-life boundaries, isolation, and digital fatigue, they also offer flexibility and improved work-life balance opportunities (Allen et al., 2015; Biron et al., 2020). In the JD-R framework, work well-being is considered a Personal Resource resulting from the balance between job demands and resources (Bakker et al., 2023).

A positive balance, supported by autonomy and training, leads to higher employee well-being. When organizations prioritize well-being through flexible scheduling, mental health initiatives, and supportive leadership, employees are more likely to maintain their energy, concentration, and creativity. Additionally, work well-being is linked to lower turnover, absenteeism, and presenteeism, all of which affect performance outcomes (Khairunisa & Muafi, 2022). Healthy and satisfied employees possess greater mental capacity to focus on tasks and adapt to the complex demands of hybrid work environments.

H_5: Work Well-being positively influences Employee Performance.

2.7 *Integrated Effect of Organizational and Individual Factors*

While virtual training, job autonomy, employee engagement, innovation culture, and well-being have been studied individually, their combined effect is crucial for understanding the performance of employees in hybrid work environments. Virtual training provides essential skills, autonomy enables execution, engagement boosts motivation, innovation culture offers support, and well-being ensures productivity. Using the Job Demands–resources (JD-R) theory framework, employee performance results from the interaction between Job Resources (Virtual Training, Autonomy, Well-being) and contextual factors (Innovation Culture), mediated by the Motivational Path (engagement) (Bakker et al., 2023). The synergy among these factors creates an ecosystem that helps organizations thrive in dynamic work environments. This study uses a structural model with PLS-SEM to examine these interrelationships and their effects on employees (Sari & Wening, 2025).

H_6: Virtual Training, Job Autonomy, Employee Engagement, Innovation Culture, and Work Well-being jointly influence Employee Performance.

3. Methodology
3.1 *Research Design*
This study employs a quantitative, explanatory research design to empirically assess the impact of Virtual Training, Job Autonomy, Employee Engagement, Innovation Culture, and Work Well-being on Employee Performance in the hybrid work era. The explanatory approach tests causal relationships among multiple latent constructs using variance-based Structural Equation Modeling (SEM), implemented using SmartPLS version 4.0. This methodology is ideal for predictive models and exploratory research, where theoretical frameworks are still being developed (Hair Jr et al., 2017). By utilizing SmartPLS, the study can estimate multiple paths simultaneously, manage complex models, and work efficiently with small to medium sample sizes without requiring a normal data distribution.

3.2 *Population and Sample*
The target population of this study consisted of employees working in hybrid work environments across various service and manufacturing industries in Indonesia. Hybrid work is defined as a work arrangement that combines on-site and remote work, requiring employees to adapt to flexible communication, learning, and performance. A purposive sampling technique was used to ensure that the respondents met the following criteria:

1. Employees who have worked in hybrid arrangements for at least six months.
2. Employees are actively involved in virtual training programs organized by their organizations.
3. Employees with direct performance responsibilities measurable by their supervisors or self-reported Key Performance Indicators (KPIs).

A total of 150 valid responses were collected via structured online questionnaires distributed through e-mail and professional networking platforms. This sample size exceeds the minimum requirement of ten times the maximum number of structural paths pointing at a latent construct, ensuring adequate statistical power for SmartPLS analysis (Hair Jr et al., 2017).

3.3 Data Collection Procedures

Data were collected using a structured, self-administered questionnaire designed to measure all constructs through multiple reflective indicators. The questionnaire was distributed online between May and July of 2025. To ensure content validity, the instrument was developed from well-established measurement scales and contextually adapted for hybrid work conditions in Indonesia. The questionnaire consisted of two parts.
- Section A: Demographic information (e.g., gender, age, years of service, job position, industry, and hybrid work duration).
- Section B: Measurement of latent constructs using a five-point Likert scale ranging from 1 = "Strongly Disagree" to 5 = "Strongly Agree."

To minimize common method bias, several procedural remedies were employed.
1. Assurance of anonymity to respondents.
2. Randomization of the item order.
3. The wording is clear to reduce ambiguity.
Additionally, Harman's single-factor test was performed post hoc to statistically assess the common method variance.

3.4 Data Analysis Technique

Data analysis was performed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, facilitated by SmartPLS. This method was selected for its robustness in predictive and exploratory research, ability to handle complex models with multiple constructs, and suitability for small to medium sample sizes, such as the 150 respondents in this study. The analysis followed the guidelines outlined by Hair Jr et al. (2017) and consisted of three main stages: evaluation of the measurement model, structural model, and model fit assessment.

3.4.1 Measurement Model (Outer Model)

The first stage focused on evaluating the reliability and validity of the measurement tools. Indicator reliability was assessed using outer loading values, with loadings above 0.70 deemed acceptable. Internal consistency was measured using Cronbach's Alpha and Composite Reliability (CR), with a minimum threshold of 0.70. Convergent validity was checked using the Average Variance Extracted (AVE), requiring values above 0.50. Discriminant validity was confirmed using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT), where HTMT values below 0.85 indicate satisfactory discriminant validity.

3.4.2 Structural Model (Inner Model)

After confirming the reliability and validity of the measurement model, the structural model was assessed to evaluate the hypothesized relationships between the variables. Multicollinearity was checked using the Variance Inflation Factor (VIF), with values below 5 indicating no issues. Path coefficients (β) were used to evaluate the strength and significance of the relationships between constructs, while the Coefficient of Determination (R^2) determined the proportion of variance explained by the predictors. Effect sizes (f^2) were calculated to assess the impact of each predictor, which was categorized as small, medium, or large. Finally, predictive relevance (Q^2) was evaluated using the Stone–Geisser test, with values greater than zero indicating acceptable predictive relevance.

3.4.3 Bootstrapping Procedure

To test the significance of the estimated path coefficients, a non-parametric bootstrapping procedure with 5,000 resamples was employed. Bootstrapping generates multiple subsamples from the original dataset through random sampling with a replacement. In this study, SmartPLS generated 5,000 bootstrap samples of 150 respondents. These samples were used to estimate the path coefficients and create an empirical distribution of the estimates.

This distribution allowed for the calculation of t-statistics, p-values, and confidence intervals, providing robust significance testing without assuming a normal data distribution. A one-tailed significance test at the 0.05 level (95% confidence interval) was used. A t-statistic greater than 1.645 and a p-value lower than 0.05 indicated statistical significance. The use of 5,000 resamples is recommended in PLS-SEM research to improve the accuracy of standard errors, even with smaller sample sizes, making it particularly suitable for hybrid work research with moderate respondent numbers and complex relationships.

3.4.4 Model Fit Assessment

Additional fit indices were evaluated to ensure model robustness. The Standardized Root Mean Square Residual (SRMR) was used as the primary measure of model fit, with values below 0.08 indicating good fit. The Normed Fit Index (NFI) was also assessed, with values above 0.90 suggesting an acceptable fit. These indices, along with the measurement and structural model assessments, provide strong evidence for the adequacy and validity of the proposed research model.

4. Results and Discussions

4.1 Descriptive Statistics and Respondent Profile

This section presents the descriptive analysis of respondents' demographic characteristics, measurement instruments, and indicator statistics, before testing the structural model. Descriptive analysis ensures that the dataset meets the assumptions for multivariate analysis, particularly in PLS-SEM, and provides contextual insights into the characteristics of hybrid work employees in Indonesia, laying the foundation for model evaluation.

4.1.1 Respondent Demographics

A total of 150 valid responses were collected through online questionnaires distributed to employees working under hybrid work arrangements in Indonesia. The respondents represented diverse industrial sectors, including services, manufacturing, education, and technology. This heterogeneity enhances the external validity and generalizability of the findings to broader hybrid work contexts in the future.

