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# Employee Productivity Improvement Strategy Through Digital Communication Technology and R&D Innovation in Jakarta Trading Companies

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**Abstract**

**Purpose:** This study analyzes the influence of CSR, innovation, and environmental policies on organizational sustainability and examines the mediating role of organizational culture in improving performance.

**Research Methodology:** A quantitative design was applied using structured questionnaires distributed to employees and management across various industries. Data were analyzed using Structural Equation Modeling (SEM) to test relationships among innovation, CSR, environmental practices, organizational culture, and organizational sustainability.

**Results:** Digital communication technology significantly enhances innovation ($\beta = 0.771$, $t = 22.06, p < 0.001$), while R&D has a smaller but significant effect ($\beta = 0.087, t = 1.96, p = 0.025$). However, digital technology does not directly affect productivity ($\beta = 0.014$, $t = 0.50$, $p = 0.308$). In contrast, R&D strongly influences productivity ($\beta = 0.996$, $t = 136.01$, $p < 0.001$), and innovation has a small positive effect ($\beta = 0.019$, $t = 2.00$, $p = 0.036$). All results meet standard significance levels ($p < 0.05$).

**Conclusions:** R&D is the primary driver of productivity, while digital communication technology mainly supports innovation rather than directly improving productivity. Innovation contributes slightly to productivity and does not mediate the relationships among variables.

**Limitations:** The study is limited to trading companies in Jakarta, uses cross-sectional data, and includes a limited set of variables. Factors such as leadership, motivation, and organizational culture were not examined.

**Contributions:** The study clarifies relationships among R&D, digital communication technology, innovation, and productivity. It shows that R&D is the most influential factor in productivity improvement, while digital tools mainly enhance innovation. The findings provide practical guidance for prioritizing R&D investment and using digital technologies strategically.

***Keywords:*** *CSR, Environmental Practice, Innovation, Organizational Culture*

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## 1. Introduction

Employee productivity in Jakarta in 2023 has shown notable dynamics, shaped by factors such as adaptation to new post-pandemic work patterns, advancements in technology, and global economic challenges (Hartijasti et al., 2024). Following the COVID-19 pandemic, many trading companies in Jakarta have implemented a hybrid working model that blends in-office and remote work. Bachri et al. (2024) and Tetteh (2024) indicate that this hybrid model positively influencesd employee productivity, resulting in a 15% increase compared to the previous year. The flexibility provided by this approach enables employees to achieve a better balance between their personal and professional lives (Bachri et al., 2024).

