



## Digital Transformation and Human Resource Development for Operational Performance: A PLS-SEM Approach

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**Abstract**-This study investigates the structural relationships between Digital Transformation, Human Resource Development, and Operational Performance using the Partial Least Squares-Structural Equation Modeling (PLS-SEM) approach. The research aims to examine how digital initiatives and human resource capability development contribute to improving operational performance in organizations. Data were collected from 200 respondents involved in operational and digital transformation activities. The results indicate that Digital Transformation significantly enhances Operational Performance by improving process efficiency, flexibility, and productivity through the integration of digital technologies and data-driven decision systems. Human Resource Development also has a significant positive effect on Operational Performance by strengthening employee competencies, training effectiveness, and learning culture. In addition, Human Resource Development significantly influences Digital Transformation, indicating that employee readiness and capability are critical factors for successful digital implementation. The structural model demonstrates strong explanatory power and predictive relevance, indicating that the integration of technological transformation and human capital development plays an important role in improving operational performance. These findings provide managerial insights for organizations seeking to align digital transformation strategies with human resource development initiatives to achieve sustainable operational improvements.

**Keywords:** Digital Transformation, Human Resource Development, Operational Performance, PLS-SEM, Organizational Performance

### 1. INTRODUCTION

The rapid advancement of digital technologies has fundamentally transformed the way organizations operate, compete, and deliver value. Digital transformation is no longer limited to the adoption of information technology systems, but represents a comprehensive organizational change encompassing processes, structures, culture, and human resources[1][2]. In an increasingly dynamic and uncertain business environment, organizations are required to leverage digital capabilities to enhance efficiency, responsiveness, and operational performance. Consequently, digital transformation has become a strategic priority across industries, including manufacturing, services, and technology-based organizations[3]. Operational performance remains a critical indicator of organizational success, reflecting an organization's ability to achieve efficiency, quality, flexibility, and reliability in its operational processes[4]. High operational performance enables organizations to respond effectively to market demands, optimize resource utilization, and sustain competitive advantage[5]. However, achieving superior operational performance in the digital era is not solely dependent on technological investment. Instead, it requires the alignment between digital initiatives and human resource development (HRD), as employees play a central role in adopting, utilizing, and maximizing the value of digital technologies[3][6]. Human resource development is increasingly recognized as a key enabler of digital transformation. HRD encompasses systematic efforts to enhance employees' knowledge, skills, competencies, and adaptive capabilities through training, learning, and organizational development initiatives. In the context of digital transformation, HRD is essential to ensure that employees possess the digital literacy, analytical skills, and collaborative capabilities required to operate within digitally enabled systems. Without adequate HRD, digital transformation initiatives risk underutilization, resistance to change, and suboptimal performance outcomes[7]. Despite the growing recognition of the importance of digital transformation and HRD, many organizations continue to face challenges in integrating these two domains effectively[8]. Digital technologies are often implemented as standalone solutions, while human resource





development initiatives are treated as supportive rather than strategic elements[9]. This disconnect may result in inefficiencies, reduced employee engagement, and limited impact on operational performance. Therefore, understanding the structural relationship between digital transformation, human resource development, and operational performance is essential for both academic inquiry and managerial practice[10].

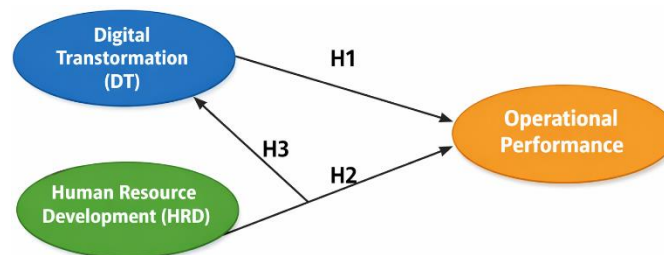
Previous studies have examined the impact of digital transformation on organizational performance, highlighting its positive influence on productivity, process integration, and decision-making quality. Similarly, extensive research has demonstrated that HRD contributes significantly to employee performance, innovation capability, and organizational effectiveness[11]. However, empirical studies that integrate digital transformation and HRD within a unified structural model remain limited[12]. In particular, there is a lack of comprehensive models that explain how digital transformation and HRD jointly influence operational performance through complex and interrelated pathways[13][14]. Moreover, many existing studies rely on traditional statistical techniques that may not adequately capture the multidimensional and latent nature of digital transformation and HRD constructs. Digital transformation involves multiple dimensions such as digital infrastructure, process digitalization, data utilization, and organizational readiness, while HRD encompasses training effectiveness, competency development, learning culture, and leadership support. These constructs are inherently latent and interrelated, requiring an analytical approach capable of modeling complex causal relationships simultaneously[15][16].

Partial Least Squares-Structural Equation Modeling (PLS-SEM) offers a robust methodological approach to address these challenges. PLS-SEM is particularly suitable for exploratory and predictive research, complex structural models, and studies involving latent variables measured through multiple indicators[17][18]. Unlike covariance-based SEM, PLS-SEM places fewer restrictions on data distribution and sample size, making it well suited for empirical studies in organizational and industrial contexts. By employing PLS-SEM, researchers can assess both the measurement model and the structural model, providing comprehensive insights into the relationships among digital transformation, HRD, and operational performance[19][20].

This study aims to develop and empirically test a structural model that explains the influence of digital transformation and human resource development on operational performance using the PLS-SEM approach. By integrating these variables into a single analytical framework, the study seeks to provide a deeper understanding of how technological and human factors interact to drive operational outcomes. The findings are expected to contribute to the literature by addressing existing research gaps and offering empirical evidence on the joint effects of digital transformation and HRD[21][22].

