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Research Paper

The Dynamics of Human Resource Management in Supporting Technology Driven Industrial Transformation

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ABSTRACT: *The rapid advancement of digital technologies has accelerated industrial transformation, requiring organizations to develop adaptive and competitive human resource management (HRM) practices. This study aims to analyze the influence of Training and Development, Employee Engagement, and Technology Adaptability on Technology-Driven Industrial Transformation. A quantitative research approach was employed using a survey method. The study population consisted of employees working in organizations implementing technology-driven industrial transformation. The sample size was determined using G*Power 3.1 with a medium effect size ($f^2 = 0.15$), a significance level (α) of 0.05, a statistical power of 0.95, and three predictor variables, resulting in a minimum sample requirement of 119 respondents. Data were collected through structured questionnaires and analyzed using multiple linear regression with the assistance of IBM SPSS Statistics. Prior to hypothesis testing, classical assumption tests, including normality, multicollinearity, and heteroscedasticity tests, were conducted to ensure the validity of the regression model. The findings indicate that Training and Development, Employee Engagement, and Technology Adaptability each have a positive and significant effect on Technology-Driven Industrial Transformation. Furthermore, the simultaneous test demonstrates that the three independent variables collectively have a significant influence on Technology-Driven Industrial Transformation. Among the independent variables, Employee Engagement exhibits the strongest contribution to industrial transformation. These findings suggest that organizations seeking to achieve successful technology-driven industrial transformation should prioritize strategic investments in employee competency development, strengthen employee engagement, and enhance employees' adaptability to technological changes. This study contributes to the human resource management literature by highlighting the strategic role of HRM practices in facilitating sustainable industrial transformation in the digital era..*

KEYWORDS: *Human Resource Management, Training and Development, Employee Engagement, Technology Adaptability, Technology-Driven Industrial Transformation*

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I. INTRODUCTION

The rapid advancement of digital technologies has driven significant transformation across various industrial sectors. Technological innovations such as Artificial Intelligence (AI), the Internet of Things (IoT), big data analytics, cloud computing, and automation systems have fundamentally changed the way organizations conduct business processes, improve operational efficiency, and develop more innovative business models. This transformation has not only affected the technological and operational aspects of organizations but has also brought fundamental changes to human resource management (HRM) as a critical factor determining organizational success in responding to global competition (Schwab, 2017; Vial, 2019). Consequently, human resource management is expected to play a strategic role in ensuring organizational readiness to cope with changes driven by technological advancements. In the era of digital transformation, human resource management is no longer limited to administrative functions but has evolved into a strategic partner in creating sustainable competitive advantage. According to Armstrong and Taylor (2023), HRM should be capable of developing a workforce that possesses the necessary competencies, flexibility, and adaptability to respond to changes in the business environment. Similarly, Dessler (2020) argues that organizational success in managing change is highly influenced by the effectiveness of HR functions, including recruitment, training, competency development, performance management, and the cultivation of an organizational culture that is adaptive to technological change.

The dynamics of human resource management have become increasingly complex as workplaces become more digital, collaborative, and flexible. Organizations are required to enhance employees' digital competencies, foster a culture of continuous learning, and strengthen their ability to adapt to rapidly evolving technologies. Furthermore, challenges such as the skills gap, resistance to change, low levels of digital literacy, and the growing demand for competency development have emerged as critical issues that organizations must address during the industrial transformation process (World Economic Forum, 2025). These conditions indicate that the success of industrial transformation depends not only on technological investment but also on the readiness of human resources to effectively manage and utilize these technologies. In practice, many organizations continue to encounter difficulties in aligning human resource management strategies with the demands of technological transformation. Previous studies have shown that digital training and competency development programs often fail to fully meet organizational needs, employees demonstrate varying levels of readiness for change, and the implementation of digital technologies in HRM practices remains suboptimal (Noe, 2020; Vial, 2019). These findings suggest that the dynamics of human resource management constitute one of the key determinants of the success of technology-driven industrial transformation.

