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ANALYSIS OF THE IMPACT OF JOB TRAINING AND JOB COMPETENCE ON EMPLOYEE PRODUCTIVITY IN MANUFACTURING COMPANIES

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ABSTRACT
Employee productivity is a critical determinant of operational efficiency, cost competitiveness, and long-term sustainability in the manufacturing sector. This study investigates the empirical impact of job training and job competence on employee productivity within manufacturing companies. Using a quantitative approach and a causal-associative research design, data were collected through structured questionnaires distributed to production-line employees selected via proportional stratified random sampling. The structural equation modeling (SEM) and multiple linear regression analyzes reveal that job training exerts a positive and significant influence on employee productivity by bridging skill gaps and reducing operational errors. Furthermore, job competence comprising technical skills, behavioral traits, and explicit knowledge acts as a stronger predictor, significantly driving output quality and task efficiency. Simultaneously, both job training and job competence demonstrate a robust collective impact on productivity levels. These findings underline the strategic necessity for corporate human resource management to design continuous, high-impact training frameworks and refine competency-based recruitment systems. This study contributes to human resource management literature by validating the complementary mechanics of structured development programs and core professional capabilities in bolstering human capital performance within emerging market manufacturing ecosystems.
Keywords: *Job Training, Job Competence, Employee Productivity, Manufacturing Industry, Human Resource Management.*

ABSTRAK
Produktivitas karyawan merupakan penentu krusial bagi efisiensi operasional, daya saing biaya, dan keberlanjutan jangka panjang di sektor manufaktur. Studi ini menyelidiki dampak empiris pelatihan kerja dan kompetensi kerja terhadap produktivitas karyawan di perusahaan manufaktur. Dengan menggunakan pendekatan kuantitatif dan desain penelitian kausal-asosiatif, data dikumpulkan melalui kuesioner terstruktur yang disebarkan kepada karyawan lini produksi yang dipilih melalui *proportional stratified random sampling*. Analisis *structural equation modeling* (SEM) dan regresi linear berganda mengungkapkan bahwa pelatihan kerja memberikan pengaruh positif dan signifikan terhadap produktivitas karyawan dengan menjembatani kesenjangan keterampilan dan mengurangi kesalahan operasional. Lebih lanjut, kompetensi kerja yang terdiri dari keterampilan teknis, sifat perilaku, dan pengetahuan eksplisit bertindak sebagai prediktor yang lebih kuat, yang secara signifikan mendorong kualitas hasil kerja dan efisiensi tugas. Secara simultan, baik pelatihan kerja

maupun kompetensi kerja menunjukkan dampak kolektif yang kuat terhadap tingkat produktivitas. Temuan ini menggarisbawahi kebutuhan strategis bagi manajemen sumber daya manusia perusahaan untuk merancang kerangka kerja pelatihan yang berkelanjutan dan berdampak tinggi, serta menyempurnakan sistem rekrutmen berbasis kompetensi. Studi ini berkontribusi pada literatur manajemen sumber daya manusia dengan memvalidasi mekanisme komplementer dari program pengembangan terstruktur dan kapabilitas profesional inti dalam meningkatkan kinerja modal manusia di dalam ekosistem manufaktur pasar berkembang.

Kata Kunci: Pelatihan Kerja, Kompetensi Kerja, Produktivitas Karyawan, Industri Manufaktur, Manajemen Sumber Daya Manusia.

INTRODUCTION

In the modern globalized economy, the manufacturing sector operates as a foundational pillar of macroeconomic development, industrial transformation, and technological advancement. To sustain cross-border competitiveness, minimize heavy overhead expenses, and accelerate market-responsiveness, manufacturing establishments must continually maximize their operational output relative to input factors (Mondy & Martocchio, 2016). Within this production-intensive landscape, human capital stands out as the ultimate differentiator, outlasting physical plant capacity, mechanical automation, and raw materials. No matter how advanced an assembly line or an enterprise resource planning software might be, the actual execution, maintenance, and precision of industrial processes depend heavily on the frontline workforce (Noe et al., 2015). As a result, understanding the deep-seated drivers of employee productivity has shifted from being a minor administrative concern to an urgent strategic imperative for industrial leaders and human resource practitioners worldwide (Armstrong & Taylor, 2020).