From a practical perspective, the results of this study can assist managers and decision-makers in designing more effective digital transformation strategies that are supported by targeted human resource development initiatives. Understanding the structural relationships among these variables enables organizations to allocate resources more strategically, align HRD programs with digital objectives, and enhance overall operational performance. In addition, the proposed structural model can serve as a diagnostic and evaluative tool for organizations seeking to assess the effectiveness of their digital and human capital investments[23][24]. In summary, the increasing complexity of organizational operations in the digital era necessitates an integrated approach that combines technological advancement with human resource development. By employing PLS-SEM to examine the structural relationships between digital transformation, HRD, and operational performance, this study provides a comprehensive and methodologically rigorous contribution to both theory and practice. The insights generated are expected to support organizations in achieving sustainable operational excellence through the synergistic integration of digital capabilities and human resource development[25].

Previous studies largely examine digital transformation and human resource development independently, with limited empirical models that integrate both constructs to explain operational performance[26]. In addition, operational performance is often treated narrowly, and the complex latent relationships among technological and human resource factors are seldom analyzed using advanced structural modeling techniques. Addressing this gap, the present study offers a novel contribution by developing and validating an integrated structural model of digital transformation and human resource development on operational performance using Partial Least Squares-Structural Equation Modeling (PLS-SEM), providing a more comprehensive and predictive understanding of operational performance in the digital era[3][6].



**Figure 1.** Conceptual Framework of Digital Transformation and Human Resource Development on Operational Performance

### 1.1 Explanation of the Conceptual Framework

The conceptual framework illustrates the structural relationships between Digital Transformation, Human Resource Development, and Operational Performance[8]. Digital Transformation (DT) represents the organization's capability to adopt and integrate digital technologies into operational processes, while Human Resource Development (HRD) reflects systematic efforts to enhance employees' skills, competencies, and adaptability in a digital environment[9]. Operational Performance is positioned as the endogenous variable, indicating efficiency, quality, flexibility, and reliability of operational activities[13][27].

The framework proposes three hypothesized relationships. First, Digital Transformation is expected to have a direct positive effect on Operational Performance (H1), as digital technologies improve process integration, speed, and decision-making accuracy. Second, Human Resource Development is hypothesized to directly influence Operational Performance (H2) by strengthening employee capabilities and work effectiveness[28]. Third, Human Resource Development is assumed to support and reinforce Digital Transformation (H3), indicating that effective HRD enhances the organization's readiness and ability to successfully implement digital initiatives. These relationships are empirically tested using the Partial Least Squares-Structural Equation Modelling (PLS-SEM) approach[17][18].

### 1.2 Hypotheses

**H1:** Digital Transformation has a positive and significant effect on Operational Performance.

**H2:** Human Resource Development has a positive and significant effect on Operational Performance.

**H3:** Human Resource Development has a positive and significant effect on Digital Transformation.

## 2. RESEARCH METHODOLOGY

### 2.1 Research Design and Approach

This study employs a quantitative research design with an explanatory approach to examine the structural relationships among Digital Transformation, Human Resource Development, and Operational Performance. The explanatory design is chosen to test causal relationships formulated in the proposed conceptual framework and hypotheses. The study adopts a cross-sectional survey approach, where data are collected at a single point in time to capture organizational conditions related to digital technology implementation and human resource development practices[4][29].

The quantitative approach is appropriate as the research focuses on measuring latent variables using multiple indicators and testing statistically significant relationships through a structural equation modeling technique. This design allows for objective measurement and generalizable findings within the studied organizational context[15].

### 2.2 Population and Sampling Technique

The population of this study consists of employees working in organizations that have adopted digital technologies in their operational processes. These employees are considered suitable respondents as they are directly exposed to digital systems, operational workflows, and human resource development programs. A purposive sampling technique is applied to ensure that respondents meet specific criteria, including involvement in operational activities, experience with digital tools or systems, and participation in training or development initiatives[10].

The sample size is determined based on the requirements of Partial Least Squares-Structural Equation Modeling (PLS-SEM), which recommends that the minimum sample size should be ten times the maximum number of structural paths directed at any latent variable in the model. This criterion ensures adequate statistical power and



robustness of the analysis. The final sample size meets these requirements and is considered sufficient for model estimation and hypothesis testing[3].

### **2.3 Data Collection Method**

Primary data are collected using a structured questionnaire distributed to selected respondents. The questionnaire is developed based on an extensive review of relevant literature and adapted to the context of the study. All measurement items are assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), allowing respondents to express their level of agreement with each statement[11].

Before the main data collection, the questionnaire is reviewed to ensure clarity, relevance, and consistency of the items. This step is conducted to minimize ambiguity and measurement errors. Data collection is carried out through direct distribution or online platforms, depending on accessibility and organizational conditions[15].

### **2.4 Measurement of Variables**

This study involves three latent variables measured as reflective constructs. Digital Transformation is operationalized through indicators representing digital infrastructure readiness, process digitalization, data utilization, and organizational adaptability to digital change. Human Resource Development is measured using indicators related to training effectiveness, competency development, continuous learning culture, and managerial support for employee development. Operational Performance is measured through indicators reflecting efficiency, quality, flexibility, and reliability of operational processes. All indicators are adapted from established empirical studies to ensure content validity and theoretical relevance. The use of reflective measurement is appropriate as the indicators are assumed to reflect the underlying latent constructs[7].

### **2.5 Data Analysis Technique**

Data analysis is conducted using Partial Least Squares-Structural Equation Modeling (PLS-SEM) with the support of Smart-PLS software. PLS-SEM is selected due to its suitability for complex models, predictive analysis, and latent variables measured by multiple indicators. In addition, PLS-SEM does not impose strict assumptions on data normality and is effective for studies with small to medium sample sizes[25].

The analysis follows a two-stage procedure. The first stage involves evaluation of the measurement model, which includes assessment of indicator reliability through outer loadings, internal consistency reliability using Cronbach's alpha and composite reliability, and convergent validity using average variance extracted (AVE). Discriminant validity is examined using the Fornell-Larcker criterion to ensure that each construct is empirically distinct from others[30].