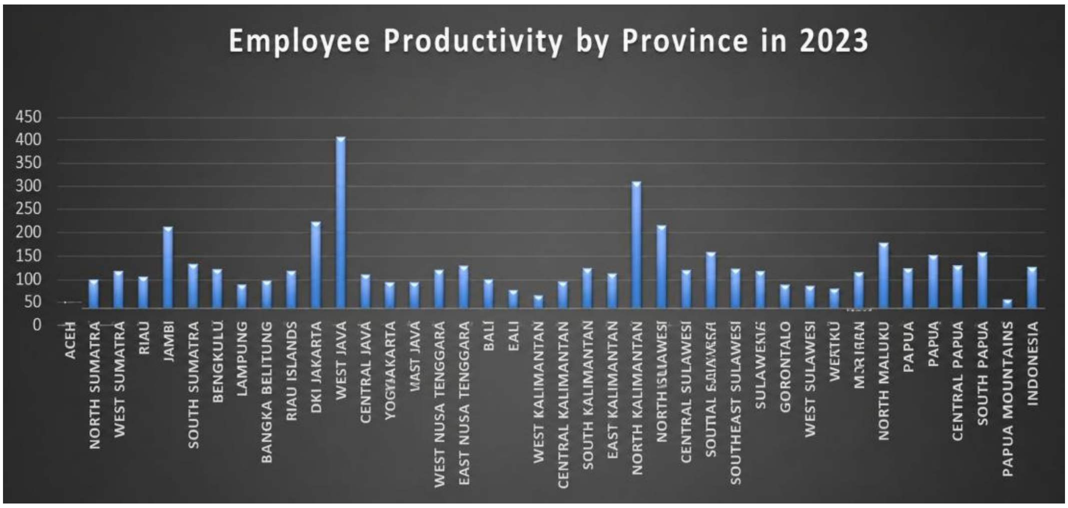


Figure 1. Employee Productivity by Province in 2023
*Source: https://bps.go.id*

Figure 1 highlights that Jakarta ranks first in employee productivity among workers in Indonesia, with an index of 404.21. This can be attributed to Jakarta's role as the nation's economic and business hub, hosting a high concentration of large corporations, creative industries, and services (Dienlin & Johannes, 2020; Nguyen et al., 2020). This competitive environment drives workers to enhance their productivity to secure or advance their positions in the labor market (Pranata, 2018). A trading company in Jakarta is a company engaged in buying and selling goods or commodities in bulk and retail, which are then distributed to local and international markets (Fachrudin et al., 2021; Friesenbichler, 2016). Jakarta is the center of trade in Indonesia; therefore, many companies are headquartered there and are involved in various trading sectors, ranging from raw materials and consumer products to export commodities (Yaw Obeng & Boachie, 2018; Yuan, 2022).

A growing challenge in some trading companies is the issue of "digital fatigue." According to Dienlin and Johannes (2020), approximately 40% of employees exhibit symptoms of digital fatigue, which adversely affects their productivity. In response, many companies have introduced "digital detox" initiatives and time management training programs to help employees address this issue. Conversely, the integration of technology and automation in the Jakarta sector significantly increases productivity. Andriyanty et al. (2021) and Judijanto et al. (2023) reported a 22% increase in employee productivity in the financial services and information technology sectors that implemented digital technology solutions in their operations.

A competitive business environment can drive employee productivity, which is a primary objective of companies (Awaliah & Hidayat, 2023; Henseler et al., 2015). High employee productivity can provide competitive advantages, operational efficiency, and sustainable business growth (Ehsan & Ali, 2019; Muhammad et al., 2022). In an era of rapid development, innovation is a key factor influencing employee productivity (Mohnen, 2019; Van Ark, 2016). The implementation of R&D strategies to enhance employee productivity also positively affects a company's competitiveness. By producing more innovative or superior products or services than their competitors, companies can gain a competitive edge in the market and increase their market share (Koutroumpis et al., 2020). R&D enables companies to continuously adapt to market changes, identify new consumer needs, and develop relevant business strategies (Bhattacharya et al., 2021; Ugur et al., 2016). This helps companies remain relevant, sustainable, and grow in the face of intense competition.

An analytical study by experts identified a theoretical research gap, possibly due to differences in research objects, industries studied, or samples selected by researchers. For instance, research conducted at PT. Haier Electrical Appliances Indonesia revealed that the work environment and discipline significantly influence employee productivity. Work discipline has a significant positive effect on employee productivity, while the work environment does not directly affect employee performance but does so indirectly through employee productivity, which is influenced by work discipline (Awaliah & Hidayat, 2023). Meanwhile, Ndruru et al. (2022) conducted research at PT. Trikarya Cemerlang Medan found that communication and motivation individually have a significant effect on employee productivity. Communication and motivation contribute 72.8% to employee productivity, with the remaining 27.2% being influenced by other factors.

## 2. Literature Review

### *2.1 Employee Productivity and Innovation*

Employee productivity is a key driver of organizational success and a competitive advantage Ehsan and Ali (2019) and Muhammad et al. (2022). Innovations in business processes, technology, and workplace structures often lead to increased productivity by enhancing operational efficiency (Mohnen, 2019; Van Ark, 2016). R&D is a crucial factor in fostering innovation, contributing to the creation of superior products and services that can elevate an organization's market position Koutroumpis et al. (2020). Furthermore, R&D plays a central role in fostering innovation by generating new knowledge, improving existing processes, and enabling the development of superior products and services (Koutroumpis et al., 2020; Ugur et al., 2016). These improvements ultimately enhance an organization's ability to compete in dynamic markets. However, the relationship between innovation and productivity is not always direct, as its impact may depend on how effectively innovation is implemented within organizational systems.

