

Impact of Workforce Training and Quality Management Practices on Production Performance

Mohammed Zayan Raji (Mittal School of Business)

zayanwade89@gmail.com

Adjepong Edmund Kofi (Mittal School of Business)

edadjepong@gmail.com

Francis Agyapong (Mittal School of Business)

agyapong4agyapong@gmail.com

Narh Justice Tetteh Kwesi (Mittal School of Business)

justicetetteh863@gmail.com

Habibu Ibrahim (School of Social Sciences, University of Ghana)

habibuibrahimgh@gmail.com

Samuel Twum (School of Computer Applications, Lovely Professional University)

samuel.12419294@lpu.in

Rafiatu Mustapha (University of Ghana Business school)

Rafiatumustapha288@gmail.com

Dr. Atul Sharma

Assistant Professor(LPU)

atulgandhoyta@gmail.com

Abstract-Manufacturing performance depends on more than machinery and technology; it also reflects employee capability, disciplined quality practices, and the ability to improve production processes over time. This study examined the relationship of workforce training, quality management practices, and continuous improvement initiatives with production performance in a manufacturing context. A quantitative, descriptive design was used and primary data were collected through a structured questionnaire from 164 respondents associated with manufacturing-related work areas. Responses were analysed in SPSS using descriptive statistics, reliability testing, Pearson correlation, multiple regression, and ANOVA. The construct means were close to the neutral range, indicating moderate rather than strong agreement with the workplace practices measured. Workforce training ($r = 0.586$), quality management ($r = 0.542$), and continuous improvement ($r = 0.514$) were each positively associated with the reported

Production Performance Score ($p < .001$). The regression model was significant, $F = 102.091$, $p < .001$, with $R^2 = 0.657$. Workforce training showed the largest standardized coefficient ($\beta = 0.457$). The findings suggest that manufacturing organisations should strengthen employee development, quality discipline, and systematic improvement activities while interpreting the results with attention to measurement limitations in the source study.

Keyword: *workforce training, quality management practices, continuous improvement, production performance, manufacturing industry, employee productivity, operational efficiency, SPSS*

I. INTRODUCTION

Manufacturing organisations continuously work to improve productivity, maintain product quality, reduce operational waste, and meet delivery expectations. In competitive production environments, these outcomes are shaped not only

by equipment and technology but also by the competence of employees, the quality practices followed on the shop floor, and the organisation's ability to improve its processes. Research on Industry 4.0 and lean manufacturing similarly

shows that human skills, digital readiness, process discipline, and continuous improvement are intertwined with organisational performance (Kamble et al., 2020; Kipper et al., 2021).

Digital transformation has increased the need for employees who can understand modern machines, adapt to new procedures, and work within more data-driven production systems. Smart manufacturing therefore requires both enabling technologies and trained human resources capable of operating, monitoring, and improving them (Mittal et al., 2020). Human-centric manufacturing research also emphasises that judgement, learning, and adaptability remain important even where automation is extensive (Lu et al., 2021).

Workforce training is relevant because it develops job-related skills, confidence, productivity, machine understanding, and the ability to complete tasks with fewer errors. Quality management practices contribute through standards, inspection, defect prevention, process monitoring, and corrective action. Quality 4.0 extends these principles by integrating quality decisions with digital information and systematic monitoring (Javaid et al., 2021). Continuous improvement complements both areas by encouraging feedback, teamwork, waste reduction, and regular refinement of production methods. Together, these practices provide a people-and-process foundation for stronger production performance.

Why Workforce Training and Quality Management Matter for Production Performance

Production performance is affected when employees are uncertain about machine operations, process requirements, or quality standards. Training reduces this gap by improving the capability to perform production tasks correctly and respond to changing technologies. At the same time, quality management helps maintain product standards and detect process problems before they develop into defects, rework, or customer complaints. Continuous improvement gives employees and managers a mechanism for learning from production problems and making incremental changes. The combined perspective is therefore relevant for manufacturing managers because productivity, quality, cost, and operational efficiency are affected by how well people and processes work together.