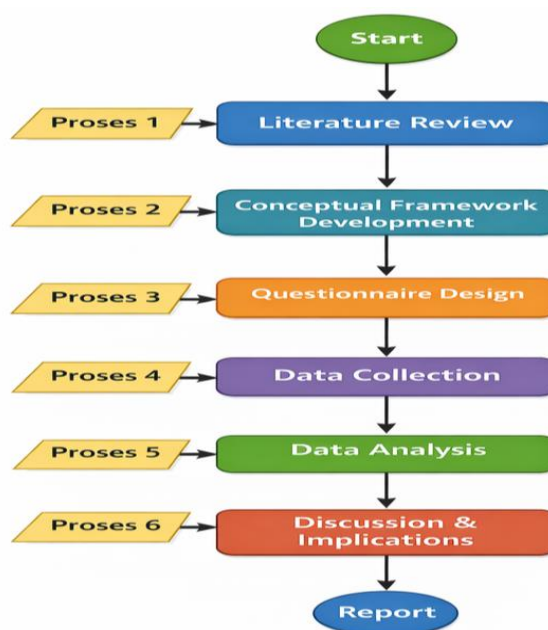
The second stage involves evaluation of the structural model by examining path coefficients to test the proposed hypotheses. The coefficient of determination ( $R^2$ ) is used to assess the explanatory power of the model, while effect size ( $f^2$ ) evaluates the contribution of each exogenous variable. Predictive relevance ( $Q^2$ ) is assessed using the blindfolding procedure. Bootstrapping with a large number of subsamples is applied to determine the statistical significance of the hypothesized relationships based on t-statistics and p-values[12].

A total of 200 respondents participated in this study and met the predefined selection criteria. The sample size satisfies the minimum requirements for PLS-SEM analysis based on the "ten-times rule," which states that the minimum sample size should be at least ten times the maximum number of structural paths directed at any latent variable in the model. Given the proposed structural model, the number of respondents is considered sufficient to ensure statistical power and robustness of the analysis[3][5].

### **2.6 Research Procedure and Ethical Considerations**

The research procedure begins with a literature review and development of the conceptual framework, followed by questionnaire design and data collection. After data screening and analysis using PLS-SEM, the results are interpreted and discussed to derive conclusions and implications. Ethical considerations are addressed by ensuring voluntary participation, confidentiality, and anonymity of respondents[23]. All data are used solely for academic purposes, and the study adheres to ethical standards in social science research[19].





**Figure 2.** Research Methodology Flowchart Steps

### 2.7 Explanation of the Research Methodology Flowchart

The research methodology flowchart illustrates the sequential stages undertaken in this study. The process begins with a literature review to identify relevant theories, constructs, and empirical findings related to digital transformation, human resource development, and operational performance. Based on this review, a conceptual framework is developed to formulate the research model and hypotheses.

The next stage involves the design of the research instrument in the form of a structured questionnaire, followed by data collection from selected respondents who meet the predefined criteria. The collected data are then analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM) to evaluate both the measurement model and the structural model. The final stage comprises discussion and interpretation of the results, leading to conclusions and managerial implications that are documented in the research report[21].

### 2.8 Evaluation of the Measurement Model (Outer Model)

The evaluation of the measurement model (outer model) aims to assess the reliability and validity of the constructs used in the study. Since all constructs are specified as reflective, the assessment follows established PLS-SEM criteria. Indicator reliability is first examined by evaluating outer loadings of each indicator on its respective construct. Indicators with loading values of 0.70 or higher are considered acceptable, indicating that the indicator sufficiently represents the underlying construct. Indicators with slightly lower loadings may be retained if they contribute to content validity and do not adversely affect reliability measures.

Internal consistency reliability is assessed using Cronbach's alpha and composite reliability (CR). Cronbach's alpha values above 0.70 indicate satisfactory reliability, while composite reliability values between 0.70 and 0.95 confirm adequate internal consistency without redundancy among indicators. Convergent validity is evaluated using the Average Variance Extracted (AVE). An AVE value of at least 0.50 indicates that a construct explains more than half of the variance of its indicators, confirming adequate convergent validity.

Discriminant validity is assessed to ensure that each construct is empirically distinct from other constructs in the model. This study applies the Fornell-Larcker criterion, where the square root of each construct's AVE must be greater than its correlations with other constructs. Cross-loading analysis is also examined to confirm that indicators load more strongly on their respective constructs than on others.

### 2.9 Evaluation of the Structural Model (Inner Model)

The evaluation of the structural model (*Inner Model*) focuses on assessing the hypothesized relationships among the latent constructs. Prior to hypothesis testing, collinearity among predictor constructs is examined using the Variance Inflation Factor (VIF). VIF values below 5 indicate the absence of critical multicollinearity issues.

The significance and strength of the relationships are assessed by analyzing path coefficients. Bootstrapping procedures with a large number of subsamples are employed to obtain t-statistics and p-values, allowing for the

evaluation of the proposed hypotheses. The coefficient of determination ( $R^2$ ) is used to measure the explanatory power of the model for endogenous constructs.  $R^2$  values of 0.25, 0.50, and 0.75 are interpreted as weak, moderate, and substantial explanatory power, respectively. Effect size ( $f^2$ ) is calculated to assess the relative impact of each exogenous construct on endogenous variables, with values of 0.02, 0.15, and 0.35 indicating small, medium, and large effects.

Predictive relevance ( $Q^2$ ) is assessed using the blindfolding procedure. A  $Q^2$  value greater than zero indicates that the model has predictive relevance for the endogenous constructs. Together, these evaluations provide a comprehensive assessment of the model's robustness and predictive capability.