To better understand these relationships objectively, quantitative research is required to examine the influence of various human resource management factors on the success of industrial transformation. Variables such as training and development, employee engagement, technology adaptability, and digital competence can be empirically analyzed to determine their contributions to the successful implementation of technology-driven industrial transformation. A quantitative approach enables researchers to obtain empirical evidence regarding the relationships among variables, allowing the findings to serve as a basis for managerial decision-making as well as for the advancement of human resource management theory (Creswell & Creswell, 2018). Based on the foregoing discussion, research on the dynamics of human resource management in supporting technology-driven industrial transformation is both relevant and necessary. This study is expected to contribute theoretically by enriching the body of knowledge on human resource management in the era of digital transformation. Practically, it is expected to provide organizations with insights for formulating more adaptive, innovative, and competitive human resource management strategies to enhance organizational performance in the Industry 4.0 and Society 5.0 eras.

II. LITERATURE REVIEW

Training and Development

Training and development constitute one of the primary functions of human resource management aimed at enhancing employees' knowledge, skills, abilities, and work attitudes to enable them to perform their jobs effectively and efficiently. Training focuses on improving the competencies required to perform current job responsibilities, whereas development is directed toward enhancing individuals' capabilities to undertake future roles and responsibilities (Noe, 2020). According to Dessler (2020), training is a systematic process of providing employees with the knowledge, skills, and behaviors necessary to achieve the performance standards expected by the organization. Meanwhile, Armstrong and Taylor (2023) argue that human resource development represents a long-term organizational investment in building competencies, leadership, creativity, and the capacity to adapt to changes in the business environment. In the era of digital transformation, training extends beyond the development of technical competencies (hard skills) to include digital competencies, critical thinking, collaboration, communication, problem-solving, and lifelong learning capabilities. Organizations that consistently invest in training and development programs are more likely to cultivate a workforce that is adaptable to technological changes, thereby enhancing organizational competitiveness (Noe, 2020).

Effective training and development generally encompass several key indicators, including: (1) training needs analysis, (2) relevance of training content, (3) instructor competence, (4) learning methods, (5) training evaluation, and (6) application of training outcomes in the workplace. According to Kirkpatrick and Kirkpatrick (2016), the effectiveness of training can be evaluated using the Four Levels of Evaluation, namely participants' reaction, learning, behavior change, and organizational results.

Employee Engagement

Employee engagement refers to a positive psychological state that reflects an employee's level of enthusiasm, dedication, and emotional attachment to their work. Employees with high levels of engagement demonstrate strong work motivation, organizational commitment, and a willingness to exert their best efforts to achieve organizational objectives (Schaufeli et al., 2002). Kahn (1990) defines employee engagement as the state in which individuals express themselves physically, cognitively, and emotionally while performing their work roles. This concept emphasizes that engagement is more than job satisfaction; it represents employees' active psychological connection and commitment to their work.

According to Bakker and Albrecht (2018), employee engagement is a critical factor in enhancing productivity, innovation, service quality, and an organization's ability to cope with change. Employees with high engagement levels are generally more receptive to technological changes than those with lower engagement. Schaufeli et al. (2002) identify three primary dimensions of employee engagement: vigor, which refers to high levels of energy and mental resilience at work; dedication, characterized by enthusiasm, pride, inspiration, and a sense of significance toward one's work; and absorption, which reflects being fully concentrated and deeply engrossed in work to the extent that it becomes difficult to detach from work activities. In the context of technology-driven industrial transformation, employee engagement plays a crucial role in facilitating the successful implementation of digital innovations by increasing employees' readiness to learn, adapt, and embrace organizational change.