A. Problem Statement

Manufacturing organisations may experience low productivity, delays, defects, rework, wastage, and poor operational efficiency when training, quality management, and continuous improvement are not aligned. The problem has become more important as production systems adopt automation and Industry 4.0 technologies, since technology adoption alone does not guarantee improved performance. Organisational readiness, employee capability, and process discipline remain necessary for effective implementation (Culot et al., 2020; Ghobakhloo, 2020). The present study therefore examines how workforce training and quality management practices relate to production performance, while also considering the contribution of continuous improvement initiatives.

B. Objectives of the Study

The objectives of this study are:

- To study the impact of workforce training on employee skills, productivity, and production performance in the manufacturing industry.
- To examine the role of quality management practices in reducing defects and improving operational efficiency.

- To analyse how continuous improvement initiatives contribute to better production performance and overall manufacturing effectiveness.

II. LITERATURE REVIEW

Abbas (2020) examined total quality management and corporate sustainability through the mediating role of knowledge management. The study is relevant because quality improvement becomes more effective when employees understand, share, and apply knowledge in day-to-day operations. It supports the view that trained employees and systematic quality practices can reinforce organisational outcomes rather than operating as separate activities.

Kipper et al. (2021) mapped the competencies required by Industry 4.0 and highlighted the need for updated technical and practical skills in technology-driven production environments. Similarly, Lu et al. (2021) argued for anthropocentric human-machine symbiosis in smart manufacturing, emphasising that human judgement and adaptability remain central to flexible production. These findings provide a strong rationale for workforce training as manufacturing systems become more technologically advanced.

Mittal et al. (2020) described the characteristics, technologies, and enabling factors of smart manufacturing. Their work indicates that digital production systems require organisational capabilities as well as technological infrastructure. Culot et al. (2020) likewise noted that Industry 4.0 involves organisational and process transformation rather than technology alone. From the perspective of the present study, this means that training, quality discipline, and process improvement are necessary complements to technological adoption.

Javaid et al. (2021) discussed the significance of Quality 4.0 for comprehensive manufacturing enhancement. The study shows how quality management is moving beyond final-product inspection toward data-supported prevention, process monitoring, and systematic improvement. Abbas (2020) further links quality management with organisational sustainability, reinforcing the importance of quality systems that are embedded in daily work rather than treated as isolated compliance activities.

Kamble et al. (2020) examined the integration of Industry 4.0 and lean manufacturing practices for sustainable organisational performance. Their findings are particularly relevant to continuous improvement, because lean practices focus on efficiency, waste

reduction, and disciplined process improvement. Bai et al. (2020) also assessed Industry 4.0 technologies from a sustainability perspective and demonstrated the broader relationship between technological advancement, operational practices, and manufacturing outcomes.

Bag et al. (2021) considered resources, institutional pressures, artificial intelligence, and sustainable manufacturing capabilities. Their work indicates that technologies and resources generate value only when organisations have the capabilities required to implement them. Adel (2022) and Leng et al. (2022) extend this discussion toward Industry 5.0, where human-centred production and collaboration between people and technology receive greater attention. This reinforces the importance of employee development and continuous learning in future manufacturing environments.

Research Gap

Prior research has examined Industry 4.0, technology adoption, lean manufacturing, sustainability, human-machine collaboration, and quality management from several perspectives. However, these themes are often studied separately. Comparatively less attention is given to examining workforce training, quality management practices, and continuous improvement initiatives together in relation to production performance from employees' perspectives. The present study addresses this gap by analysing the three practice areas within one quantitative framework and assessing their reported relationships with production performance.