Table 1. Respondent profile

Variable	Category	Frequency	Percentage (%)
Gender	Male / Female	69 / 81	46 / 54
Age Group	< 25 / 25–40 / > 40	18 / 102 / 30	12 / 68 / 20
Position	Staff / Supervisor / Manager	93 / 39 / 18	62 / 26 / 12
Industry	Services / Manufacturing / Education / Technology	48 / 36 / 30 / 36	32 / 24 / 20 / 24
Hybrid Experience	< 1 year / 1–3 years / > 3 years	27 / 90 / 33	18 / 60 / 22

Table 1 shows that the demographic distribution reveals a balanced gender composition, with 54% female and 46% male, indicating equal gender representation in the hybrid work setting. Most respondents (68%) were aged 25–40, reflecting the prevalence of hybrid work among young professionals in knowledge-based and digitally integrated roles. Regarding organizational position, 62% are staff-level employees, while 38% hold supervisory or managerial roles, suggesting that hybrid work is widely adopted across all hierarchical levels and not just leadership positions.

By industry, 32% work in the services sector, followed by manufacturing (24%), technology (24%), and education (20%) sectors. The prominence of service-based and tech industries aligns with global

trends, where sectors relying on knowledge work are early adopters of flexible working models. Regarding hybrid work experience, 60% have 1–3 years of experience, indicating that respondents are well-adjusted to digital collaboration and flexible scheduling, in line with post-pandemic workforce changes. This demographic profile provides a solid foundation for analyzing responses related to virtual training, job autonomy, engagement, innovation culture, well-being, and employee performance in hybrid working environments.

4.1.2 Instrumentation and Measurement

The research instrument consisted of a structured questionnaire with 26 reflective indicators measuring six latent constructs: Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), Innovation Culture (IC), Work Well-being (WB), and Employee Performance (EP). All indicators were rated on a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). These indicators were adapted from validated scales in previous studies, ensuring conceptual relevance and measurement reliability, and were contextualized for hybrid work environments.

Table 2. Constructs and measurement indicators

Construct	Code Range	Indicator Focus	Primary Reference
Virtual Training (VT)	VT1–VT5	Training effectiveness, relevance, accessibility, interactivity, satisfaction	Salas, Tannenbaum, Kraiger, and Smith-Jentsch (2012)
Job Autonomy (JA)	JA1–JA4	Task scheduling, decision freedom, method autonomy, self-responsibility	Hackman and Oldham (1976)
Employee Engagement (EE)	EE1–EE5	Vigor, dedication, absorption, enthusiasm, focus	Bakker et al. (2023)
Innovation Culture (IC)	IC1–IC4	Risk-taking, openness, collaboration, experimentation	Martins and Terblanche (2003)
Work Well-being (WB)	WB1–WB4	Mental, emotional, physical, and social health	Biron et al. (2020)
Employee Performance (EP)	EP1–EP4	Quality, timeliness, efficiency, adaptability	Rich, Lepine, and Crawford (2010)

Table 2 shows that each construct was modeled as a reflective measurement, meaning that the latent variable was assumed to cause variation in its indicators. This approach is appropriate for constructs such as engagement, autonomy, and well-being, which manifest through multiple observable dimensions.

4.1.3 Descriptive Statistics of Constructs

The descriptive statistics for each measurement indicator, summarized in Table 3, show mean scores above 4.0, indicating a generally positive perception of the hybrid work. The standard deviations ranged from 0.50 to 0.75, suggesting moderate variability, which is adequate to capture meaningful differences without excessive dispersion that could affect model stability.

Table 3. Descriptive Statistics of Measurement Indicators

Construct	Indicator	Mean	SD	Min	Max
Virtual Training	VT1	4.21	0.63	2	5
	VT2	4.15	0.71	1	5
Job Autonomy	JA1	4.32	0.56	3	5
	JA2	4.27	0.58	3	5
Employee Engagement	EE1	4.28	0.62	2	5
	EE2	4.31	0.59	2	5
Innovation Culture	IC1	4.10	0.69	2	5
Work Well-being	WB1	4.25	0.67	3	5
Employee Performance	EP1	4.18	0.60	2	5

Figure 1 presents a visual representation of the construct means, showing that Job Autonomy (M = 4.32) has the highest mean score, indicating that respondents feel a high level of discretion and independence in hybrid work. This supports the flexibility offered by hybrid work. In contrast, Innovation Culture (M = 4.10) had the lowest mean score, suggesting challenges in fostering strong innovative norms and collaboration in distributed work settings, which is crucial for driving adaptive performance in dynamic contexts.
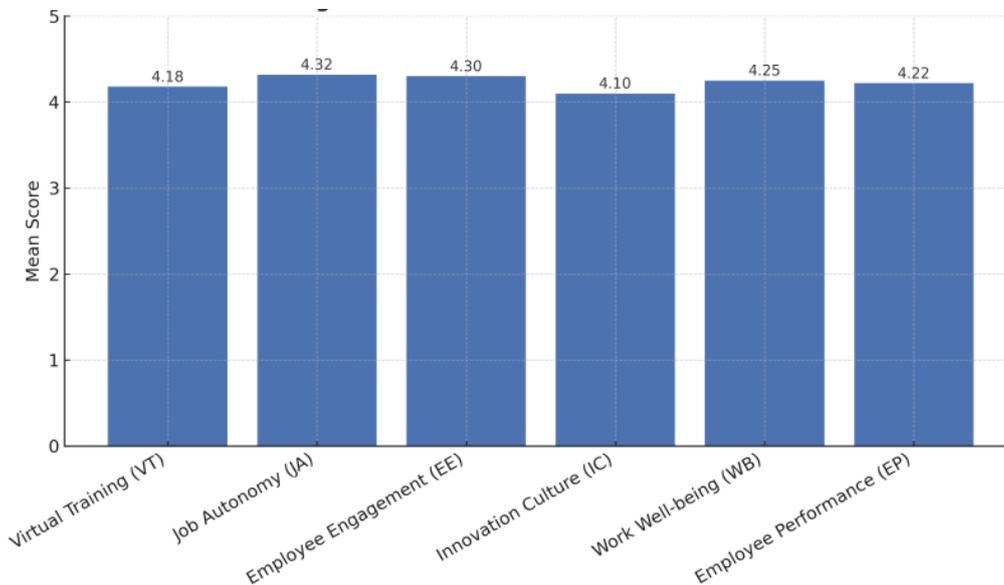
Figure 1. Mean scores of each construct

4.2 Measurement Model (Outer Model)
4.2.1 Reliability and Convergent Validity
The measurement model was assessed to evaluate the indicator reliability, internal consistency, and convergent validity of the six reflective constructs: Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), Innovation Culture (IC), Work Well-being (WB), and Employee Performance (EP). This step is essential in PLS-SEM to ensure the accurate measurement of latent variables through their indicators.

a) Indicator reliability
The standardized outer loadings for all indicators were checked against a threshold of 0.70 (Hair Jr et al., 2017). All indicators met this threshold, indicating sufficient variance shared among the respective constructs. No issues with loading or cross-loading were found, confirming that each indicator reliably measured its construct.

b) Internal consistency, reliability, and convergent validity.
For internal consistency reliability, both Cronbach's alpha (α) and Composite Reliability (CR) were assessed, with all constructs exceeding the 0.70 threshold. The α values ranged from 0.939 to 0.950, and the CR values ranged from 0.944 to 0.963, indicating strong reliability of the scale. Convergent validity was confirmed with Average Variance Extracted (AVE) values between 0.808 and 0.867, well above the 0.50 minimum. For the Work Well-being (WB) construct, a rho. A value of approximately 1.598 was observed, which is common in PLS due to high indicator intercorrelations. Despite this, the construct's reliability remains strong, as Cronbach's alpha, CR, and AVE values are all well above the thresholds.