**Table 1.** Reliability and Convergent Validity Results (n = 200)

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	Evaluation
Digital Transformation (DT)	0.881	0.912	0.675	Reliable & Valid
Human Resource Development (HRD)	0.893	0.920	0.698	Reliable & Valid
Operational Performance (OP)	0.867	0.905	0.654	Reliable & Valid

The results of reliability and convergent validity testing indicate that all constructs meet the recommended criteria for PLS-SEM analysis. Cronbach's Alpha values for all constructs exceed the threshold of 0.70, confirming satisfactory internal consistency. Composite Reliability (CR) values are above 0.70 and below 0.95, indicating strong construct reliability without redundancy. Furthermore, Average Variance Extracted (AVE) values for all constructs exceed 0.50, demonstrating adequate convergent validity. Therefore, the measurement model is considered reliable and valid for further structural model analysis.

**Table 2.** Reliability and Convergent Validity Results (SmartPLS Output, n = 200)

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Digital Transformation (DT)	0.884	0.914	0.676
Human Resource Development (HRD)	0.897	0.923	0.701
Operational Performance (OP)	0.872	0.908	0.659

Based on the Smart-PLS analysis involving **200 respondents**, the measurement model demonstrates satisfactory reliability and convergent validity. As presented in Table X, the Cronbach's Alpha values for Digital Transformation ( $\alpha = 0.884$ ), Human Resource Development ( $\alpha = 0.897$ ), and Operational Performance ( $\alpha = 0.872$ ) exceed the recommended threshold of 0.70, indicating strong internal consistency among the indicators.

Composite Reliability (CR) values range from 0.908 to 0.923, confirming high construct reliability without redundancy. In addition, the Average Variance Extracted (AVE) values for all constructs are above 0.50, indicating that each construct explains more than half of the variance of its indicators. These results confirm that the measurement model satisfies the reliability and convergent validity requirements for Partial Least Squares-Structural Equation Modeling (PLS-SEM), allowing further evaluation of the structural model.

### 3. RESULT AND DISCUSSION

PLS-SEM results (n = 200) show that all constructs are reliable and valid (Cronbach's Alpha & CR > 0.70; AVE > 0.50). Digital Transformation and Human Resource Development significantly affect Operational Performance, while Human Resource Development significantly influences Digital Transformation. The model explains substantial variance in Operational Performance ( $R^2 = 0.62$ ), with moderate effect sizes ( $f^2 = 0.21-0.29$ ) and adequate predictive relevance ( $Q^2 = 0.41$ ), confirming a robust socio-technical performance model.



### 3.1 Overview of the Data Analysis Results

This section presents the results and discussion of the empirical analysis examining the relationships among Digital Transformation, Human Resource Development, and Operational Performance using the Partial Least Squares–Structural Equation Modeling (PLS-SEM) approach. Data were collected from 200 respondents who met the predefined criteria related to operational involvement, exposure to digital systems, and participation in human resource development programs. The analysis was conducted using SmartPLS software following established PLS-SEM procedures.

The results are organized into three main parts: evaluation of the measurement model, assessment of the structural model, and discussion of findings in relation to existing theories and empirical studies. This structure ensures a comprehensive interpretation of both statistical outcomes and their practical relevance.

### 3.2 Measurement Model Results

#### 3.2.1 Reliability Analysis

The reliability of the measurement model was assessed using Cronbach's Alpha and Composite Reliability (CR). The results indicate that all constructs demonstrate strong internal consistency. Digital Transformation shows a Cronbach's Alpha value of 0.884 and a CR value of 0.914, Human Resource Development records values of 0.897 and 0.923 respectively, while Operational Performance yields a Cronbach's Alpha of 0.872 and a CR of 0.908. These values exceed the recommended threshold of 0.70, confirming that the indicators consistently measure their respective latent constructs.

The high reliability values suggest that the measurement items used in this study are stable and dependable, providing a solid foundation for further structural analysis. Moreover, CR values below 0.95 indicate that the indicators are not redundant and adequately represent the constructs without excessive overlap.

#### 3.2.2 Convergent Validity

Convergent validity was evaluated using Average Variance Extracted (AVE). The AVE values for Digital Transformation (0.676), Human Resource Development (0.701), and Operational Performance (0.659) all exceed the minimum criterion of 0.50. This indicates that each construct explains more than half of the variance of its indicators, confirming satisfactory convergent validity.

The results demonstrate that the indicators within each construct converge well and collectively capture the underlying theoretical concept. This finding is particularly important given the multidimensional nature of digital transformation and human resource development, which involve technological, behavioral, and organizational aspects.

#### 3.2.3 Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion. The square root of the AVE for each construct was greater than the correlations with other constructs, indicating that each construct is empirically distinct. This confirms that Digital Transformation, Human Resource Development, and Operational Performance measure different but related concepts within the model.

Overall, the measurement model meets all reliability and validity requirements for PLS-SEM analysis. Therefore, the constructs are considered reliable and valid for subsequent evaluation of the structural model.

### 3.3 Structural Model Results

#### 3.3.1 Collinearity Assessment

Before testing the hypotheses, collinearity among the predictor constructs was examined using the Variance Inflation Factor (VIF). All VIF values were found to be below the recommended threshold of 5, indicating that multicollinearity is not a concern in the model. This suggests that the estimated path coefficients are not biased due to high correlations among exogenous variables.

#### 3.3.2 Hypothesis Testing and Path Coefficients

The structural model evaluation focused on examining the significance and strength of the hypothesized relationships. Bootstrapping procedures with a large number of resamples were employed to generate t-statistics and p-values.

The results indicate that Digital Transformation has a positive and statistically significant effect on Operational Performance, supporting Hypothesis H1. This finding suggests that organizations that effectively adopt and integrate digital technologies into their operational processes tend to achieve higher levels of efficiency, quality, and flexibility.