### *2.2 Digital Communication Technology*

Digital communication tools have become integral to modern organizations. The adoption of technologies such as collaboration platforms, email, and virtual meeting tools significantly boosts innovation by enabling real-time knowledge sharing and improving communication among teams Hashim et al. (2022). However, despite their positive effects on innovation, digital tools have shown minimal impact on productivity directly, as evidenced by this study (Dienlin & Johannes, 2020). However, despite its strong contribution to innovation, digital communication technology does not always translate directly into higher employee productivity. Some studies indicate that its impact on productivity is often indirect and mediated through innovation processes rather than producing immediate efficiency gains (Dienlin & Johannes, 2020; Ma & Zhang, 2022; Van Ark, 2016). This suggests that the effectiveness of digital tools depends on how they are integrated into organizational workflows and supported by complementary managerial practices.

### *2.3 R&D and Employee Productivity*

R&D plays a critical role in improving employee productivity by enhancing the development of new technologies and processes that drive efficiency. As shown by studies such as those by Bhattacharya et al. (2021) and Tetteh (2024), R&D efforts directly correlate with increased market share and overall firm productivity by enabling companies to adapt to market demands and technological advancements. Previous studies show that Research and Development (R&D) plays a crucial role in improving productivity through innovation and efficiency gains (Mohnen, 2019; Ugur et al., 2016). Digital Communication Technology is also widely recognized as an important driver of innovation and organizational performance by enabling faster information exchange and collaboration (Dienlin & Johannes, 2020; Hashim et al., 2022). However, its direct effect on productivity remains inconsistent, as some studies suggest that its impact is often indirect through innovation processes (Ma & Zhang, 2022; Van Ark, 2016). In addition, innovation itself is generally associated with higher productivity, although its effect may vary depending on organizational context and implementation (Kahn et al., 2022; Tetteh, 2024). These findings indicate that the relationships between R&D, digital technology, innovation, and productivity are complex and require further empirical investigation.

## 3. Methodology

### *3.1 Research Design*

This study employs a quantitative verification method, using explanatory research to examine variable status and inter-variable influence, ultimately explaining causal relationships through hypothesis testing (Judijanto et al., 2023). Hassine (2022) noted that verification research aims to reassess previous theories, potentially strengthening or disproving them.

This study focuses on employees of trading companies in Jakarta's trading and service sectors. Data were collected through questionnaires and documentation, with purposive sampling used to select participants. A Likert scale was applied for measurement, and validity testing was conducted using SPSS 23 and Smart PLS 3.0.

### *3.2 Population and Sample*

According to Hair (2021), a population consists of objects or subjects with specific qualities and characteristics that are studied to draw conclusions. The study population included 4,580 employees of trading companies in Jakarta.

The researchers used purposive sampling to select 368 samples, a method that targets individuals or groups meeting specific criteria (Ma & Zhang, 2022), ensuring that the information collected was relevant and detailed and aligned with the research objectives.

### *3.3 Data Collection*

A questionnaire is a data collection method where respondents are given a series of written questions or statements to be answered. It can consist of closed or multiple-choice questions, where predefined answer options are provided to the respondents. The questionnaire in this study included 107 statements related to the variables outlined in the variable operationalization. This is a closed questionnaire, which means that the responses are restricted to specific options determined by the researcher.

### *3.4 Data Analysis*

The data were analyzed using SmartPLS 3 path analysis software. This study aimed to examine the relationships between digital communication technology, research and development, innovation, and employee productivity.

 

## 4. Results and Discussion

### *4.1 Object of Research*

This study examines 15 trading companies, comprising 7 B2B and 8 B2C enterprises, offering products such as smartphones, computers, air conditioners, refrigerators, clothing, food, and beverages. B2B companies cater to the needs of other businesses, while B2C companies target end consumers directly. The analysis aims to highlight the differences in strategies and employee work culture between these two types of companies.