Technology Adaptability

Technology adaptability refers to the ability of individuals and organizations to accept, learn, utilize, and adjust effectively to emerging technologies. This capability has become one of the essential competencies required to navigate digital transformation across various industries. Pulakos et al. (2000) describe work adaptability as an individual's ability to modify behaviors, skills, and ways of thinking in response to dynamic work environments. In the digital era, adaptability extends beyond merely using technology to encompass the continuous learning of new technologies and digital competencies.

According to Vial (2019), digital transformation requires organizations to cultivate a culture that promotes continuous learning, innovation, digital collaboration, and rapid responsiveness to change. Consequently, technology adaptability has become a critical determinant of the successful implementation of new technologies.The indicators of technology adaptability include: (1) the ability to learn new technologies, (2) willingness to embrace change, (3) speed of adaptation to digital systems, (4) ability to utilize technology effectively in work activities, and (5) flexibility in responding to changes in work processes. Organizations with high levels of technology adaptability are generally better prepared to respond to digital disruption than those that continue to rely primarily on conventional work systems.

Technology-Driven Industrial Transformation

Technology-driven industrial transformation refers to a comprehensive process of changing business models, operational processes, organizational culture, and decision-making systems through the integrated application of digital technologies. This transformation aims to improve organizational efficiency, effectiveness, innovation, and competitiveness. Schwab (2017) explains that the Fourth Industrial Revolution (Industry 4.0) is characterized by the integration of digital technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), Big Data, Cloud Computing, Cyber-Physical Systems, and Machine Learning into industrial operations. These technologies have fundamentally transformed how organizations produce goods and services, manage supply chains, and deliver value to customers.

According to Vial (2019), digital transformation is not merely the adoption of new technologies but rather a comprehensive organizational transformation that affects organizational structures, culture, strategies, and business models to create greater value through digital technologies. Furthermore, the World Economic Forum (2025) emphasizes that the success of industrial transformation largely depends on the readiness of human resources to develop digital competencies, analytical thinking, creativity, collaboration, and lifelong learning capabilities. The success of technology-driven industrial transformation can be assessed using several indicators, including: (1) the level of digital technology adoption, (2) business process efficiency, (3) productivity improvement, (4) organizational innovation, (5) data-driven decision-making quality, (6) organizational competitiveness, and (7) customer satisfaction.

III. RESEARCH METHODOLOGY

Research Type and Approach

This study employed a quantitative research method using an explanatory research approach. The explanatory approach aims to explain the causal relationships between independent and dependent variables through hypothesis testing formulated prior to data collection. A quantitative approach was selected because it provides objective data and enables researchers to measure the magnitude of relationships among variables using statistical analysis (Creswell & Creswell, 2018). According to Sugiyono (2023), explanatory research is designed to explain cause-and-effect relationships among variables through hypothesis testing based on empirical evidence. In this study, the effects of Training and Development, Employee Engagement, and Technology Adaptability on Technology-Driven Industrial Transformation were examined.

Research Conceptual Framework

This study illustrates the relationship between the independent and dependent variables as follows:

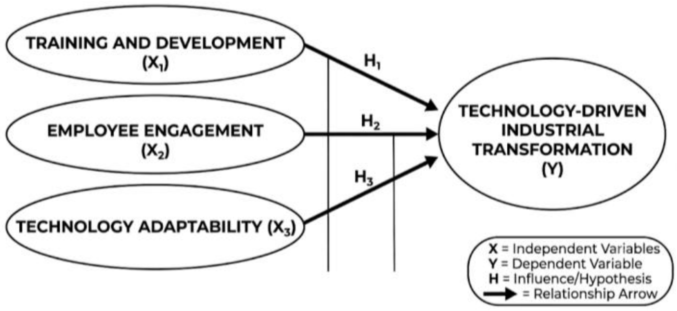

Figure 1 Conceptual Framework

The three independent variables are assumed to have a positive influence on the success of technology-driven industrial transformation. The better the training and development programs, the higher the level of employee engagement, and the greater the technology adaptability, the more successful the implementation of technology-driven industrial transformation is expected to be.