III. RESEARCH METHODOLOGY

Research Design

The study used a quantitative and descriptive research design. The descriptive component was used to summarise respondent characteristics and the pattern of Likert-scale responses, while inferential analysis was used to examine relationships among the study variables. The design was aligned with three research objectives covering workforce training, quality management practices, and continuous improvement initiatives in relation to production performance.

Data Collection Methodology

Primary data were collected through a structured questionnaire. Section A covered demographic information, including age group, gender, educational qualification, department, work experience, and job position. Section B contained nineteen usable Likert-

scale statements organised around workforce training, quality management practices, and continuous improvement. Responses were recorded on a five-point scale where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. Secondary material from journal articles and research papers was used to develop the academic background and interpret the findings.

Sampling Technique

The target population consisted of individuals connected with manufacturing-related work areas and familiar with production activities, training practices, quality control, and workplace improvement processes. A convenience sampling technique was used, which is a non-probability approach based on accessibility and willingness to participate. The final dataset contained 164 valid responses from workers, technicians, supervisors, quality inspectors, managers, and other respondents across production-related departments. Because convenience sampling was used, the results should be interpreted as evidence from the study sample rather than as a statistically representative estimate for the entire manufacturing industry.

Data Analysis Plan

The responses were organised and analysed in SPSS. Frequency and percentage analysis described the respondent profile. Means and standard deviations summarised the Likert-scale items and objective-wise construct scores. Cronbach's Alpha was used for reliability assessment. Pearson correlation examined associations among workforce training, quality management, continuous improvement, and the reported Production Performance Score. Multiple regression, ANOVA, standardized coefficients, and variance inflation factors were used to assess the reported predictive model and multicollinearity.

IV. DATA ANALYSIS

Descriptive Analysis

The analysis was based on 164 valid responses. The demographic profile was diverse across age, education, department, work experience, and job position. The largest age group was 36–45 years (29.3%), followed by 46–55 years (25.0%). Maintenance represented the largest department category (25.0%), while Quality Control (20.7%), Human Resource (20.1%), and Operations (18.9%) also formed substantial parts of the sample. Supervisors (22.6%) and technicians (22.0%) were the two largest job-position categories.

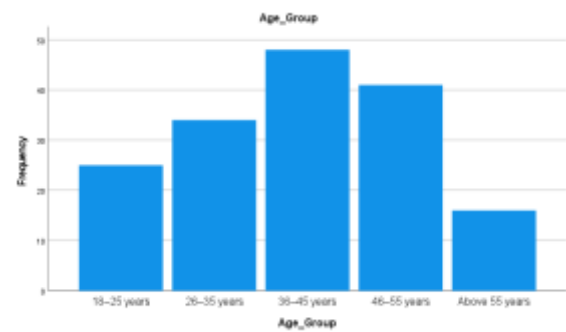


Figure 1. Age group distribution of respondents

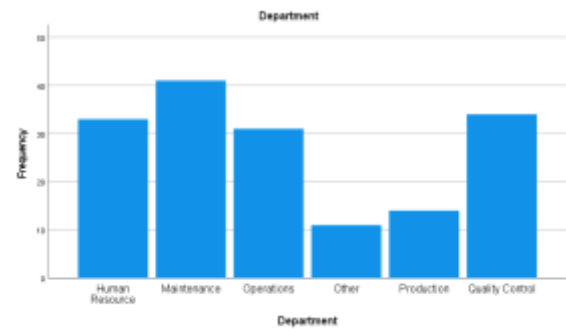


Figure 2. Department distribution of respondents

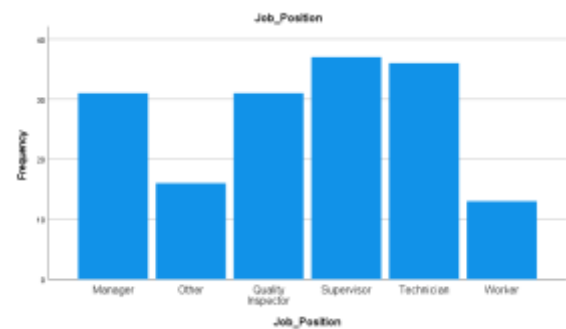


Figure 3. Job position distribution of respondents

Across the nineteen Likert-scale statements, the reported mean values were generally between 2.41 and 2.93, indicating responses close to the disagree-to-neutral range rather than strong agreement. Objective-wise, workforce training had the highest reported mean, followed by continuous improvement and quality management. These values suggest that respondents held moderate views about the extent to which the measured practices were present or effective in their work context.