Table 1. Respondents Demographic

| Demography | Characteristic | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 211 | 57.3 |
| | Female | 157 | 42.7 |
| | **Total** | 368 | 100.0 |
| Age | 17-20 years | 30 | 8.0 |
| | 21-30 years | 45 | 12.2 |
| | 31-40 years | 155 | 42.1 |
| | 41-50 years | 134 | 36.4 |
| | >50 years | 4 | 1.3 |
| | **Total** | 368 | 100.0 |
| Education | High School | 25 | 7.0 |
| | Scholar | 312 | 84.7 |
| | Master's/Doctoral | 31 | 8.3 |
| | **Total** | 368 | 100.0 |
| Occupation | Operator | 42 | 11.4 |
| | Supervisor | 114 | 31.0 |
| | Manager | 50 | 13.6 |
| | Others | 162 | 44.0 |
| | **Total** | 368 | 100.0 |

Based on Table 1 presents respondent demographics, including gender, age, education, company type, and position. Among the 368 respondents, males dominated with 211 individuals (57.3%), while females made up the rest. Most respondents were aged 31-40 (155 respondents or 42.1%) and 41-50 (134 respondents or 36.4%). The majority held an undergraduate degree (312 respondents or 84.7%), with the remainder having high school or doctoral-level education. Supervisors constitute the largest group of workers (31%), followed by managers and operators.

### *4.2 Convergent Validity Test (Loading Factor)*

The measurement model (outer model) will be evaluated using structural equation modeling (SEM) with a partial least squares (SmartPLS) approach. The initial evaluation involves analyzing the factor loading values for the indicators of several variables: Digital Communication Technology ($X_1$), R&D ($X_2$), Innovation ($Z$), and Employee Productivity ($Y$). The researcher will determine whether the factor loading of each variable meets the Smart PLS threshold of $0.7$ or higher (Hair, 2021).

Outer loading, or Loading Factor (LF), represents the correlation between each measurement item and its corresponding variable, indicating how well the item reflects the variable (Hair, 2021; Henseler et al., 2015). While there is no universal standard, Hair (2021) suggest a threshold of $LF \geq 0.70$. However, Chin (1998) considers LF values $\geq 0.60$ acceptable. This study follows Chin's recommendation, using

$LF \geq 0.60$ as the benchmark. Table 2 presents the first estimation of the loading factors based on Chin's criteria.

Table 2. The Convergent Validity Test Result

| Variable | Indicator | Outer Loading | Condition | Information |
|---|---|---|---|---|
| Employee Productivity (Y) | EP1 | 0.648 | >0.6 | Valid |
| | EP2 | 0.654 | >0.6 | Valid |
| | EP3 | 0.745 | >0.6 | Valid |
| | EP4 | 0.693 | >0.6 | Valid |
| | EP5 | 0.803 | >0.6 | Valid |
| | EP6 | 0.764 | >0.6 | Valid |
| | EP7 | 0.699 | >0.6 | Valid |
| | EP8 | 0.694 | >0.6 | Valid |
| | EP9 | 0.656 | >0.6 | Valid |
| | EP10 | 0.661 | >0.6 | Valid |
| Innovation (Z) | INV1 | 0.643 | >0.6 | Valid |
| | INV2 | 0.634 | >0.6 | Valid |
| | INV3 | 0.603 | >0.6 | Valid |
| | INV4 | 0.652 | >0.6 | Valid |
| | INV5 | 0.620 | >0.6 | Valid |
| | INV6 | 0.636 | >0.6 | Valid |
| | INV7 | 0.676 | >0.6 | Valid |
| | DCT1 | 0.636 | >0.6 | Valid |
| | DCT2 | 0.731 | >0.6 | Valid |
| Digital Communication Technology (X1) | DCT3 | 0.672 | >0.6 | Valid |
| | DCT4 | 0.755 | >0.6 | Valid |
| | DCT5 | 0.703 | >0.6 | Valid |
| | DCT6 | 0.746 | >0.6 | Valid |
| | DCT7 | 0.646 | >0.6 | Valid |
| | DCT8 | 0.653 | >0.6 | Valid |
| | DCT9 | 0.643 | >0.6 | Valid |
| | DCT10 | 0.612 | >0.6 | Valid |
| Research and Development (X2) | RD1 | 0.658 | >0.6 | Valid |
| | RD2 | 0.648 | >0.6 | Valid |
| | RD3 | 0.656 | >0.6 | Valid |
| | RD4 | 0.736 | >0.6 | Valid |
| | RD5 | 0.692 | >0.6 | Valid |
| | RD6 | 0.693 | >0.6 | Valid |
| | RD7 | 0.757 | >0.6 | Valid |
| | RD8 | 0.691 | >0.6 | Valid |
| | RD9 | 0.704 | >0.6 | Valid |
| | RD10 | 0.654 | >0.6 | Valid |
| | RD11 | 0.662 | >0.6 | Valid |