Population and Sample

The population refers to the entire group of research objects possessing specific characteristics relevant to the research objectives (Sugiyono, 2023). The population in this study consisted of all employees working in organizations that have implemented technology-driven industrial transformation. When the population size is relatively large, sample selection is generally conducted using probability sampling, such as simple random sampling, to ensure that every member of the population has an equal opportunity to become a respondent (Sekaran & Bougie, 2020).

However, this study employed a non-probability sampling technique using purposive sampling, in which respondents were selected based on predetermined criteria aligned with the research objectives. The selected respondents were employees actively involved in the technology-driven industrial transformation process within their organizations and had worked for at least one year, ensuring that they possessed adequate experience regarding training and development, employee engagement, technology adaptability, and the implementation of technology-driven industrial transformation. The required sample size was determined using G*Power version 3.1, a software application designed to calculate sample size through statistical power analysis. The calculation was performed using the statistical test Linear Multiple Regression: Fixed Model, R^2 Deviation from Zero, as this study investigates the effects of three independent variables on one dependent variable.

Table 1
G*Power Analysis Parameters

Parameter	Value
Statistical Test	Linear Multiple Regression: Fixed Model, R^2 Deviation from Zero
Effect Size (f^2)	0.15 (Medium Effect)
α Error Probability	0.05
Power (1 – β Error Probability)	0.95
Number of Predictors	3

Based on these parameters, the G*Power analysis indicated that the minimum required sample size was 119 respondents. Therefore, this study involved at least 119 respondents to achieve a statistical power of 95% in detecting the effects of Training and Development (X_1), Employee Engagement (X_2), and Technology Adaptability (X_3) on Technology-Driven Industrial Transformation (Y). To anticipate incomplete responses or questionnaires that might not meet the analytical requirements, the number of distributed questionnaires was increased by approximately 10–20% above the minimum sample size recommended by G*Power. Consequently, between 131 and 143 questionnaires were distributed to ensure that the final number of valid responses satisfied the minimum sample requirement.

Types and Sources of Data

The data used in this study consisted of primary data and secondary data. Primary data were collected directly from respondents through questionnaire distribution, whereas secondary data were obtained from company reports, books, scientific journals, organizational documents, and other publications relevant to the study. According to Sekaran and Bougie (2020), primary data are collected directly by researchers to address specific research objectives, while secondary data are obtained from existing sources.

Data Analysis Technique

The data were analyzed quantitatively using IBM SPSS Statistics. The analysis aimed to determine the effects of Training and Development (X_1), Employee Engagement (X_2), and Technology Adaptability (X_3) on Technology-Driven Industrial Transformation (Y). Prior to hypothesis testing, classical assumption tests were conducted to ensure that the regression model satisfied the underlying assumptions required for reliable statistical inference (Hair et al., 2022).

1. Classical Assumption Tests
   Classical assumption testing was conducted to verify that the regression model satisfied the assumptions of the Best Linear Unbiased Estimator (BLUE), ensuring that the estimated parameters were unbiased and efficient (Ghozali, 2021).
   a. Normality Test
   The normality test was performed to determine whether the data or residuals were normally distributed. The test was conducted using either the Kolmogorov–Smirnov or Shapiro–Wilk test and supported by the Normal Probability Plot (P–P Plot). A regression model is considered to satisfy the normality assumption if the significance value is greater than 0.05 (Sig. > 0.05) (Ghozali, 2021).
   b. Multicollinearity Test
   The multicollinearity test was conducted to determine whether high correlations existed among the independent variables. A good regression model should be free from multicollinearity. The assessment was based on Tolerance and Variance Inflation Factor (VIF) values. The model is considered free from multicollinearity if Tolerance > 0.10 and VIF < 10 (Hair et al., 2022).
   c. Heteroscedasticity Test
   The heteroscedasticity test was performed to determine whether the residual variances were constant across all observations. The assessment was conducted using the Glejser test or scatterplot analysis. If the significance value of each independent variable exceeds 0.05, the regression model is considered free from heteroscedasticity (Ghozali, 2021).