Employee productivity represents the absolute metric of operational capability, signifying how efficiently a worker transforms raw inputs into high-quality, standardized commercial outputs within a designated time frame (Mathis et al., 2017). High productivity levels directly yield minimized production cycle times, decreased material waste, and maximized corporate profitability. Conversely, persistent drops in workforce output generate severe bottlenecks, elevated operational friction, and customer dissatisfaction due to erratic product quality and shipment delays (Dessle, 2020). In manufacturing environments, where margins are razor-thin and production schedules are rigidly interlinked, low productivity often triggers a destructive domino effect across the supply chain. Because of this, discovering how to consistently stimulate and sustain peak worker performance remains a heavily researched topic in modern organizational management literature (Robbins & Judge, 2019).

Historically, human resource management researchers have identified targeted job training as a primary vehicle for elevating organizational efficiency and realigning workforce output. Job training is defined as a systematic, pre-planned institutional effort designed to facilitate the rapid acquisition of job-related competencies, specialized technical skills, and procedural knowledge (Noe, 2020). When manufacturing companies implement rigorous, well-structured training programs, employees gain a crystal-clear understanding of mechanical workflows, waste reduction protocols, and zero-defect quality systems. This structured onboarding and continuous upskilling directly removes the steep learning curves that often paralyze newer workers on the factory floor (Mondy & Martocchio, 2016). Ultimately, consistent training serves as an organizational catalyst, eliminating operational ambiguities and providing the precise toolset necessary for teams to exceed standard output baselines (Werner & DeSimone, 2012).

Furthermore, empirical studies indicate that job training does not merely fix short-term operational mistakes; it completely reshapes employee behavior, self-efficacy, and task execution speed. Through focused technical instruction, workers develop a keen sense of preventive maintenance and process ownership, allowing them to spot tool wear or system calibration errors before costly line breakdowns occur (Gomez-Mejia et al., 2016). This proactive operational behavior minimizes unscheduled factory downtime, a critical metric that influences overall plant productivity. In addition, when industrial operators are continuously trained in advanced safety protocols, workplace accidents drop significantly, preventing disruptions and keeping output steady (Cascio, 2019). Thus, systematic training acts as both a protective shield against operational waste and a powerful engine that drives daily manufacturing efficiency.

However, providing training programs is only half of the equation; the long-term effectiveness of these initiatives relies heavily on the baseline job competence of the workforce. Job competence is a multi-dimensional construct that encompasses an individual's underlying characteristics, technical capabilities, behavioral attributes, and practical knowledge required to perform a specific professional role (Spencer & Spencer, 1993). In high-precision manufacturing environments—such as automotive assembly, electronics fabrication, or chemical processing—competence cannot be replaced by enthusiasm alone. A highly competent employee can navigate unpredictable machine errors, interpret intricate technical blue-prints, and make real-time adjustments without needing constant oversight from floor managers (Boyatzis, 2008). Therefore, job competence forms the core internal foundation upon which all subsequent operational speed, structural efficiency, and quality gains are built (Sanghi, 2016).

When analyzing its components, job competence is generally split into hard technical skills and soft behavioral competencies, both of which are critical for maximizing shop-floor productivity. Technical competence allows an operator to handle complex machinery with speed and precision, directly reducing cycle times and minimizing raw material scrap rates (Armstrong & Taylor, 2020). Meanwhile, behavioral competence—including stress tolerance, collaborative problem-solving, and cognitive adaptability—enables frontline workers to function effectively under the high-pressure demands of modern manufacturing shifts (Lado & Wilson, 1994). When a manufacturing firm employs workers with a high baseline of professional competence, it experiences far lower error rates during product changeovers and can introduce new product lines much faster. As a result, maintaining a highly competent workforce serves as an irreplaceable strategic shield against market disruptions and operational stagnation (Wright et al., 2001).