Based on Table 2 each indicator has a loading factor value greater than 0.70, the final results of the Convergent Validity test demonstrate that all indicators are valid and satisfy the Convergent Validity.

### *4.3 Discriminant Validity*

The cross-loading values reflect how strongly eindicacorrelatesawithiits own construct compared to other constructs, offering crucial insight into discriminant validity (Hashim et al., 2022; Hossain et al., 2021). A commonly accepted benchmark is that an indicator's loading on its intended construct should be at least 0.6—and notably higher than its loadings on other constructs (Li et al., 2022). Discriminant validity is confirmed when the square root of the Average Variance Extracted (AVE) for each construct exceeds its correlations with any other construct, and each AVE itself is above 0.5 to ensure convergent validity. In the current model, all constructs meet these criteria—their AVE roots surpass inter-construct correlations, and the AVE values exceed 0.5—indicating strong discriminant validity and clear measurement distinctions among constructs.

Table 3. Average Variance Extracted (AVE) Test Result

| Variable | Condition | AVE |
|---|---|---|
| Employee Productivity (Y) | > 0.5 | 0.595 |
| Innovation (Z) | > 0.5 | 0.548 |
| Digital Communication Technology (X1) | > 0.5 | 0.557 |
| Research & Development (X2) | > 0.5 | 0.585 |

Table 3 describes that every variable has a good AVE value. For Employee Productivity, Innovation, Digital Communication Technology, Research, and Development already have a score of 0.5.

Table 4. Discriminant Validity Test Result (Fornell-Larcker Criterion)

| Variable | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Innovation (Z) | 0.913 | | | |
| Employee Productivity (Y) | 0.557 | 0.783 | | |
| Research & Development ($X_2$) | 0.491 | 0.781 | 0.921 | |
| Digital Communication Technology ($X_1$) | 0.546 | 0.789 | 0.914 | 0.908 |

Based on Table 4, the results of the discriminant validity test using the Fornell-Larcker criterion show that each construct has a higher square root of AVE value compared to its correlations with other constructs. This indicates that each variable shares more variance with its own indicators than with other variables in the model. For example, Innovation (Z) has a value of 0.913, which is higher than its correlations with Employee Productivity (Y), Research & Development ($X_2$), and Digital Communication Technology ($X_1$). Therefore, it can be concluded that the model meets the requirements of discriminant validity, confirming that each construct is distinct and measures a different concept (Cin et al., 2017; Friesenbichler, 2016).

When each construct's $\sqrt{AVE}$ exceeds its correlations with all other constructs, we can conclude that the model meets the discriminant validity standards. This means that each construct explains more of its own indicators' variance than it shares with others. Additionally, because all AVE values in this model exceeded $0.50$, convergent validity was confirmed.

Regarding reliability, both Cronbach's Alpha and Composite Reliability (CR) were calculated for all latent variables. With Cronbach's Alpha$\geq 0.70$ and CR $\geq 0.70$ for each construct, the instruments demonstrated strong internal consistency and dependability. This indicates that the questionnaire items reliably measured their intended constructs, ensuring that the overall measurement model was both valid and reliable.