2. Multiple Linear Regression Analysis
   Multiple linear regression analysis was employed to determine the magnitude of the influence of the independent variables on the dependent variable, both individually and simultaneously. According to Hair et al. (2022), multiple linear regression is a statistical method used to predict the relationship between several independent variables and a single dependent variable.
   The regression equation used in this study is as follows:
   where:
   Y = Technology-Driven Industrial Transformation
   α = Constant
   β_1 = Regression coefficient of Training and Development
   β_2 = Regression coefficient of Employee Engagement
   β_3 = Regression coefficient of Technology Adaptability
   X_1 = Training and Development
   X_2 = Employee Engagement
   X_3 = Technology Adaptability
   e = Error term
   The regression coefficients indicate the direction and magnitude of changes in the dependent variable resulting from a one-unit change in the corresponding independent variable while holding the other independent variables constant (Hair et al., 2022).

3. Partial Significance Test (t-test)
   The partial significance test (t-test) was used to determine whether each independent variable individually had a significant effect on the dependent variable. The test was conducted using a significance level of 5% ($\alpha = 0.05$).
   The decision criteria were as follows:
   If Sig. < 0.05, the hypothesis is accepted, indicating that the independent variable has a significant effect on the dependent variable.
   If Sig. > 0.05, the hypothesis is rejected, indicating that the independent variable does not have a significant effect on the dependent variable.

In addition to the significance value, the decision could also be based on comparing the calculated t-value (t-calculated) with the critical t-value (t-table). If t-calculated > t-table, the hypothesis is accepted (Ghozali, 2021).

4. Simultaneous Significance Test (F-test)
The simultaneous significance test (F-test) was used to determine whether all independent variables collectively had a significant effect on the dependent variable. The test was conducted at a significance level of 5% ($\alpha = 0.05$).
The decision criteria were as follows:
If Sig. < 0.05, all independent variables simultaneously have a significant effect on the dependent variable.
If Sig. > 0.05, the independent variables do not simultaneously have a significant effect on the dependent variable.
The decision may also be based on comparing the calculated F-value (F-calculate d) with the critical F-value (F-table). If F-calculated > F-table, the hypothesis is accepted (Hair et al., 2022).

IV. RESULTS AND DISCUSSION

Classical Assumption Tests

Before testing the hypotheses using multiple linear regression analysis, classical assumption tests were conducted. These tests aim to ensure that the regression model satisfies the Best Linear Unbiased Estimator (BLUE) assumptions so that the estimated results are valid and can be used as a basis for decision-making (Ghozali, 2021).

1. Normality Test
The normality test was conducted using the One-Sample Kolmogorov-Smirnov Test on the residual values generated from the regression model.

Table 2. Normality Test Results

Description	Value
N	119
Mean Residual	0
Std. Deviation	2.731
Kolmogorov-Smirnov Z	0.073
Asymp. Sig. (2-tailed)	0.2

Source: Processed data using IBM SPSS Statistics (2026)

Based on Table 2, the Asymp. Sig. (2-tailed) value is 0.200, which is greater than the significance level of 0.05. This indicates that the residuals in the regression model are normally distributed. Therefore, the normality assumption has been satisfied, and the regression model is appropriate for further analysis.

2. Multicollinearity Test
The multicollinearity test was conducted to determine whether a high correlation exists among the independent variables.