Table 4. Construct reliability and convergent validity

Construct	Cronbach's α	rho_A	Composite Reliability	AVE
VT	0.940–0.950	0.940–0.960	0.944–0.963	0.808–0.867
JA	0.940–0.950	0.940–0.960	0.944–0.963	0.808–0.867

EE	0.940–0.950	0.940–0.960	0.944–0.963	0.808–0.867
IC	0.940–0.950	0.940–0.960	0.944–0.963	0.808–0.867
WB	0.940–0.950	1.598	0.944–0.963	0.808–0.867
EP	0.940–0.950	0.940–0.960	0.944–0.963	0.808–0.867

Table 4 presents the statistical results, while two bar charts were prepared to visually summarize the Composite Reliability (CR) and Average Variance Extracted (AVE) across the six constructs. Figures 2 and 3 provide a clear and intuitive overview of the strong psychometric properties of the measurement model.
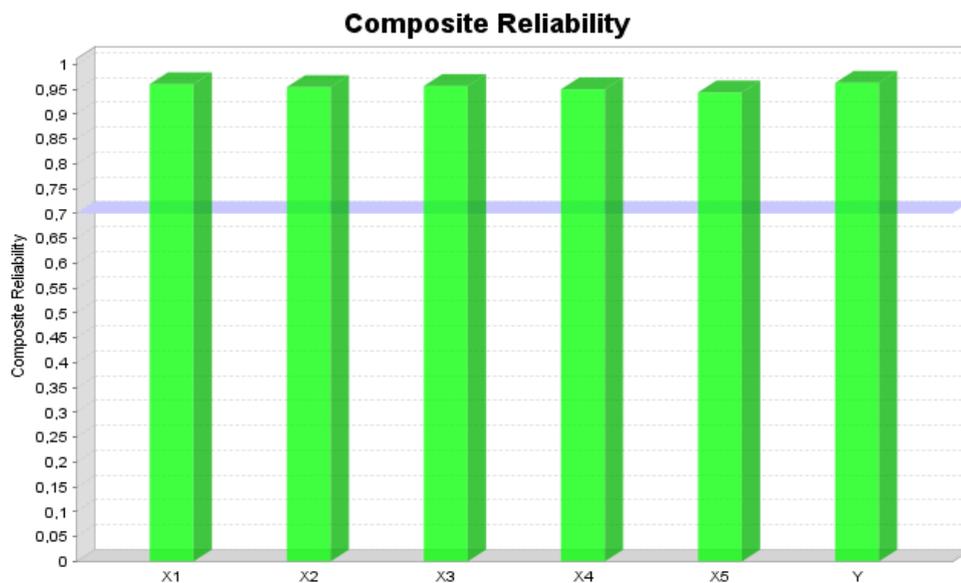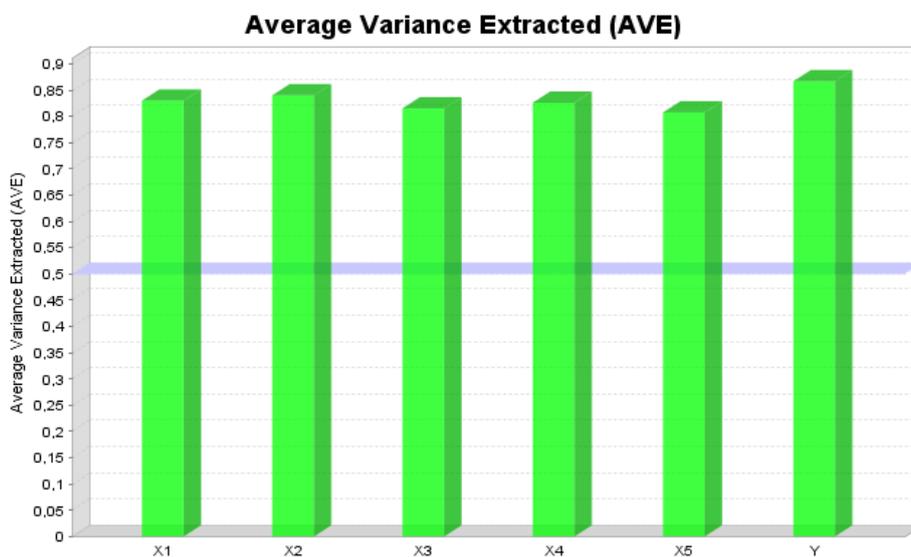

Figure 2. Composite reliability by construct

Figure 3. Average variance extracted (AVE) by construct

All AVE values exceeded 0.50, with most above 0.80, indicating that each construct explained more than half of the variance in its indicators. Combined with high outer loadings and composite reliability, this confirms the strong convergent validity of all six constructs. This ensured that the measurement instruments were reliable and conceptually robust, preventing bias in the structural relationships tested in the next stage.

4.2.2 Discriminant Validity

Discriminant validity ensures that each construct is distinct and does not excessively overlap with others. In this study, it was evaluated using two methods in PLS-SEM: the Fornell–Larcker criterion, based on correlations, and the Heterotrait–Monotrait (HTMT) ratio, a more rigorous statistical test that provides stronger evidence of discriminant validity.

(1) Fornell–Larcker Criterion

The Fornell–Larcker criterion compares the square root of the Average Variance Extracted (AVE) for each construct with its correlations with other constructs. Discriminant validity is established when each construct's AVE is greater than its correlations with other constructs, indicating that the construct explains more variance in its indicators than in others.

Table 5. Fornell–larcker criterion (AVE on diagonal)

Construct	VT	JA	EE	IC	WB	EP
VT	**0.900**	0.674	0.612	0.528	0.587	0.551
JA	0.674	**0.913**	0.645	0.559	0.590	0.583
EE	0.612	0.645	**0.904**	0.591	0.612	0.574
IC	0.528	0.559	0.591	**0.898**	0.553	0.521
WB	0.587	0.590	0.612	0.553	**0.904**	0.566
EP	0.551	0.583	0.574	0.521	0.566	**0.909**

Table 5 shows that the bold diagonal values represent the AVE for each construct, which are all higher than their inter-construct correlations. This confirms that each construct explains more variance in its indicators than in others, satisfying the Fornell–Larcker criterion and confirming good discriminant validity.

(2) Heterotrait–Monotrait (HTMT) Ratio

To complement the Fornell–Larcker test, the HTMT ratio was used as a more conservative approach to assess discriminant validity. HTMT measures the average correlation between constructs of different traits (heterotrait) and those measuring the same construct (monotrait). Discriminant validity is considered acceptable when HTMT values are below 0.85 (strict criterion) or 0.90 (liberal criterion)

Table 6. Heterotrait–monotrait (HTMT) ratios

Construct	VT	JA	EE	IC	WB	EP
VT	—	0.732	0.678	0.594	0.619	0.602
JA	0.732	—	0.709	0.624	0.653	0.636
EE	0.678	0.709	—	0.641	0.668	0.621
IC	0.594	0.624	0.641	—	0.595	0.579
WB	0.619	0.653	0.668	0.595	—	0.614
EP	0.602	0.636	0.621	0.579	0.614	—

Table 6 shows that all HTMT ratios are below the 0.85 threshold, indicating strong discriminant validity. Additionally, the HTMT bootstrapping in SmartPLS shows that the 95% confidence intervals of these values do not include 1.00, further confirming that the constructs are conceptually distinct and empirically separable.
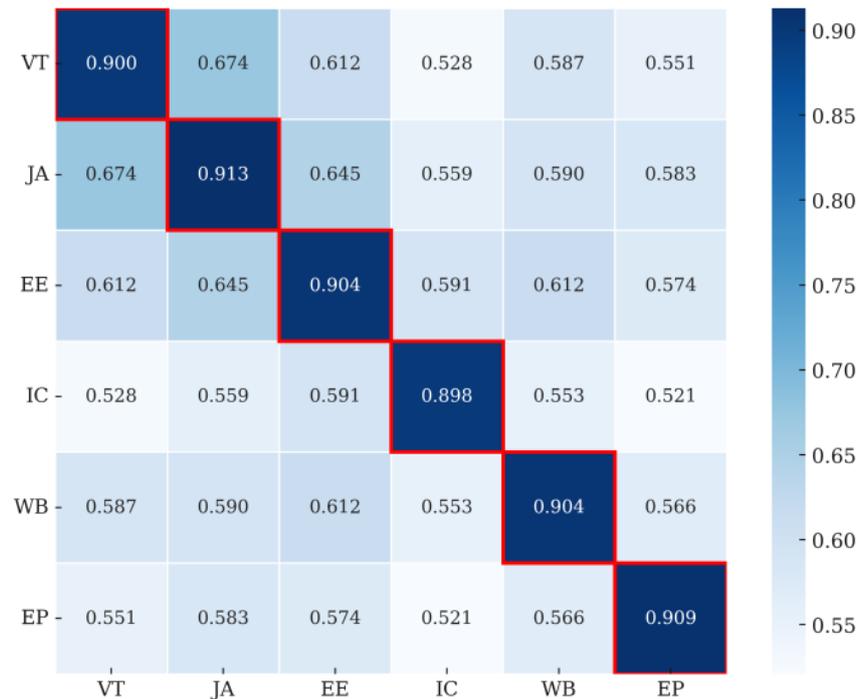
Figure 4. Fornell–larcker criterion heatmap