 

Table 5. Validity and Reliability Construct Test Result

| Variable | Cronbach's Alpha | Composite Reliability | Information |
|---|---|---|---|
| Employee Productivity (Y) | 0.886 | 0.907 | Reliable |
| Innovation (Z) | 0.825 | 0.866 | Reliable |
| Digital Communication Technology ($X_1$) | 0.867 | 0.893 | Reliable |
| Research & Development ($X_2$) | 0.893 | 0.912 | Reliable |

Based on Table 5, the results of the validity and reliability test show that all constructs meet the required criteria. The Cronbach's Alpha values for all variables are above 0.70, indicating good internal consistency. Similarly, the Composite Reliability values for all constructs exceed 0.70, confirming strong reliability. Employee Productivity (Y), Innovation (Z), Digital Communication Technology ($X_1$), and Research & Development ($X_2$) all demonstrate reliable measurement instruments. Therefore, it can be concluded that the indicators used in this study are consistent and dependable in measuring their respective constructs (Koutroumpis et al., 2020).

### *4.4 Structural Model Test (Inner Model)*

The Structural Model Test evaluates how well a model functions within a given context by assessing its robustness, reliability, and predictive capability. This process is grounded in a conceptual framework and relies heavily on inner model analysis, particularly the R-squared ($R^2$) value, to evaluate model fit (**Hair2021**). $R^2$, ranging from 0 to 1, shows how much variance in the dependent variables is explained by the independent variables; the higher the $R^2$, the better the predictive accuracy. However, $R^2$ tends to increase as more predictors are added, even if those predictors contribute little, which means that $R^2$ must be interpreted in context. Ultimately, the R-squared value for each dependent variable was determined through data analysis to assess whether the model provided meaningful explanatory and predictive power.

Table 6. R-Square Test Result

| Variable | R-Square |
|---|---|
| Innovation | 0.703 |
| Employee Productivity | 0.992 |

Based on Table 6, the $R^2$ coefficient measures the proportion of variance in the dependent variable that is explained by the model, ranging from 0 to 1, and indicates how effectively the model captures the variation in the data. For Innovation ($R^2 = 0.703$), approximately 70.3% of the variation was accounted for by the model. This is considered a good fit, especially in fields such as economics or social sciences, where values between 0.5 and 0.7 are viewed positively. This indicates that the predictors are meaningfully linked to innovation outcomes, offering robust explanatory power.

In contrast, Employee Productivity ($R^2 = 0.992$) shows that the model explains an astonishing 99.2% of the variance, which is exceptionally high. While this suggests near-perfect predictive power, such a high $R^2$ may also indicate overfitting, where the model captures noise or sample-specific patterns rather than true general relationships.

Table 7. F-Square Test Result

| Variable | F-Square | Information |
|---|---|---|
| Innovation > Employee Productivity | 0.010 | Weak |
| R&D > Innovation | 0.011 | Weak |
| R&D > Employee Productivity | 43.110 | Strong |
| Digital Communication Tech > Innovation | 0.835 | Medium |
| Digital Communication Tech > Emp. Productivity | 0.001 | Weak |

Based on Table 7, the $F^2$ (F-square) metric is used in structural equation modeling to assess the effect size or practical impact of one construct on another construct. According to Cohen (1988), which is widely cited in the PLS-SEM literature, $F^2$ values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effect sizes, respectively, as shown in Table 6. Innovation → Employee Productivity ($F^2 = 0.010$), which falls below 0.02, indicating a negligible effect, meaning innovation has little practical influence on productivity. R&D → Innovation ($F^2 = 0.011$), also below the small threshold, showing a very weak effect, suggesting that R&D contributes minimally to innovation in this model. R&D → Employee Productivity ($F^2 = 43.110$), this extraordinarily large value—far above 0.35—indicates a very strong effect, with R&D exerting a dominant influence on productivity. Digital Communication Technology → Innovation ($F^2 = 0.835$), again well above 0.35, highlights a large effect, demonstrating that digital communication technologies significantly drive innovation. Digital Communication Technology → Employee Productivity ($F^2 = 0.001$): also negligible, showing virtually no effect on productivity. Overall, R&D strongly impacts employee productivity, and digital communication technology significantly enhances innovation. The other pathways have minimal practical influence and might warrant reconsideration or further exploration if they are expected to play major roles.