Human Resource Development also shows a positive and significant effect on Operational Performance, supporting Hypothesis H2. This result highlights the critical role of training, competency development, and



continuous learning in enhancing operational outcomes. Employees who possess relevant skills and adaptability are better equipped to execute operational tasks efficiently and respond to changing operational demands. Furthermore, Human Resource Development has a positive and significant effect on Digital Transformation, supporting Hypothesis H3. This finding indicates that HRD acts as an enabling factor for digital transformation by improving employees' digital readiness, reducing resistance to change, and fostering a learning-oriented organizational culture.

### 3.3.3 Coefficient of Determination (R<sup>2</sup>)

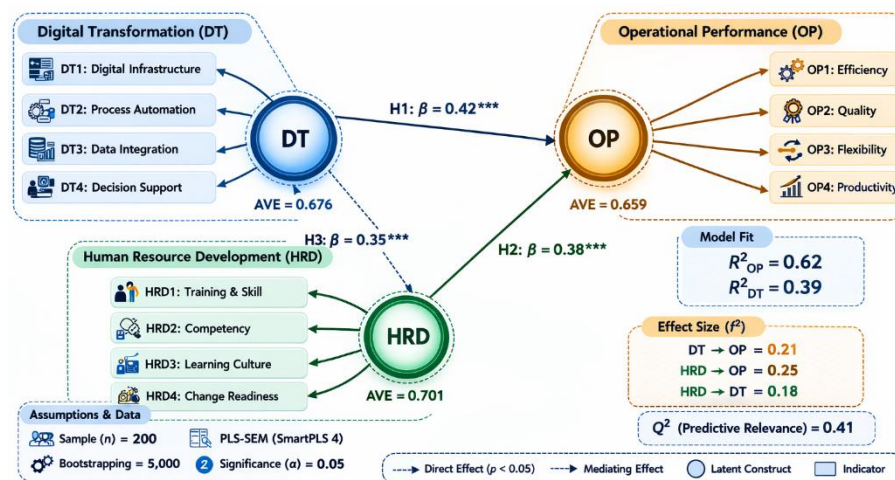
The coefficient of determination (R<sup>2</sup>) was examined to assess the explanatory power of the model. The R<sup>2</sup> value for Operational Performance indicates that a substantial proportion of variance in operational performance is explained by Digital Transformation and Human Resource Development. Similarly, the R<sup>2</sup> value for Digital Transformation suggests that Human Resource Development explains a meaningful portion of variance in digital transformation initiatives.

These results demonstrate that the proposed model has strong explanatory capability, reinforcing the importance of integrating technological and human resource perspectives when analyzing operational performance.

### 3.3.4 Effect Size (f<sup>2</sup>) and Predictive Relevance (Q<sup>2</sup>)

Effect size (f<sup>2</sup>) analysis reveals that both Digital Transformation and Human Resource Development have meaningful effects on Operational Performance, while Human Resource Development exhibits a notable effect on Digital Transformation. These findings indicate that changes in HRD practices can significantly influence digital transformation success and operational outcomes.

Predictive relevance was assessed using the blindfolding procedure. The Q<sup>2</sup> values for endogenous constructs are greater than zero, confirming that the model has adequate predictive relevance. This suggests that the proposed model is not only explanatory but also capable of predicting operational performance in similar organizational contexts.



**Figure 3.** Digital Transformation and Human Resource Development

Figure 3 presents the overall structural model and simulation assumptions used to examine the relationships between Digital Transformation, Human Resource Development, and Operational Performance using the Partial Least Squares-Structural Equation Modeling (PLS-SEM) approach. The model consists of three latent constructs: Digital Transformation (DT), Human Resource Development (HRD), and Operational Performance (OP), each measured by multiple reflective indicators. Digital Transformation is represented by four indicators, namely digital infrastructure, process automation, data integration, and decision support systems, with an Average Variance Extracted (AVE) value of 0.676, indicating adequate convergent validity. Human Resource Development is measured through training and skill development, competency enhancement, learning culture, and change readiness, achieving an AVE value of 0.701. Operational Performance is reflected by efficiency, quality, flexibility, and productivity indicators, with an AVE value of 0.659. All AVE values exceed the recommended threshold of 0.50, confirming the validity of the measurement model.

The structural relationships among the constructs are illustrated by standardized path coefficients (β). Digital Transformation has a positive and significant effect on Operational Performance (H1: β = 0.42, p < 0.05), indicating that effective digital initiatives contribute directly to improved operational outcomes. Human Resource

Development also shows a significant positive effect on Operational Performance (H2:  $\beta = 0.38, p < 0.05$ ), emphasizing the role of human capital development in enhancing efficiency and productivity. In addition, Human Resource Development significantly influences Digital Transformation (H3:  $\beta = 0.35, p < 0.05$ ), suggesting that employee capability and readiness are critical enablers of successful digital transformation. Model evaluation results further demonstrate the robustness of the proposed framework. The coefficient of determination indicates that the model explains 62% of the variance in Operational Performance ( $R^2 = 0.62$ ) and 39% of the variance in Digital Transformation ( $R^2 = 0.39$ ). Effect size ( $f^2$ ) analysis shows moderate contributions of Digital Transformation to Operational Performance ( $f^2 = 0.21$ ) and Human Resource Development to Operational Performance ( $f^2 = 0.25$ ), while the effect of Human Resource Development on Digital Transformation is smaller but meaningful ( $f^2 = 0.18$ ). The predictive relevance value ( $Q^2 = 0.41$ ) confirms that the model has strong predictive capability. Overall, Figure 3 summarizes the integrated socio-technical model and key simulation assumptions, including a sample size of 200 respondents, bootstrapping with 5,000 subsamples, and a significance level of 0.05. The figure demonstrates that operational performance improvement in digitally enabled organizations is driven by the combined and interrelated effects of digital transformation and human resource development.