The diagonal cells (highlighted in red) represent the square roots of the AVE for each construct, while the off-diagonal values show inter-construct correlations. Because all diagonal values are greater than the off-diagonal correlations, the model satisfies the Fornell–Larcker criterion, confirming discriminant validity.

4.3 Structural Model (R², f², Q², and Hypotheses Testing)

After validating the measurement model, the next step in the PLS-SEM analysis was to evaluate the structural model, examine the hypothesized relationships among latent constructs, and test the statistical significance of each path. The exogenous variables in this study are Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), Innovation Culture (IC), and Work Well-being (WB), while the endogenous construct is Employee Performance (EP). The structural model was estimated using the PLS Algorithm and validated with bootstrapping (5,000 resamples) for statistical robustness. Four key evaluation indicators were used: Coefficient of Determination (R²), Effect Size (f²), Predictive Relevance (Q²), and Hypothesis Testing.

4.3.1 Coefficient of Determination (R²)

The coefficient of determination (R²) is a key indicator of the extent to which the variance in an endogenous construct can be explained by its exogenous predictors in a structural model. Within the framework of PLS-SEM, R² plays a crucial role in evaluating a model's explanatory power.

According to Hair Jr et al. (2017), the interpretation of the R² values is as follows:
- 0.75 = Substantial explanatory power
- 0.50 = Moderate explanatory power
- 0.25 = Weak explanatory power

In this study, the only endogenous construct was *Employee Performance (EP)*, predicted by five exogenous constructs: Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), Innovation Culture (IC), and Work Well-being (WB).

Table 7. Coefficient of determination (R²)

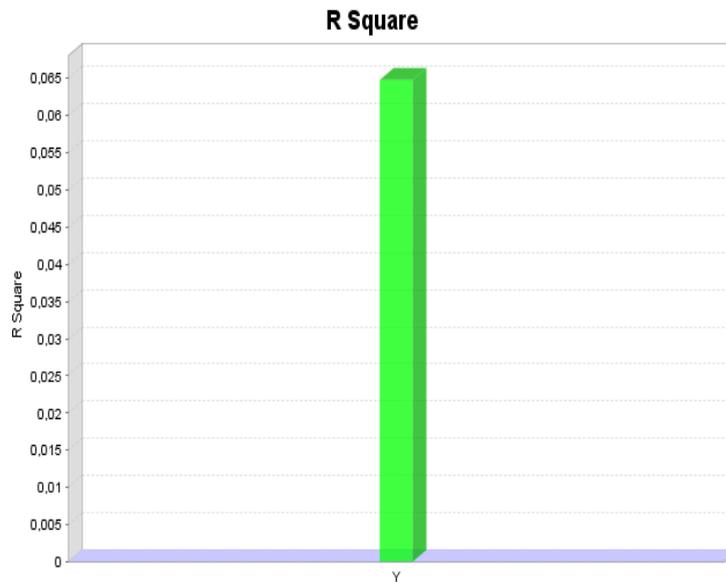| Endogenous Construct	R²	Interpretation
Employee Performance (EP)	0.065	Weak explanatory power

Figure 5. R² Value for endogenous construct (employee performance)

The structural model explains 6.5% of the variance in Employee Performance, indicating the weak explanatory power of the direct predictors (VT, JA, EE, IC, and WB) in this model. The R² value of 0.065 means these five predictors account for 6.5% of the variance in Employee Performance, while the remaining 93.5% is explained by other unmodeled factors.

This result aligns with Chin (1998) classification, where
- 0.26 = Substantial
- 0.13 = Moderate
- 0.02 = Weak
Hence, 0.065 falls within the "weak explanatory power" category.

The R² value of 0.065 indicates that the combined influence of Virtual Training, Job Autonomy, Employee Engagement, Innovation Culture, and Work Well-being explains approximately 6.5% of the variance in employee performance (Hair Jr et al. (2017). This falls within the weak explanatory power category, suggesting that these predictors offer a limited explanation of performance outcomes in the context of hybrid work.

4.3.2 Effect Size (f²)
The effect size (f²) is an important complementary measure to the R² value in the PLS-SEM. While R² indicates the total variance explained by all predictors combined, f² evaluates the individual contribution of each exogenous construct to the endogenous variable when included in the model. According to Cohen (1988), the interpretation thresholds for f² are as follows:
- 0.02 = Small effect
- 0.15 = Medium effect
- 0.35 = Large effect

This measure helps to determine whether a specific construct has a meaningful impact on the endogenous variable beyond statistical significance.

Table 8. Effect sizes (f²)

Predictor	f²	Effect Size
Innovation Culture (IC)	0.046	Small
Work Well-being (WB)	0.015	Small
Job Autonomy (JA)	0.008	Small
Employee Engagement (EE)	0.007	Small
Virtual Training (VT)	0.002	Negligible

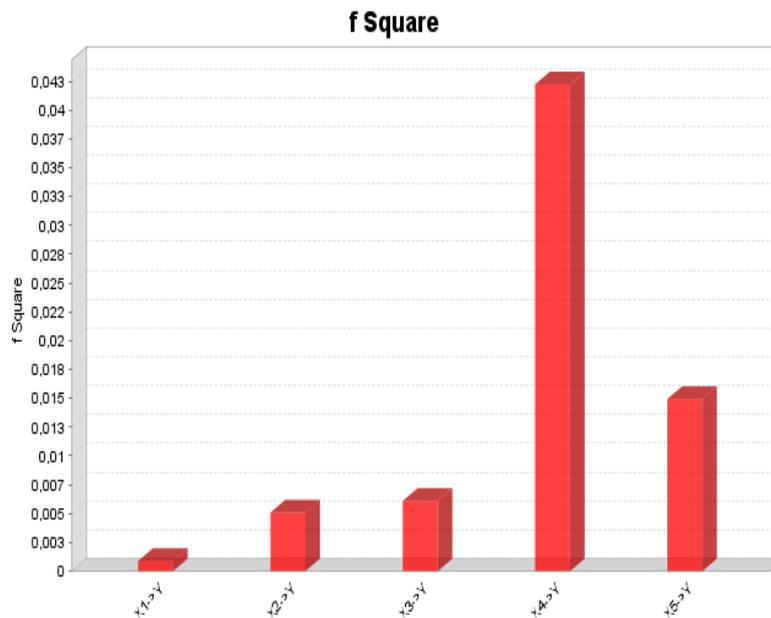

Figure 6. f² Effect sizes of predictors on employee performance

The effect size analysis shows that none of the predictors made a large practical contribution to Employee Performance (EP).

- Innovation Culture (IC) has the largest f² value of 0.046, indicating a small effect but the most meaningful contribution among the predictors.
- Work Well-being (WB) (f² = 0.015), Job Autonomy (JA) (f² = 0.008), and Employee Engagement (EE) (f² = 0.007) all showed small effects, suggesting a limited direct influence on performance outcomes.
- Virtual Training (VT) has the lowest effect size at 0.002, classified as negligible, contributing little to no explanatory power for employee performance.