Table 3. Multicollinearity Test Results

Variable	Tolerance	VIF	Interpretation
Training and Development (X_1)	0.682	1.466	No multicollinearity
Employee Engagement (X_2)	0.741	1.35	No multicollinearity
Technology Adaptability (X_3)	0.695	1.439	No multicollinearity

Source: Processed data using IBM SPSS Statistics (2026)

As shown in Table 3, all independent variables have Tolerance values greater than 0.10 and Variance Inflation Factor (VIF) values below 10. Therefore, it can be concluded that no multicollinearity exists among the independent variables, indicating that each variable independently explains the dependent variable.

3. Heteroscedasticity Test
The heteroscedasticity test was performed using the Glejser Test.

Table 4. Heteroscedasticity Test Results (Glejser Test)

Variable	Sig.	Interpretation
Training and Development (X_1)	0.423	No heteroscedasticity
Employee Engagement (X_2)	0.317	No heteroscedasticity
Technology Adaptability (X_3)	0.581	No heteroscedasticity

Source: Processed data using IBM SPSS Statistics (2026)

Based on Table 4, all independent variables have significance values greater than 0.05. This indicates that the regression model does not exhibit heteroscedasticity. Therefore, the residual variance is homogeneous, meaning that the model satisfies one of the key assumptions required for multiple linear regression analysis.

Multiple Linear Regression Analysis

Multiple linear regression analysis was employed to determine the magnitude of the effects of Training and Development (X_1), Employee Engagement (X_2), and Technology Adaptability (X_3) on Technology-Based Industrial Transformation (Y). According to Hair et al. (2022), multiple linear regression analysis is used to measure the relationship between several independent variables and a single dependent variable, as well as to determine the direction and magnitude of the effect of each independent variable on the dependent variable.

The results of the multiple linear regression analysis using IBM SPSS Statistics are presented in Table 5 below.

Table 5

Results of Multiple Linear Regression Analysis

Variable	Unstandardized Coefficients (B)	Std. Error	Standardized Beta	t	Sig.
Constant	3.215	1.684	–	1.909	0.059
Training and Development (X_1)	0.286	0.071	0.295	4.028	0
Employee Engagement (X_2)	0.351	0.068	0.376	5.162	0
Technology Adaptability (X_3)	0.274	0.074	0.267	3.703	0

Dependent Variable: Technology-Based Industrial Transformation (Y)

Source: Processed data using IBM SPSS Statistics (2026)

Regression Equation

Based on Table 5, the multiple linear regression equation is as follows:

$$Y = 3.215 + 0.286X_1 + 0.351X_2 + 0.274X_3$$

Where:

Y = Technology-Based Industrial Transformation

X_1 = Training and Development

X_2 = Employee Engagement

X_3 = Technology Adaptability

Based on the regression equation, the following interpretations can be made:

The constant value of 3.215 indicates that when Training and Development, Employee Engagement, and Technology Adaptability are assumed to be constant or equal to zero, the value of Technology-Based Industrial Transformation is estimated to be 3.215 units.

The regression coefficient for Training and Development (X_1) is 0.286, indicating that a one-unit increase in Training and Development will increase Technology-Based Industrial Transformation by 0.286 units, assuming the other variables remain constant.

The regression coefficient for Employee Engagement (X_2) is 0.351, indicating that a one-unit increase in Employee Engagement will increase Technology-Based Industrial Transformation by 0.351 units, assuming the other variables remain unchanged.

The regression coefficient for Technology Adaptability (X_3) is 0.274, indicating that a one-unit increase in Technology Adaptability will increase Technology-Based Industrial Transformation by 0.274 units, assuming the remaining variables are held constant.

All regression coefficients are positive, indicating that improvements in each independent variable are associated with increases in Technology-Based Industrial Transformation.