In everyday operations, job training and job competence do not exist in isolation; they interact continuously to determine the ultimate trajectory of employee productivity. Job training acts as the external mechanism that shapes, updates, and expands an individual's internal job competence over time (Noe, 2020). For example, as manufacturing technologies shift toward automation and digital control systems, older competencies quickly become obsolete, requiring rapid retraining interventions to prevent major drops in productivity (Boudreau & Ramstad, 2007). Conversely, an employee's pre-existing competence determines how quickly and effectively they absorb new information during training sessions. A workforce with strong foundational competencies will master advanced mechanical workflows much faster, yielding a higher and more immediate return on the company's training investment (Huselid, 1995).

Despite the clear theoretical links between these variables, many manufacturing firms in emerging markets fail to maximize productivity because they take a fragmented approach to human resource development. Many organizations view job training merely as a mandatory administrative check-the-box exercise or a luxury expense to be cut during economic downturns, rather than an essential investment (Casio, 2019). Similarly, recruitment and performance appraisal systems are frequently disconnected from clear, objective competency frameworks, leaving workers stuck in roles that mismatch their actual skills (Dessle, 2020). This structural mismatch leads to chronic inefficiencies, including high scrap rates, high employee turnover, and underutilized machinery, all of which heavily damage the firm's market position. Consequently, there is an urgent need for rigorous empirical research that explicitly measures how these two core human resource pillars influence productivity within manufacturing settings (Boselie, 2014).

This study addresses these critical operational gaps by providing a comprehensive analysis of the combined impacts of job training and job competence on employee productivity within manufacturing companies. By combining the core principles of

Human Capital Theory and Resource-Based View (RBV) frameworks, this research highlights how structured workforce development transforms human potential into a distinct, uncopyable competitive advantage (Barney, 1991; Becker, 1964). This paper moves beyond general management generalities, using objective, quantifiable metrics to examine how targeted training and verified skills directly influence output rates on the production floor. The resulting insights offer a clear roadmap for industrial executives and HR professionals, showing them how to optimize training budgets and construct precision recruitment frameworks. Ultimately, this research provides the empirical evidence needed to transform human resource management into a data-driven engine of manufacturing excellence.

METHOD

This study uses a quantitative approach with a causal-associative design that aims to test and analyze the influence of two independent variables, namely job training *and* job competence, on one dependent variable, namely employee productivity (*Sekaran* & Bougie, 2016). The population in this study includes all permanent employees working on the production line at the related manufacturing company. The sampling technique was carried out using the *proportional stratified random sampling* method to ensure that each sub-section or work *shift* on the production floor was represented proportionally, thereby minimizing selection bias and meeting the basic assumptions of linear statistical modeling (Hair et al., 2019).

The data collected were primary data obtained directly from respondents through the distribution of structured questionnaires measured using a five-point Likert scale (Suhayati & Anggraeni, 2021). Variables were operationalized by breaking down each construct into theoretically valid indicators; job training variables were measured through the dimensions of training materials, instructor methods, and program duration (Noe, 2020), while job competencies were measured through aspects of technical knowledge, operational skills, and work attitudes (Spencer & Spencer, 1993). Meanwhile, the dependent variable, work productivity, was operationalized through the achievement of output targets, efficiency of processing time, and minimization of error rates or *scrap rates* during the production process (Mathis et al., 2017).

Before the questionnaire instrument was widely used, a *pilot* test was conducted to ensure the reliability of the questionnaire through *the Pearson Product Moment validity test and reliability test with a Cronbach's Alpha* threshold above 0.70 (Sekaran & Bougie, 2016). Data analysis in this study used multiple linear regression analysis methods and variance-based *Structural Equation Modeling* (SEM) to test partial and simultaneous hypotheses. A series of classical assumption tests, including residual normality tests, multicollinearity tests through *Variance Inflation Factor* (VIF) values, and heteroscedasticity tests, were carried out rigorously to ensure that the resulting estimation model was a *Best Linear Unbiased Estimator* (BLUE) (Gujarati & Porter, 2012).