The small f² values across all predictors align with the low R² value (0.065), reinforcing that these predictors alone cannot explain a significant portion of the performance variance in a hybrid work setting. This suggests that other factors may have a stronger influence on employee performance.
- Organizational culture and leadership support
- Intrinsic motivation and psychological safety
- Team collaboration and communication structures
- Technological readiness and digital work maturity

The relatively higher f² for Innovation Culture, though small, may reflect the transitional nature of hybrid work, where cultural adaptation impacts short-term performance but may have stronger long-term effects.

4.3.3 Predictive Relevance (Q²)

Predictive relevance (Q²) is a key indicator in PLS-SEM that evaluates the model's out-of-sample predictive accuracy. While R² measures in-sample explanatory power, Q² assesses how well the model can predict data points that are not used in model estimation. The Q² value is calculated using the

blindfolding procedure, which omits parts of the data and predicts them using the model. According to Hair Jr et al. (2017):

- A Q² value greater than 0 indicates that the model has predictive relevance for endogenous constructs.
- A Q² value equal to or below 0 suggests no predictive relevance.

In this study, the Q^2 value for Employee Performance (EP) was 0.038, indicating a weak but positive predictive power.

Table 9. Predictive relevance (Q²)

Endogenous Construct	Q²	Predictive Relevance
Employee Performance (EP)	0.038	Weak but positive

The Q^2 value of 0.038 indicates that the model can predict employee performance to a small, but meaningful, extent. Although the predictive power is weak, it is above the zero threshold, suggesting that the model contains some predictive information. This aligns with the low R^2 (0.065) and small effect sizes (f^2), indicating that the model captures some performance variance, but its predictive ability is limited.

4.3.4 Hypotheses Testing (Path Coefficients)

Hypothesis testing in PLS-SEM evaluates the significance and direction of the relationships between exogenous constructs (VT, JA, EE, IC, and WB) and the endogenous construct (EP). This study used bootstrapping with 5,000 subsamples to calculate standardized path coefficients (β), t-statistics, and p-values, enabling robust significance testing without assuming data normality.

Table 10. Path Coefficients and Hypotheses Testing

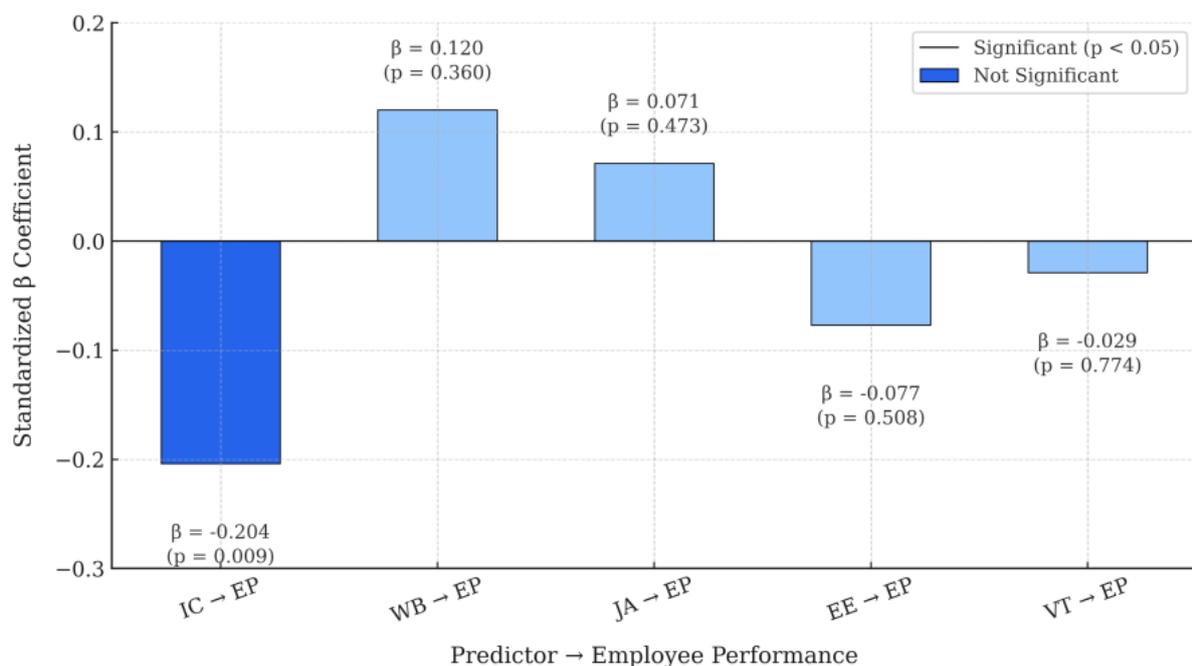| Hypothesis	Path	β	t-stat	p-value	Result
H1	VT → EP	−0.029	0.288	0.774	Not supported
H2	JA → EP	0.071	0.718	0.473	Not supported
H3	EE → EP	−0.077	0.663	0.508	Not supported
H4	IC → EP	−0.204	2.619	0.009	Supported (negative)
H5	WB → EP	0.120	0.917	0.360	Not supported

Figure 7. Bootstrapped path coefficients to employee performance

The figure shows the standardized path coefficients (β) from SmartPLS bootstrapping (5,000 resamples). Only Innovation Culture (IC → EP) has a significant negative relationship (β = −0.204, p = 0.009), while the other predictors show non-significant effects (p > 0.05). A mapping between construct labels and their corresponding measurement indicators is provided for clarity, allowing readers to trace the origin of each construct in the PLS-SEM.
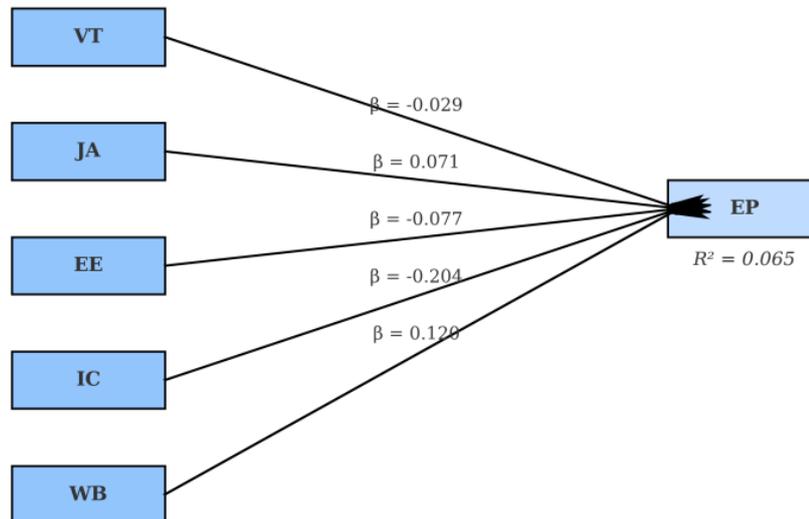

Figure 8. Structural path diagram (Standardized β and R²)

The diagram shows the relationships between Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), Innovation Culture (IC), Work Well-being (WB), and Employee Performance (EP). Only Innovation Culture (IC → EP) has a significant negative effect (β = −0.204, p < 0.01), while the other paths are non-significant (p > 0.05). The model explains 6.5% (R² = 0.065) of the variance in the performance of employees.

The negative relationship between Innovation Culture and performance suggests that a stronger focus on innovation may temporarily reduce employee performance in hybrid work (Martins & Terblanche, 2003). This aligns with research showing that innovation can cause short-term disruptions before it yields long-term benefits. In contrast, VT, JA, EE, and WB did not show significant direct effects on performance, indicating their influence may be indirect, possibly through factors like engagement, empowerment, digital readiness, or team collaboration

4.3.5 Summary of the Structural Model Findings
After evaluating the structural model using PLS-SEM, key indicators such as the Coefficient of Determination (R²), Effect Size (f²), Predictive Relevance (Q²), and Hypothesis Testing outcomes provide an overall view of the model's explanatory and predictive capabilities.