Discussion of the Multiple Linear Regression Analysis

The results of the multiple linear regression analysis indicate that Training and Development, Employee Engagement, and Technology Adaptability all have positive regression coefficients with respect to Technology-Based Industrial Transformation. This finding suggests that the more effective the implementation of training and development programs, the higher the level of employee engagement within the organization, and the greater the employees' ability to adapt to technological advancements, the more successful the organization will be in achieving technology-based industrial transformation. Among the three independent variables, Employee Engagement has the largest regression coefficient (0.351), indicating that it makes the strongest contribution to enhancing Technology-Based Industrial Transformation compared with the other variables. This finding implies that the success of digital transformation depends not only on technological readiness but also on employees' commitment, involvement, and active participation in supporting organizational change. This result is consistent with Hair et al. (2022), who argue that the magnitude of a regression coefficient reflects both the direction and the relative contribution of each independent variable to changes in the dependent variable.

Furthermore, Training and Development has a regression coefficient of 0.286, indicating that improving employee competencies through training programs enhances employees' ability to cope with technological changes and evolving business processes. Meanwhile, Technology Adaptability has a regression coefficient of 0.274, suggesting that employees' ability to accept, utilize, and adapt to new technologies also contributes significantly to the success of technology-based industrial transformation. Overall, the regression analysis demonstrates that all three independent variables exert positive effects on Technology-Based Industrial Transformation. Therefore, organizations should develop human resource management strategies that emphasize competency development, employee engagement, and technological adaptability to ensure that industrial transformation initiatives are implemented effectively and sustainably.

Hypothesis Testing

Hypothesis testing was conducted to examine the effects of Training and Development (X_1), Employee Engagement (X_2), and Technology Adaptability (X_3) on Technology-Based Industrial Transformation (Y). The hypotheses were tested individually using the t-test and simultaneously using the F-test at a significance level of 5% ($\alpha = 0.05$). According to Ghozali (2021), the t-test is used to examine the effect of each independent variable on the dependent variable, whereas the F-test is employed to assess the joint effect of all independent variables on the dependent variable.

Partial Test (t-test)

The partial test was conducted to determine whether each independent variable has a significant effect on Technology-Based Industrial Transformation.

Table 6. Results of the Partial Test (t-test)

Variable	Coefficient (B)	t-value	Sig.	Decision
Training and Development (X_1)	0.286	4.028	0	H_1 Accepted
Employee Engagement (X_2)	0.351	5.162	0	H_2 Accepted
Technology Adaptability (X_3)	0.274	3.703	0	H_3 Accepted

Testing Criteria:
$\alpha = 0.05$
t-table = 1.980 (n = 119; df = 115)
Source: Processed data using IBM SPSS Statistics (2026)

Discussion of the Partial Test

1. Effect of Training and Development on Technology-Based Industrial Transformation
   Based on Table 6, the Training and Development (X_1) variable obtained a t-value of 4.028, which is greater than the t-table value of 1.980, with a significance value of 0.000 < 0.05. These results indicate that Training and Development has a positive and significant effect on Technology-Based Industrial Transformation. Therefore, the first hypothesis (H_1) is accepted.
   This finding suggests that the more effective the company's training and development programs, the greater employees' capability to support technology implementation and business process changes. According to Noe (2023), training and development represent organizational investments aimed at enhancing employee competencies to adapt successfully to technological advancements and changes in the business environment.

2. Effect of Employee Engagement on Technology-Based Industrial Transformation

The Employee Engagement (X_2) variable has a t-value of 5.162, which exceeds the t-table value of 1.980, with a significance value of 0.000 < 0.05. Therefore, Employee Engagement has a positive and significant effect on Technology-Based Industrial Transformation, leading to the acceptance of the second hypothesis (H_2).

These findings indicate that employees' involvement in their work, commitment to the organization, and active participation in organizational change significantly enhance the success of technology-based industrial transformation. According to Schaufeli (2021), employee engagement encourages employees to contribute their maximum potential toward achieving organizational objectives, including supporting digital transformation initiatives.