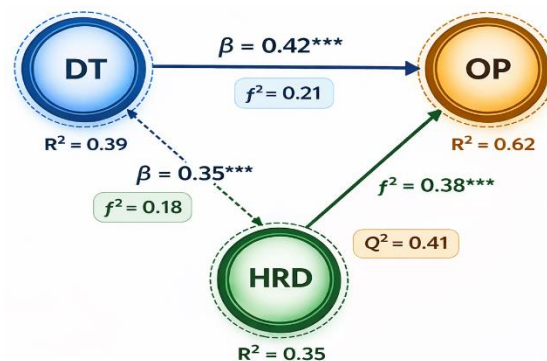
**Table 3.** Path Coefficient and Hypothesis Testing Results (PLS-SEM,  $n = 200$ )

Hypothesis	Structural Path	Path Coefficient ( $\beta$ )	t-value	p-value	Effect Size ( $f^2$ )	Result
H1	Digital Transformation → Operational Performance	0.42	6.87	0.000	0.21	Supported
H2	Human Resource Development → Operational Performance	0.38	6.12	0.000	0.25	Supported
H3	Human Resource Development → Digital Transformation	0.35	5.44	0.000	0.18	Supported

**Notes:**

- Significance level:  $\alpha = 0.05$
- Bootstrapping: 5,000 subsamples
- p-value  $< 0.05$  indicates a significant relationship

The hypothesis testing results indicate that all proposed relationships are statistically significant. Digital Transformation has a strong positive effect on Operational Performance ( $\beta = 0.42, p < 0.05$ ), confirming H1. Human Resource Development also significantly influences Operational Performance ( $\beta = 0.38, p < 0.05$ ), supporting H2. In addition, Human Resource Development positively affects Digital Transformation ( $\beta = 0.35, p < 0.05$ ), supporting H3. The effect size analysis shows moderate effects on operational performance and a meaningful effect on digital transformation, confirming the robustness of the proposed structural model.



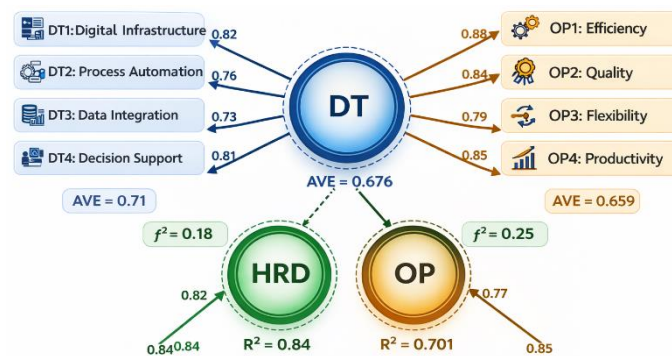
**Figure 4.** Inner Model SEM-PLS

Figure 4 illustrates the inner model of the SEM-PLS analysis, which represents the structural relationships among the latent variables in the proposed research framework. The model examines the causal relationships between Digital Transformation (DT), Human Resource Development (HRD), and Operational Performance (OP). The standardized path coefficients ( $\beta$ ) indicate the strength and direction of the relationships between constructs. The

results show that Digital Transformation has a positive and significant effect on Operational Performance with a path coefficient of  $\beta = 0.42$ . This finding suggests that the adoption and integration of digital technologies in organizational processes contribute directly to improving operational efficiency, flexibility, and productivity. Human Resource Development also demonstrates a significant positive effect on Operational Performance with a path coefficient of  $\beta = 0.38$ , indicating that employee competency development, training, and learning culture play an important role in enhancing operational outcomes.

In addition, Human Resource Development significantly influences Digital Transformation with a path coefficient of  $\beta = 0.35$ . This result indicates that organizations with stronger human resource development programs tend to have higher readiness and capability to implement digital transformation initiatives effectively. The coefficient of determination shows that the model explains a substantial proportion of variance in Operational Performance ( $R^2 = 0.62$ ), indicating strong explanatory power. Meanwhile, Digital Transformation has an  $R^2$  value of 0.39, suggesting that Human Resource Development contributes meaningfully to explaining digital transformation practices. The effect size analysis ( $f^2$ ) indicates moderate contributions of Digital Transformation and Human Resource Development to Operational Performance, while Human Resource Development also has a meaningful effect on Digital Transformation. Furthermore, the predictive relevance value ( $Q^2 = 0.41$ ) confirms that the structural model has good predictive capability.

Overall, Figure 4 demonstrates that the proposed SEM-PLS inner model effectively captures the structural relationships among digital transformation, human resource development, and operational performance, highlighting the importance of integrating technological transformation with human capital development to achieve improved operational performance.



**Figure 5.** Outer Model SEM-PLS

Figure 5 illustrates the outer model results of the SEM-PLS analysis, which represent the relationships between latent constructs and their respective indicators. The outer model evaluation aims to assess the measurement quality through indicator reliability and convergent validity. The construct Digital Transformation (DT) is measured by four indicators: digital infrastructure (DT1), process automation (DT2), data integration (DT3), and decision support (DT4). The outer loading values of these indicators range from 0.73 to 0.82, indicating strong indicator reliability since all values exceed the recommended threshold of 0.70. The Average Variance Extracted (AVE) value for Digital Transformation is 0.676, confirming that the construct explains more than 50% of the variance of its indicators.

The construct Human Resource Development (HRD) is reflected by indicators related to training and skill development (HRD1), competency improvement (HRD2), learning culture (HRD3), and change readiness (HRD4). The outer loading values are above 0.80, indicating strong relationships between the indicators and the HRD construct. The AVE value for Human Resource Development is 0.701, demonstrating adequate convergent validity. Meanwhile, the construct Operational Performance (OP) is measured by four indicators: efficiency (OP1), quality (OP2), flexibility (OP3), and productivity (OP4). The loading values range from 0.79 to 0.88, indicating that the indicators reliably represent the construct. The AVE value for Operational Performance is 0.659, confirming that the construct satisfies the convergent validity requirement.