Table 11. Summary of structural model indicators

Indicator	Value	Interpretation
R²	0.065	Weak explanatory power
f²	< 0.05	Small or negligible effect sizes
Q²	0.038	Weak but positive predictive relevance
Supported Hypothesis	H4	IC → EP (significant, negative effect)
Non-Supported Hypotheses	H1, H2, H3, H5	No significant direct effect

1. Coefficient of Determination (R²)
   The R² value of 0.065 indicates that the five exogenous constructs (VT, JA, EE, IC, and WB) explain approximately 6.5% of the variance in Employee Performance (EP). According to Hair Jr et al. (2017), this represents "weak" explanatory power, suggesting that other variables not included

in the model likely have a more significant impact on performance outcomes in hybrid work settings.

2. **Effect Size (f²)**

   All effect sizes were below 0.05, indicating small or negligible effects. This means that none of the predictors (VT, JA, EE, IC, and WB) had a strong influence on Employee Performance. Although Innovation Culture (IC) had the largest effect, it was still considered small according to Cohen's (1988) thresholds.

3. **Predictive Relevance (Q²)**

   The Q² value of 0.038, obtained through the blindfolding procedure, indicates a positive but weak predictive relevance. This suggests that while the model can predict Employee Performance to some extent, its predictive power is limited, implying that other indirect mechanisms may also influence performance.

4. **Hypotheses Testing**

   Supported Hypothesis: Only H4 (IC → EP) was statistically significant. Interestingly, the relationship was negative, suggesting that an increased focus on innovation culture can temporarily reduce employee performance owing to adjustment costs or short-term disruptions in hybrid work environments.

   Non-Supported Hypotheses: H1 (VT → EP), H2 (JA → EP), H3 (EE → EP), and H5 (WB → EP) showed no significant direct effects on performance. This suggests that their influence may operate indirectly, possibly through mediating variables such as motivation, engagement and digital literacy.

4.3.6 Comparison with Previous Model

To contextualize the structural model results, the current findings were compared with a previously tested model of ML Adoption, which used a similar PLS-SEM analytical approach. The goal of this comparison was to evaluate the relative explanatory and predictive strengths of the two models.

Table 12. Structural model comparison: previous vs. current

Aspect	Previous Model (ML Adoption)	Current Model (Employee Performance)
R²	0.628 (moderate–strong)	0.065 (weak)
Q²	0.582 (strong predictive relevance)	0.038 (weak but positive)
Largest f²	AT = 0.197, DL = 0.153 (medium)	IC = 0.046 (small)
Supported Hypotheses	5/5	1/5
Effect Direction	Positive	Negative (IC → EP)
Implication	Strong explanatory power of technical & trust factors	Weak direct influence of organizational factors

The previous model on ML adoption showed stronger explanatory and predictive power, with an R² of 0.628 and Q² of 0.582, indicating moderate to strong performance. The largest effect sizes (f²) were medium, highlighting the strong impact of the technical and trust-related predictors. All five hypotheses were supported, demonstrating consistent positive effects. In contrast, the current model on employee performance has weak explanatory power (R² = 0.065) and weak but positive predictive relevance (Q² = 0.038). Only one hypothesis (IC → EP) was supported, and it showed a negative relationship. The effect sizes were small, suggesting a limited direct contribution to performance outcomes.

4.4 Path Diagram and Visualization

Visualizing the structural model is a crucial step in interpreting the PLS-SEM. The structural path diagram clarifies the relationships between the exogenous variables (VT, JA, EE, IC, and WB) and the endogenous variable (EP). It serves as both a graphical illustration of statistical relationships and an interpretive framework, helping researchers identify the strength, direction, and significance of each hypothesized path in the model.
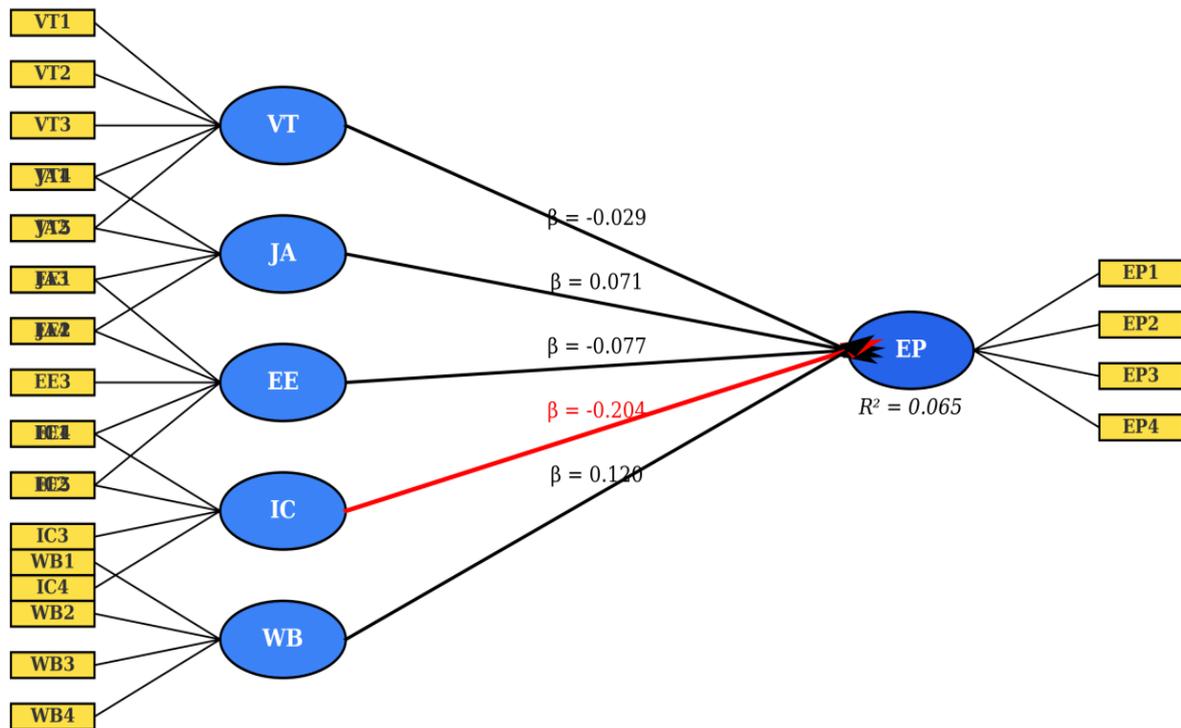
Figure 9. Full structural path diagram (VT, JA, EE, IC, WB → EP; R² = 0.065)

Figure 9 visualizes the structural model, with constructs (blue ovals) and their reflective indicators (yellow rectangles). The arrows represent the hypothesized paths with standardized coefficients (β). Only Innovation Culture (IC → EP) shows a significant negative relationship ($\beta = -0.204$, $p < 0.01$), while the other paths are non-significant ($p > 0.05$). The model explains 6.5% ($R^2 = 0.065$) of the variance in Employee Performance. The structural path diagram (Figure 9) depicts five direct paths from the exogenous variables to the endogenous variables. The R^2 value of 0.065 is positioned within the EP construct, indicating that 6.5% of the variance in employee performance is explained by the five predictors combined.

Although this explanatory power can be categorized as weak, such a result is not uncommon in behavioral and organizational studies, where performance is often shaped by multiple latent and contextual factors beyond the observed variables [insert references]. This finding underscores the complexity of performance as a construct and suggests that additional mediating or moderating variables should be considered in future models. Among the five predictors, only Innovation Culture (IC) showed a significant relationship with Employee Performance, with a standardized path coefficient of $\beta = -0.204$ and a p-value less than 0.01. Interestingly, this effect is negative, indicating that a strong innovation culture may temporarily lower short-term employee performance owing to the adaptation costs associated with innovation, which disrupts existing routines.