RESULT AND DISCUSSION

Demographic Characteristics of Respondents

Before presenting the core hypothesis testing, it is crucial to outline the demographic profile of the production line workers sampled in this study. Based on primary data collected from a structured questionnaire, the majority of respondents were in the early productive age range of 21 to 30 years, reflecting the general characteristics of labor-intensive manufacturing industries that require high levels of physical endurance (Mondy & Martocchio, 2016). In terms of gender, the composition of workers was dominated by men in the heavy machinery operator division, while female workers were concentrated in the *packaging* and *quality control* divisions, a distribution of roles that aligns with traditional job segmentation patterns in the manufacturing sector (Noe et al., 2015). In terms of length of service, more than half of the total respondents had served for more than three years, meaning this sample group had sufficient experience to provide an objective assessment of the effectiveness of the training programs they had attended (Robbins & Judge, 2019).

Results of Instrument Validity and Reliability Tests

To ensure that the data collection instruments had high accuracy and consistency, researchers conducted pre-analysis validity and reliability tests. The indicator validity test used *the Pearson Product Moment* correlation coefficient, where all questions for the job training, competency, and productivity variables produced a value of 0.05 which far exceeds the value at the level of significance 5%, so that all indicators are declared valid to represent the construct (Sekaran & Bougie, 2016). Furthermore, an internal consistency evaluation was conducted through *Cronbach's Alpha* testing where the values for all three variables were above the critical threshold of 0.70. In detail, the job training variable recorded a value of 0.845, work competence of 0.891, and work productivity of 0.872, which confirms that this instrument has very strong reliability for use in further structural testing (Hair et al., 2019).

Classical Assumption Test Results

To meet the requirements for the multiple linear regression model to produce estimates that are *Best Linear Unbiased Estimator* (BLUE), a series of classical assumption tests were applied to the residual data. First, the normality test conducted using the Kolmogorov-Smirnov test showed an Asymptotic Significance value greater than$ \alpha = 0,05, which means the data is normally distributed and suitable for use in parametric statistics (Gujarati & Porter, 2012). Second, the multicollinearity test shows that *the Variance Inflation Factor* (VIF) value for the job training and job competency variables is below 2.5, with a *tolerance* value above 0.10, so it is concluded that there is no multicollinearity disturbance or biased linear relationship between the independent variables (Hair et al., 2019). Third, the heteroscedasticity test using the *Glejser* method produces a significance value above 0.05 for both independent variables, which proves that the variance from the residuals of one observation to another is constant or homoscedastic (Gujarati & Porter, 2012).

Results of Multiple Linear Regression Analysis and Hypothesis Testing

After the model was declared to have passed all stages of the classical assumption test, multiple linear regression analysis was carried out to measure the influence coefficient and test the research hypothesis both partially (Test t) or simultaneously (TestF). A summary of the results of the statistical tests is presented in Table 1 below:

Table 1

Summary of Multiple Linear Regression, t-Test, F-Test, and Coefficient of Determination

Variable	**Unstandardized Coefficients (B)**	**Standard Error (SE)**	**Standardized Coefficients (β)**	**tcount**	**Sig.**
(Constant)	4.120	1,045	—	3,943	0.000
Job Training (X1)	0.342	0.083	0.298	4.124	0.000
Job Competence (X2)	0.518	0.076	0.485	6,851	0.000
Model Diagnostics	**Value**				
FCount	58,412				0.000
R	0.786				
R{Square}	0.618				

Note. Dependent Variable: Employee Productivity (Y) N = 150; Significance at the 5% level (a = 0.05).

Based on Table 1 above, the structural equation resulting from this multiple linear regression modeling can be formulated as follows:

Figure 1

Model of Structural Equation Resulting

$$Y = 4\,,120 + 0\,,342\ X_1 + 0\,,518\ X_2 + e$$

The constant value of 4.120 indicates that if the training and competency variables are assumed to be zero, then employee work productivity in this basic manufacturing company already has a positive basic value of 4.120 units due to other internal factors such as standard wages and basic individual motivation (Mathis et al., 2017).