Table 8. Hypothesis Testing Results

| No | Hypothesis | $\beta$ | SD | T-Statistic | P-Value | Description | Results |
|---|---|---|---|---|---|---|---|
| H1 | Digital Communication Tech → Innovation | 0.771 | 0.035 | 22.057 | 0.000 | Significant Positive | Accepted |
| H2 | R&D → Innovation | 0.087 | 0.044 | 1.961 | 0.025 | Significant Positive | Accepted |
| H3 | Digital Communication Tech → Employee Productivity | 0.014 | 0.029 | 0.502 | 0.308 | Not-Significant Positive | Rejected |
| H4 | R&D → Employee Productivity | 0.996 | 0.007 | 136.010 | 0.000 | Significant Positive | Accepted |
| H5 | Innovation → Employee Productivity | 0.019 | 0.001 | 1.999 | 0.036 | Significant Positive | Accepted |

Based on Table 8, summarizes the hypothesis-testing outcomes for the key structural paths in the model. All path coefficients ($\beta$) were standardized, and their significance was assessed using t-statistics and p-values. Overall, the guidelines for evaluating significance in PLS-SEM indicate that a t-statistic above approximately 1.96 (for a 95% confidence level) and a p-value below 0.05 denote a statistically significant positive effect. Digital Communication Technology → Innovation has a $\beta$ of 0.771, $t = 22.057$, and $p < 0.001$. This indicates a strong and highly significant positive effect, confirming that digital communication technologies robustly foster innovation (Hossain et al., 2021; Kahn et al., 2022).

R&D → Innovation yields $\beta = 0.087$, $t = 1.961$, $p = 0.025$—just passing the threshold ($t \approx 1.96$ and $p < 0.05$), signifying a modest but statistically significant positive effect of R&D on innovation. Digital Communication Technology → Employee Productivity shows a $\beta$ of 0.014, $t = 0.502$, $p = 0.308$. Because the t-value is very low and the p-value exceeds 0.05, this indicates an insignificant effect, and the hypothesis is rejected accordingly. R&D → Employee Productivity stands out with $\beta = 0.996$, $t = 136.01$, $p < 0.001$, signifying a near-perfect, highly significant positive relationship, indicating that R&D is a dominant driver of employee productivity. Innovation → Employee Productivity has $\beta = 0.019$, $t = 1.999$, $p = 0.036$. Although the coefficient is small, it meets the significance criteria, indicating a statistically significant but modest positive effect.

In summary, four out of five hypothesized paths are supported: Digital Communication Technology and R&D both significantly influence innovation (strong and moderate, respectively), R&D strongly drives productivity, and innovation contributes modestly to productivity. Only the direct effect of Digital Communication Technology on productivity is unsupported. These findings adhere to conventional hypothesis-testing standards, where high t-values and p-values below $0.05$ provide confidence in accepting the hypothesized relationships.

Table 9. Mediation Test Results

| No | Hypothesis | $\beta$ | SD | T-Statistic | P-Value | Description | Results |
|---|---|---|---|---|---|---|---|
| 1 | Digital Communication Tech → Innovation → Employee Productivity | 0.014 | 0.008 | 1.804 | 0.036 | Not-Significant | Rejected |
| 2 | R&D → Innovation → Employee Productivity | 0.002 | 0.001 | 1.178 | 0.120 | Not-Significant | Rejected |

Based on Table 9, the mediation analysis tested whether innovation mediates the relationship between digital communication technology and employee productivity and whether innovation mediates the impact of R&D on Employee Productivity. Both indirect paths were found to be non-significant. For the path Digital Communication Technology → Innovation → Employee Productivity, the standardized indirect effect ($\beta = 0.014$, $t = 1.804$, $p = 0.036$) does not meet the common significance threshold ($t < 1.96$ for 95% confidence, $p > 0.05$), leading to the rejection of the mediation hypothesis. Similarly, the path R&D → Innovation → Employee Productivity has an indirect effect of $\beta = 0.002$ with $t = 1.178$ and $p = 0.120$, which is clearly non-significant, resulting in rejection of this mediation as well.