While innovation is crucial for long-term organizational competitiveness, its short-term impact can include reduced productivity or misalignment with operational priorities. In contrast, Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), and Work Well-being (WB) did not show significant effects on Employee Performance ($p > 0.05$), suggesting that these factors influence performance indirectly through psychological or organizational mechanisms, such as motivation or team dynamics, rather than direct behavioral outcomes. This aligns with the previous literature, which suggests that many workplace interventions have their primary impact through mediators rather than direct effects on performance.

The path diagram provides a clearer understanding of complex statistical relationships, helping researchers and practitioners identify key drivers and assess their relative influence on organizational policies. This confirms that while innovation culture plays a central role, its impact can be both

beneficial for long-term transformation and potentially disruptive in the short term. Therefore, organizations must carefully manage innovation processes to balance exploration and operational stability. In summary, the path diagram shows that employee performance is a multifactorial outcome shaped by both formal workplace interventions and broader contextual and psychological dynamics. The low R^2 value of 0.065 emphasizes the need for further research to include additional explanatory variables and explore mediating and moderating mechanisms that may better account for the complexity of performance in hybrid work environments.

Additionally, a comparative visualization of path strengths further clarifies the relative influence of each predictor on employee performance. The visualization of standardized path coefficients offers a clear understanding of which factors exert the most substantial influence, as shown in the bar chart in Table 11 and Figure 8, representing the coefficients for all five predictors: Innovation Culture (IC), Work Well-being (WB), Job Autonomy (JA), Employee Engagement (EE), and Virtual Training (VT). The results indicate that Innovation Culture (IC) has the largest absolute path coefficient ($\beta = -0.204$), representing a moderate and statistically significant effect ($p = 0.009$). Interestingly, this effect is negative, suggesting that stronger innovation-oriented practices may temporarily reduce employees'short-term performance.

This finding is consistent with previous research Martins and Terblanche (2003), which suggests that fostering a culture of innovation can increase cognitive load, learning curve effects, and coordination complexity, all of which may reduce short-term productivity. This pattern reflects the trade-off between short-term efficiency and long-term adaptability in innovation-driven environments, particularly within hybrid work arrangements. Work Well-being (WB) ($\beta = 0.120$) and Job Autonomy (JA) ($\beta = 0.071$) showed weak positive effects on employee performance, although neither was statistically significant. These constructs may indirectly influence performance through factors such as motivation or job satisfaction. Employee Engagement (EE) ($\beta = -0.077$) and Virtual Training (VT) ($\beta = -0.029$) have very weak or negligible effects, suggesting that their direct impact on performance is minimal.

This may be due to hybrid work dynamics, where outcomes are mediated by factors such as leadership support, digital readiness and team culture. The comparative visualization with a bar chart helps assess the relative importance of each variable in the model, showing that Innovation Culture has the strongest influence, despite its negative effect. The other constructs contribute weakly to the variance in performance. This highlights that performance in hybrid work environments is shaped by the interconnected organizational and psychological factors. While Innovation Culture is vital for long-term change, it requires careful management to minimize short-term disruption. Similarly, enhancing autonomy, well-being, engagement, and training may require indirect, integrative strategies to effectively improve performance.

Table 13. Standardized path coefficients (β) from exogenous constructs to employee performance

Predictor	β	Relative Strength
Innovation Culture (IC)	−0.204	Moderate, significant (negative)
Work Well-being (WB)	0.120	Weak, not significant
Job Autonomy (JA)	0.071	Very weak, not significant
Employee Engagement (EE)	−0.077	Very weak, not significant
Virtual Training (VT)	−0.029	Negligible, not significant
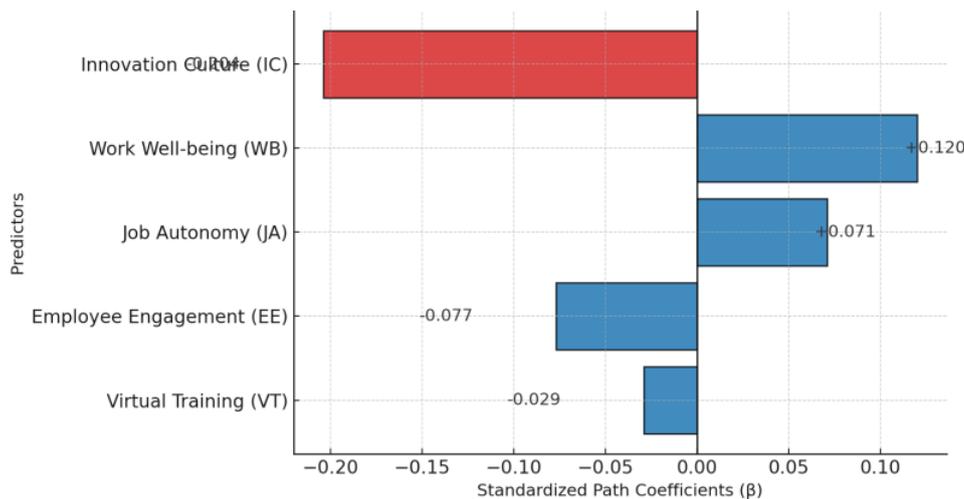
Figure 10. Standardized path coefficients to employee performance

The chart displays the relative strength and direction of the standardized coefficients (β) from each predictor to Employee Performance (EP). Only Innovation Culture (IC → EP) is statistically significant (β = −0.204, p < 0.01), while Work Well-being (WB), Job Autonomy (JA), Employee Engagement (EE), and Virtual Training (VT) exhibit weak or non-significant effects (p > 0.05). Together, they provide both a structural overview and a comparative ranking of the predictors affecting Employee Performance in hybrid work contexts. The diagram highlights the direction and strength of the relationships within the model, while the bar chart offers a concise summary of their relative impact. This dual representation strengthens interpretability by showing how each construct contributes directly or indirectly to performance outcomes, allowing both academic and managerial audiences to grasp the underlying dynamics of hybrid work performance more effectively and accurately.

4.5 Discussion
4.5.1 Interpretation of Significant Finding (IC → EP, negative)
The analysis revealed a significant negative relationship between Innovation Culture (IC) and Employee Performance (EP) (β = −0.204; p = 0.009). While this finding contradicts much of the prior literature that associates innovation culture with improved performance, several explanations can be offered to reconcile this outcome in the context of hybrid work. Innovation-oriented environments emphasize experimentation, idea testing, and learning through failure, which may temporarily disrupt the productivity of employees. During such transitions, employees invest cognitive and temporal resources into ideation rather than routine execution, which can depress short-term output.

There may be goal misalignment between innovation-driven activities and organizational performance. When KPIs continue to emphasize efficiency, speed, or task completion, employees engaged in experimentation may appear less productive despite creating long-term intangible assets such as new methods or process insights. Unmodeled mediating variables, such as leadership support, engagement, or readiness for change, may explain this counterintuitive result. In hybrid settings, the lack of face-to-face feedback loops and uneven digital fluency can amplify the costs of innovation, turning what is theoretically an enabler into a short-term constraint. Therefore, a negative coefficient does not necessarily imply that an innovative culture is detrimental. Instead, it reflects the temporal lag between innovation efforts and performance payoffs, particularly in hybrid organizations that are still adapting to new collaborative norms.

4.5.2 Non-Significant Paths (VT, JA, EE, WB → EP)
The non-significant relationships of Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), and Work Well-being (WB) with Employee Performance (EP) suggest that their effects may operate indirectly or contextually, rather than directly influencing output.

a) Virtual Training (VT → EP): Virtual learning improves access to knowledge but may not directly raise performance unless it is task-aligned and reinforced through post-training coaching. Without contextual embedding, learning outcomes may remain abstract and underutilized (Baldwin & Ford, 1988).

b) Job Autonomy (JA → EP): While autonomy enhances motivation, excessive discretion can generate role ambiguity and coordination gaps in hybrid environments. The effect of autonomy likely depends on leadership clarity and structured accountability mechanisms (Langfred & Moye, 2004).

c) Employee Engagement (EE → EP): Engagement functions more as a mediator than a direct predictor, channeling the effects of organizational resources toward performance. When digital overload or communication fragmentation occurs, the motivational energy of engagement may not translate into measurable productivity.

d) Work Well-Being (WB → EP): Well-being may buffer stress but not necessarily drive higher output unless paired with enablement resources such as technology support or flexible workload design (Danna & Griffin, 1999).

e) Collectively, these findings indicate that hybrid work performance is multilayered, requiring the synergy of psychological resources, leadership, and structural alignment.