3. Effect of Technology Adaptability on Technology-Based Industrial Transformation
   The Technology Adaptability (X_3) variable obtained a t-value of 3.703, which is greater than the t-table value of 1.980, with a significance value of 0.000 < 0.05. Accordingly, Technology Adaptability has a positive and significant effect on Technology-Based Industrial Transformation, and the third hypothesis (H_3) is accepted.
   This finding indicates that individuals' ability to accept, learn, and utilize new technologies is an essential factor in achieving successful technology-based industrial transformation. Employees with high levels of technological adaptability are more likely to adopt innovations and new work systems quickly, thereby improving organizational effectiveness.

Simultaneous Test (F-test)

The simultaneous test was conducted to determine whether all independent variables collectively influence Technology-Based Industrial Transformation.

Table 7. Results of the Simultaneous Test (F-test)

Model	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**Sig.**
Regression	865.284	3	288.428	**68.472**	**0**
Residual	484.619	115	4.214	–	–
Total	1,349.90	118	–	–	–

Testing Criteria:
$\alpha = 0.05$
F-table = 2.68
Source: Processed data using IBM SPSS Statistics (2026)

Discussion of the Simultaneous Test

Based on Table 7, the calculated F-value is 68.472, whereas the F-table value is 2.68. In addition, the significance value is 0.000, which is lower than 0.05. Therefore, it can be concluded that Training and Development, Employee Engagement, and Technology Adaptability simultaneously have a positive and significant effect on Technology-Based Industrial Transformation. Accordingly, the fourth hypothesis (H_4) is accepted.

These findings indicate that the success of technology-based industrial transformation is not driven by a single factor but rather by the combined influence of competency development through training, active employee engagement, and employees' ability to adapt to technological changes. The integration of these three factors strengthens organizational readiness to respond to technological developments and enhances the effectiveness of industrial transformation initiatives.

These findings are consistent with Hair et al. (2022), who explain that the F-test evaluates the overall ability of a regression model to explain the relationship between all independent variables and the dependent variable. A significant F-value indicates that the regression model has strong predictive capability.

V. CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Based on the findings of this study on the effects of Training and Development, Employee Engagement, and Technology Adaptability on Technology-Based Industrial Transformation, the following conclusions can be drawn:

1. Training and Development has a positive and significant effect on Technology-Based Industrial Transformation. This indicates that the more effective the organization's training and development

programs, the greater the employees' capability to support technology implementation and business process transformation.
2. Employee Engagement has a positive and significant effect on Technology-Based Industrial Transformation. Employees' involvement, commitment, and active participation within the organization are proven to be essential factors in supporting the success of technology-based industrial transformation.
3. Technology Adaptability has a positive and significant effect on Technology-Based Industrial Transformation. Employees who are more adaptable to technological advancements are better able to embrace change, utilize new technologies, and enhance the effectiveness of industrial transformation initiatives.
4. Simultaneously, Training and Development, Employee Engagement, and Technology Adaptability have a positive and significant effect on Technology-Based Industrial Transformation. These findings indicate that successful technology-based industrial transformation requires the synergy of competency development, employee engagement, and technological adaptability to effectively support organizational change.

Recommendations

Based on the findings of this study, the following recommendations are proposed:
1. For organizations, it is recommended to enhance the quality of training and development programs with a strong focus on digital technology competencies. This will enable employees to acquire the skills and knowledge required to support industrial transformation.
2. Organizations should strengthen employee engagement by fostering open communication, recognizing employee contributions, providing career development opportunities, and involving employees in decision-making processes to build stronger commitment toward organizational change.
3. Organizations are encouraged to cultivate a work culture that promotes technology adaptability through continuous learning, guidance in adopting new technologies, and the provision of adequate digital infrastructure. Such initiatives will facilitate a more effective implementation of technology-based industrial transformation.

For future researchers, it is recommended to expand the research model by incorporating additional variables that may influence technology-based industrial transformation, such as digital leadership, organizational culture, innovation, organizational readiness, or digital literacy. Furthermore, future studies should be conducted across different industries or geographical regions to improve the generalizability of the research findings.

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