In practical terms, this means that although Digital Communication Technology and R&D may influence innovation, these effects do not translate into measurable indirect impacts on Employee Productivity through innovation. Instead, any productivity gains likely arise through other direct mechanisms not captured by innovation as a mediator. Predictive relevance ($Q^2$) value is used to measure the goodness of the structural fit model on the inner model (Campbell & Banerjee, 2012). The model has a predictive relevance value if the $Q$-Square value is greater than 0 (zero). The following computation shows the $R^2$ value for each endogenous variable used in this study:

Table 10. The Construct Cross-Validation Redundancy Test Results ($Q^2$)

| **Variable** | **SSO** | **SSE** | **$Q^2$ (1 - SSE/SSO)** |
|---|---|---|---|
| Innovation (Z) | 2464 | 1745 | 0.292 |
| Employee Productivity (Y) | 3080 | 1945 | 0.368 |
| Digital Communication Tech (X1) | 3080 | 2113 | 0.314 |
| R&D | 3388 | 2138 | 0.369 |

Based on Table 10, the $Q^2$ statistic evaluates the predictive relevance of the structural model. A positive $Q^2$ value indicates that the model can accurately reconstruct and predict the data of endogenous variables. Innovation ($Q^2 = 0.292$): A $Q^2$ above zero demonstrates that the model has predictive relevance for innovation. A value between $0.25$ and $0.5$ suggests a moderate to strong ability to predict innovation based on its predictors. Employee Productivity ($Q^2 = 0.368$): Similarly positive and between $0.25$ and $0.5$, indicating good predictive power for employee productivity. Digital Communication Technology ($Q^2 = 0.314$): Also falls within the moderate-to-strong predictive range, showing that the model effectively predicts values for this construct. R&D ($Q^2 = 0.369$): At $0.369$, this construct has strong predictive relevance, meaning that the outputs for R&D are reliably estimated by the model.

All $Q^2$ values significantly exceeded zero, confirming that the model possessed predictive relevance for each of these endogenous constructs. By conventional thresholds ($0.02$ small, $0.15$ medium, $0.35$ large), the $Q^2$ scores of approximately $0.3$–$0.37$ reflect moderate-to-high predictive accuracy, reinforcing the model's robustness in forecasting unseen data points for innovation, productivity, technology use, and R&D capacity. In summary, the model is well-suited for making predictions across these key variables, striking a good balance between explanatory and predictive performance.

## 5. Conclusions

The results show that the model has strong predictive validity, with $Q^2$ values ranging from 0.29 to 0.37, indicating moderate to strong relevance. Most hypotheses are supported, as indicated by t-statistic values greater than 1.96 and p-values below 0.05, except for one unsupported hypothesis. Digital Communication Technology has a significant positive effect on Innovation ($\beta = 0.771, p < 0.001$), while R&D has a very strong impact on Employee Productivity ($\beta = 0.996, p < 0.001$). However, Digital Communication Technology does not directly influence Productivity, and Innovation does not significantly mediate the relationships.

In practical terms, improving productivity should focus on strengthening R&D through agile approaches such as sprints and cross-functional collaboration. Digital Communication Technology is mainly effective in enhancing innovation, especially when combined with AI-driven tools that reduce routine tasks. Supported by training, SMART objectives, and employee well-being programs, these strategies can help organizations achieve balanced and sustainable improvements in both innovation and productivity.


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## Author Contributions

A contributed to the conceptualization of the study, data collection, formal analysis, writing of the original draft, and provided supervision throughout the research process. SR was responsible for the methodology, validation of results, and writing—review & editing of the manuscript. S handled the data curation, analysis, and contributed to the writing of the original draft. S was involved in the investigation phase, as well as the writing—review & editing and final approval of the manuscript. AA provided supervision, resources, and reviewed the final draft of the article.

## Conflicts of Interest

The authors declare no conflict of interest in the publication of this research. This study was conducted independently, and there are no financial or personal influences on the results.

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