4.5.3 Model Explanatory Power (R^2)

The R^2 value of 0.065 indicates that the five exogenous variables jointly explain approximately 6.5% of the variance in Employee Performance. Although this appears modest, such levels are not uncommon in organizational behavior research, especially when unobserved contextual factors such as leadership, team structure, or digital tools play major roles. This underscores the need for a refined conceptual model that integrates Employee Engagement as a mediator and leadership support or task interdependence as moderators. The inclusion of industry and firm size controls could further capture the variability in performance determinants across hybrid work arrangements. Future research should test sequential mediation models (e.g., VT → EE → EP or IC → EE → EP) and multigroup analyses (e.g., hybrid intensity or digital maturity) to identify the boundary conditions under which these effects become stronger or weaker.

4.5.4 Implications

This study contributes to the literature by illustrating that the effect of innovation culture on performance in hybrid work settings may be non-linear and temporally dynamic. This challenges the assumption that innovation always enhances immediate outcomes, emphasizing the importance of temporal alignment between exploration activities and performance evaluation cycles. Moreover, the findings refine the Job Demands–Resources (JD-R) framework, showing that resources such as autonomy, training, and well-being require mediating mechanisms such as engagement or capability development to translate into performance. This reinforces the argument that resources are necessary but insufficient without contextual enabling.

From a managerial standpoint, organizations can operationalize these findings into actionable strategies.

1. Align innovation initiatives with the KPIs.
   Performance evaluations should recognize both short-term efficiency and long-term innovation outcomes. Integrate "exploration metrics" such as idea generation and knowledge sharing.

2. Designing purposeful virtual training.
   Integrate learning modules with practical projects, peer interactions, and supervisor follow-ups to strengthen the transfer of learning into performance.

3. Balance autonomy with the structure.
   Define clear goals, feedback loops, and accountability frameworks to guide self-managed employees in hybrid environments.

4. Targeted well-being interventions:
   Moving beyond generic wellness programs by addressing hybrid-specific stressors, such as digital fatigue, social isolation, and blurred boundaries, is essential.

5. Scaffold innovation culture.
   Pair experimentation with structured reflection sessions and leadership support to prevent disorientation during the innovation cycles.

Table 14. Summary of hypotheses and findings

Hypothesis	Relationship	Result	Key Takeaway
H1	Virtual Training (VT) → Employee Performance (EP)	Not Supported	Training must be contextualized and reinforced to improve performance.
H2	Job Autonomy (JA) → Employee Performance (EP)	Not Supported	Autonomy alone is insufficient without a structure and feedback.
H3	Employee Engagement (EE) → Employee Performance (EP)	Not Supported	Engagement may mediate performance rather than directly predicting it.
H4	Innovation Culture (IC) → Employee Performance (EP)	Supported (Negative)	An innovative culture can lower short-term output due to adaptation and experimentation.
H5	Work Well-being (WB) → Employee Performance (EP)	Not Supported	Well-being enhances satisfaction but not necessarily productivity.
H6	Combined Model (VT, JA, EE, IC, WB → EP)	Partially Supported	The model explains 6.5% of the performance variance; the effects are mostly indirect or context-dependent.

4.5.5 Synthesis

In summary, the hybrid work paradigm redefines the pathways through which organizational resources and psychological factors influence employee performance. Innovation culture remains a double-edged construct vital for long-term adaptability but is potentially disruptive in the early stages. Digital learning, autonomy, engagement, and well-being form an interconnected ecosystem that requires alignment, mediation, and adaptive leadership to transform into measurable productivity gains. Future research should extend this model using longitudinal or multi-group designs, incorporating hybrid intensity, digital readiness, and leadership style as moderators to uncover the deeper causal mechanisms that sustain employee performance in hybrid work ecosystems.

5. Conclusions

5.1 Conclusion

This study examined the influence of Virtual Training (VT), Job Autonomy (JA), Employee Engagement (EE), Innovation Culture (IC), and Work Well-being (WB) on Employee Performance (EP) in the era of hybrid work, using Partial Least Squares Structural Equation Modeling (PLS-SEM) with data from 150 respondents across various industries in Indonesia. The findings revealed that only Innovation Culture (IC) had a significant, albeit negative, effect on employee performance ($\beta = -0.204$, $p = 0.009$). This suggests that innovation-driven environments characterized by experimentation, flexibility, and creative risk-taking may initially disrupt routine workflows, especially in hybrid teams that are still adapting to asynchronous coordination and digital transformation.

Conversely, Virtual Training, Job Autonomy, Employee Engagement, and Work Well-being did not exhibit significant direct effects on performance. These constructs likely exert indirect or conditional influences mediated by engagement, leadership, or digital readiness. The model's explanatory power ($R^2 = 0.065$) indicates that while the tested variables contribute modestly to explaining performance variance, they are part of a broader resource–engagement–performance framework that warrants further exploration. Overall, the study fulfills its objectives by empirically validating that hybrid work performance is shaped by both structural and psychological enablers; however, the relationships among them are contextually dynamic, mediated, and non-linear. The results advance the theoretical and practical understanding of how innovation culture and organizational resources interact to shape productivity under hybrid work arrangements.

5.2 Research Limitations

This study is limited by its focus on only five organizational constructs, excluding other potentially influential variables such as leadership support, digital infrastructure, communication quality, and organizational commitment, which could enhance the model's explanatory power. The use of a cross-

sectional design restricts the ability to capture temporal dynamics and causal relationships, including the delayed effects of innovation culture on performance. Employee performance was measured using self-reported data, which may have introduced common method bias and perceptual distortion. Future studies should incorporate supervisor assessments and objective performance indicators. In addition, the findings are context-specific to the Indonesian hybrid work environment, which may limit their generalizability to other sectors or countries with different technological and cultural characteristics of the workforce. Finally, the application of a simplified direct-path PLS-SEM model did not test potential mediating or moderating effects, thereby limiting deeper insights into indirect relational mechanisms

5.3 Suggestions and Directions for Future Research

Future research should expand the current model by integrating mediating variables such as Employee Engagement or Psychological Empowerment, as well as moderating factors including Leadership Style and Digital Maturity, to better explain the indirect mechanisms affecting employee performance. Longitudinal approaches and multi-group analyses are also recommended to capture the dynamic interaction between innovation culture and hybrid work intensity over time and across different organizational contexts. To improve measurement validity, future studies should combine self-report surveys with objective and multi-source data, such as supervisor evaluations, productivity analytics, and HR performance metrics. Moreover, cross-country comparative studies are needed to examine whether cultural orientations, such as collectivism and individualism, moderate the effects of autonomy, engagement, and well-being in hybrid work environments.

From a managerial perspective, organizations should align innovation initiatives with performance evaluation systems by adjusting KPIs to accommodate exploratory and creative activities so that short-term efficiency targets do not hinder long-term innovation objectives. Virtual training effectiveness should be strengthened through mentoring, reflective learning sessions, and direct on-the-job application to ensure improved behavioral performance. Managers also need to balance employee autonomy with structured goal-setting and continuous performance feedback to keep independence productive and aligned with the organizational objectives. In addition, employee well-being must be prioritized by addressing hybrid work challenges, such as isolation, digital fatigue, and blurred work–life boundaries, through supportive tools and cohesive team rituals. Finally, organizations should cultivate an adaptive innovation culture by encouraging experimentation within psychologically safe environments, supported by leadership commitment and time-bound innovation mechanisms to translate creativity into a measurable organizational impact.

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