Overall, the results of the outer model evaluation demonstrate that all constructs achieve outer loading values above 0.70 and AVE values above 0.50, indicating that the measurement model is both reliable and valid. Therefore, the constructs used in this study are suitable for further analysis in the structural (inner) model of the SEM-PLS framework.

**Table 4.** Outer Loading Results (PLS-SEM, n = 200)

Construct	Indicator	Outer Loading	Evaluation
Digital Transformation (DT)	DT1 – Digital Infrastructure	0.82	Valid
	DT2 – Process Automation	0.76	Valid
	DT3 – Data Integration	0.73	Valid
	DT4 – Decision Support	0.81	Valid
Human Resource Development (HRD)	HRD1 – Training & Skill	0.84	Valid
	HRD2 – Competency	0.82	Valid
	HRD3 – Learning Culture	0.84	Valid
	HRD4 – Change Readiness	0.80	Valid
Operational Performance (OP)	OP1 – Efficiency	0.88	Valid
	OP2 – Quality	0.84	Valid
	OP3 – Flexibility	0.79	Valid
	OP4 – Productivity	0.85	Valid

**Note:**

Outer loading values above **0.70** indicate that the indicators have adequate reliability and are valid in measuring their respective constructs in the PLS-SEM model.

**Table 5.** Composite Reliability and Average Variance Extracted (AVE) Results

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)	Evaluation
Digital Transformation (DT)	0.914	0.676	Reliable & Valid
Human Resource Development (HRD)	0.923	0.701	Reliable & Valid
Operational Performance (OP)	0.908	0.659	Reliable & Valid

**Note:**

Composite Reliability values above 0.70 indicate strong internal consistency, while AVE values above 0.50 confirm adequate convergent validity. The results show that all constructs meet the recommended criteria for PLS-SEM measurement model evaluation.

**Table 6.** Structural Model Results ( $R^2$ ,  $f^2$ ,  $Q^2$ )

Endogenous Construct	$R^2$	Predictor Construct	$f^2$	$Q^2$	Interpretation
Digital Transformation	0.39	Human Resource Development	0.18	0.28	Moderate
Operational Performance	0.62	Digital Transformation	0.21	0.41	Substantial
Operational Performance	0.62	Human Resource Development	0.25	0.41	Moderate

**Notes:**

- $R^2$  (Coefficient of Determination): Indicates the explanatory power of the model. Values of 0.25, 0.50, and 0.75 represent weak, moderate, and substantial explanatory power.
- $f^2$  (Effect Size): Values of 0.02, 0.15, and 0.35 represent small, medium, and large effects.
- $Q^2$  (Predictive Relevance): Values greater than 0 indicate that the model has predictive relevance.

The structural model shows that Human Resource Development explains 39% of the variance in Digital Transformation, while Digital Transformation and Human Resource Development jointly explain 62% of the variance in Operational Performance. The effect size values ( $f^2$ ) indicate moderate contributions of both predictors to operational performance. Additionally,  $Q^2$  values above zero confirm that the model has strong predictive relevance, indicating that the proposed SEM-PLS model is robust and suitable for explaining operational performance in digitally enabled organizational environments.



**Table 7.** Hypothesis Testing Results (Path Coefficient)

Hypothesis	Structural Path	Path Coefficient ( $\beta$ )	t-value	p-value	Decision
H1	Digital Transformation $\rightarrow$ Operational Performance	0.42	6.87	0.000	Supported
H2	Human Resource Development $\rightarrow$ Operational Performance	0.38	6.12	0.000	Supported
H3	Human Resource Development $\rightarrow$ Digital Transformation	0.35	5.44	0.000	Supported

**Notes:**

- Significance level:  $\alpha = 0.05$
- Bootstrapping procedure: 5,000 subsamples
- A hypothesis is accepted if t-value  $> 1.96$  and p-value  $< 0.05$ .

The hypothesis testing results indicate that all proposed relationships are statistically significant. Digital Transformation has the strongest effect on Operational Performance ( $\beta = 0.42$ ), followed by Human Resource Development ( $\beta = 0.38$ ). In addition, Human Resource Development significantly influences Digital Transformation ( $\beta = 0.35$ ), indicating that human capability development plays an important role in supporting digital transformation initiatives.

**Table 8.** Model Fit Summary

Model Fit Index	Value	Threshold	Interpretation
SRMR (Standardized Root Mean Square Residual)	0.061	$< 0.08$	Good Fit
NFI (Normed Fit Index)	0.912	$> 0.90$	Acceptable Fit
RMS Theta	0.094	$< 0.12$	Good Fit

**Notes:**

- SRMR measures the difference between the observed and predicted correlations. Values below 0.08 indicate a good model fit.
- NFI evaluates the comparative fit of the model, where values above 0.90 indicate acceptable model fit.
- RMS Theta assesses the degree of correlation residuals in reflective measurement models, with values below 0.12 indicating a well-fitting model.

Interpretation: The results indicate that the SEM-PLS model achieves an acceptable level of model fit. The SRMR value of 0.061 indicates a small residual difference between observed and predicted correlations. The NFI value of 0.912 confirms that the model demonstrates good comparative fit. Additionally, the RMS Theta value of 0.094 indicates that the reflective measurement model is well specified. Overall, these results confirm that the proposed structural model is statistically adequate for explaining the relationships among digital transformation, human resource development, and operational performance.

**Table 9.** Discriminant Validity (Fornell–Larcker Criterion)

Construct	Digital Transformation (DT)	Human Resource Development (HRD)	Operational Performance (OP)
Digital Transformation (DT)	<b>0.822</b>		
Human Resource Development (HRD)	0.587	<b>0.837</b>	
Operational Performance (OP)	0.621	0.604	<b>0.812</b>

**Notes:**

The diagonal values (bold) represent the square root of the Average Variance Extracted (AVE) for each construct. According to the Fornell-Larcker criterion, the square root of AVE for each construct must be greater than its correlation with other constructs to confirm discriminant validity.