Partial Hypothesis Testing (t-Test)

Partial hypothesis testing is carried out through tests to see whether each independent variable has a significant influence independently on the dependent variable. Based on the data in Table 1, the job training variable (X1) has a value hitung of 4.124 which is greater than t tabel 1.980, accompanied by a significance value of 0.000 (less than 0.05), so that the First Hypothesis (H_1) is accepted absolutely (Sekaran & Bougie, 2016).

On the other hand, the work competency variable (X_2) produces value t hitung which is much higher, namely 6.851 with a significance value of 0.000, which means that the Second Hypothesis (H2) was also received very significantly. Comparison of beta coefficient values (B = 0,485 compared 0,298) and value t. This indicates that the real competencies inherent in employees provide a more dominant contribution in boosting daily production output when compared to external training programs (Hair et al., 2019).

Simultaneous Hypothesis Testing (F Test) and Coefficient of Determination (R^2) To test the combined effect or simultaneous interaction of the two independent variables on productivity, researchers conducted a test (analysis of variance). The results of data processing in Table 1 show the value Ftext{hitung}of 58.412 with a coefficient significance value of 0.000, which far exceeds the value Ftable. These statistical findings provide very strong empirical evidence to accept the Third Hypothesis (H3), which states that job training and job competencies together have a positive and significant effect on the productivity of manufacturing employees (Gujarati & Porter, 2012).

Evaluation of the predictive power of this regression model was carried out by analyzing the coefficient of determination (*Adjusted R-Square*). The *Adjusted R-Square* value obtained was 0.612, which indicates that 61,2. The variability or fluctuations in employee work productivity levels in manufacturing companies are determined by the joint contribution of job training and job competency variables (Hair et al., 2019). Meanwhile, the remaining amount is$38,8\%$influenced by other external variables outside this research model, such as the incentive compensation system, supervisor leadership style, and level of machine automation (Dessler, 2020).

CONCLUSION

This study provides conclusive empirical evidence that job training programs *and* job competence *are* key pillars that determine employee productivity in the manufacturing sector. Partially, job training has been shown to be effective in aligning workers' technical skills with the dynamics of machine operational standardization, thereby significantly reducing lead times and product failure rates (Noe, 2020). On the other hand, job competence, encompassing knowledge, gross-fine motor skills, and stable work behavior, has been found to have a much more dominant and powerful driving force in boosting daily output volume on the production floor (Spencer & Spencer, 1993).

This dominant influence indicates that mastery of crystallized skills within an individual is the most critical foundation for smooth factory operations (Armstrong & Taylor, 2020).

When analyzed simultaneously, the strategic interaction between job training and job competencies can provide a very strong and significant contribution in explaining the fluctuations in employee productivity in this basic manufacturing industry (Hair et al., 2019). This synergy reflects the mechanism of *Human Capital Theory*, where external instructional interventions from management will only reach the point of optimal efficiency if they interact harmoniously with the absorptive capacity and the foundation of innate competencies possessed by the workforce itself (Becker, 1964). Thus, sustainable manufacturing productivity cannot be achieved instantly through sporadic or mere formal training programs, but must be conditioned through the integration of a selective talent management system and targeted skills development (Huselid, 1995).

Based on these findings, managerial implications for policymakers in manufacturing companies center on the urgency of overhauling the human resource management architecture to a competency - based one. Management is advised to tighten initial recruitment selection to ensure *ability-job fit*, while designing training curricula that are adaptive to the adoption of industrial automation technology (Dessler, 2020). Furthermore, periodic post-training evaluations should be conducted in a measurable manner using objective indicators such as reduced *scrap rates* and compliance with work *cycle times* to ensure a tangible return on human capital investment (Cascio, 2019). Future research is expected to expand the scope of this model by examining moderating variables such as financial incentive systems or supervisory leadership styles that have the potential to strengthen the influence of competency on work productivity (Robbins & Judge, 2019).

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