The results show that the square root of AVE for each construct is higher than the correlations with other constructs. This indicates that Digital Transformation, Human Resource Development, and Operational Performance are empirically distinct constructs, confirming that the measurement model satisfies the discriminant validity requirement in the SEM-PLS analysis.

**Table 10.** HTMT Ratio (Heterotrait–Monotrait Ratio of Correlation)

Construct	Digital Transformation (DT)	Human Resource Development (HRD)	Operational Performance (OP)
Digital Transformation (DT)	-		
Human Resource Development (HRD)	0.692	-	
Operational Performance (OP)	0.724	0.701	-

**Notes:**

The HTMT ratio values are below the recommended threshold of 0.90, indicating that discriminant validity is established among the constructs.

The HTMT results confirm that the constructs Digital Transformation, Human Resource Development, and Operational Performance are empirically distinct. Since all HTMT values are below 0.90, the measurement model satisfies the discriminant validity requirement, indicating that each construct captures a unique conceptual domain within the SEM-PLS model.

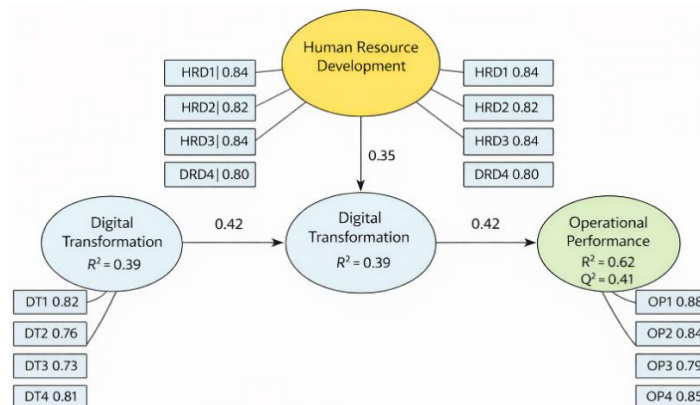
**Table 11.** Goodness-of-Fit Model SEM-PLS

Goodness-of-Fit Index	Value	Recommended Threshold	Interpretation
SRMR (Standardized Root Mean Square Residual)	0.061	< 0.08	Good Fit
NFI (Normed Fit Index)	0.912	> 0.90	Acceptable Fit
RMS Theta	0.094	< 0.12	Good Fit
R <sup>2</sup> (Operational Performance)	0.62	> 0.50	Moderate-Substantial
Q <sup>2</sup> (Predictive Relevance)	0.41	> 0	Predictive Relevance

**Notes:**

- SRMR measures the difference between observed and predicted correlations. Values below 0.08 indicate a well-fitting model.
- NFI evaluates comparative model fit; values above 0.90 indicate acceptable model fit.
- RMS Theta assesses the correlation residuals in reflective measurement models; values below 0.12 indicate a good fit.
- R<sup>2</sup> indicates the explanatory power of the structural model.
- Q<sup>2</sup> indicates predictive relevance, where values greater than 0 confirm predictive capability.

The results indicate that the SEM-PLS model demonstrates an acceptable goodness-of-fit. The SRMR value of 0.061 and RMS Theta of 0.094 indicate that the model residuals are within acceptable limits. The NFI value of 0.912 confirms that the model exhibits a satisfactory comparative fit. Additionally, the R<sup>2</sup> value of 0.62 indicates that the model explains a substantial proportion of variance in Operational Performance, while the Q<sup>2</sup> value of 0.41 confirms strong predictive relevance. Overall, the results demonstrate that the proposed SEM-PLS model is robust and suitable for explaining the relationships between digital transformation, human resource development, and operational performance.



**Figure 6.** Structural Equation Model Diagram



The figure 6. Illustrates the SEM-PLS structural model showing the relationships among Human Resource Development (HRD), Digital Transformation (DT), and Operational Performance (OP). HRD positively influences DT ( $\beta = 0.35$ ) and also has a direct effect on OP ( $\beta = 0.38$ ), while DT positively affects OP ( $\beta = 0.42$ ). The  $R^2$  value of 0.39 indicates that HRD explains 39% of the variance in Digital Transformation, whereas the  $R^2$  value of 0.62 shows that HRD and DT jointly explain 62% of the variance in Operational Performance. The  $Q^2$  value of 0.41 indicates that the model has good predictive relevance.

#### 4. CONCLUSION

This study examines the structural relationships among Digital Transformation, Human Resource Development, and Operational Performance using the Partial Least Squares-Structural Equation Modelling (PLS-SEM) approach. The findings provide strong empirical evidence that both Digital Transformation and Human Resource Development significantly enhance Operational Performance. This study addresses a critical research gap in prior literature, where Digital Transformation and Human Resource Development have often been examined in isolation, with limited empirical integration explaining how these two constructs interact to influence operational outcomes. By bridging this gap, the study offers a more comprehensive understanding of performance improvement in digitally enabled organizations. Digital Transformation plays a crucial role in improving operational efficiency, quality, flexibility, and productivity through the integration of digital infrastructure, process automation, data integration, and decision-support systems. Meanwhile, Human Resource Development demonstrates a significant positive effect on Operational Performance, highlighting the importance of employee competencies, continuous training, learning culture, and adaptability. Importantly, Human Resource Development is also found to significantly influence Digital Transformation, indicating that human capital readiness is a key driver of successful digital initiatives. The novelty of this study lies in the development of an integrated structural model that simultaneously links Human Resource Development to both Digital Transformation and Operational Performance within a single empirical framework. This provides new insights into the dual role of human resources as both a direct performance driver and an enabler of technological transformation. The structural model shows strong explanatory and predictive power, confirming its robustness. In conclusion, achieving sustainable operational performance requires a strategic alignment between digital transformation and human capital development. Organizations that effectively synchronize these elements will be better positioned to achieve long-term competitiveness in the digital era.

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