Objective-Wise Analysis

Table 1. Objective-Wise Descriptive Statistics

Construct	Mean	SD
Workforce Training	2.6751	0.61212
Quality Management	2.5967	0.55856
Continuous Improvement	2.6159	0.63786

The three construct means are all below the neutral midpoint of 3.00, although the differences among them are small. Workforce Training ($M = 2.6751$, $SD =$

0.61212) received the comparatively highest assessment. Continuous Improvement followed ($M = 2.6159$, $SD = 0.63786$), while Quality Management had the lowest mean ($M = 2.5967$, $SD = 0.55856$). These descriptive results should therefore be interpreted as moderate or near-neutral perceptions rather than as strong endorsement of the practices.

Reliability Testing

The overall reliability analysis for the nineteen items produced Cronbach's Alpha = 0.437. This value indicates weak internal consistency when all items are treated as one combined scale. Because the questionnaire contains conceptually different areas—workforce training, quality management, and continuous improvement—the overall Alpha should not be described as strong or acceptable evidence of a single homogeneous construct. Construct-specific reliability values were not reported in the source study and have not been invented in this paper.

Correlation Analysis

Pearson correlation showed positive and statistically significant relationships between each of the three reported predictors and Production Performance Score. Workforce Training had the strongest bivariate association ($r = 0.586$, $p < .001$), followed by Quality Management ($r = 0.542$, $p < .001$) and Continuous Improvement ($r = 0.514$, $p < .001$). The relationships are moderate and indicate association rather than proof of causation. Workforce Training and Quality Management were weakly correlated with each other ($r = 0.214$, $p = .006$), and Quality Management was weakly correlated with Continuous Improvement ($r = 0.216$, $p = .005$). The Workforce Training–Continuous Improvement association was weak and not statistically significant ($r = 0.136$, $p = .082$).

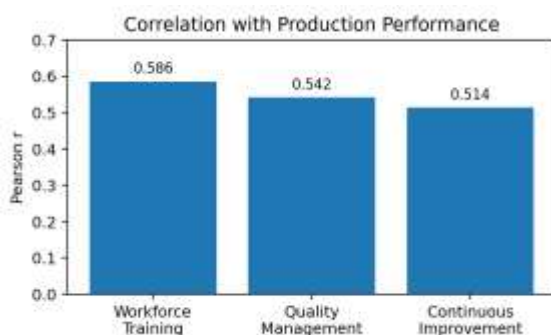


Figure 4. Correlation of study predictors with Production Performance Score

Regression Analysis

The source regression model entered Workforce Training Score, Quality Management Score, and Continuous Improvement Score simultaneously, with

Production Performance Score as the dependent variable. The model reported $R = 0.810$, $R^2 = 0.657$, adjusted $R^2 = 0.650$, and a standard error of estimate of 0.32778. The ANOVA result was statistically significant, $F(3, 160) = 102.091$, $p < .001$. Accordingly, the reported model accounted for 65.7% of the variance in Production Performance Score within the study sample.

All three standardized coefficients were positive and statistically significant. Workforce Training had the largest standardized coefficient ($\beta = 0.457$, $B = 0.414$, $SE = 0.043$, $t = 9.593$, $p < .001$), followed by Continuous Improvement ($\beta = 0.373$, $B = 0.325$, $SE = 0.041$, $t = 7.837$, $p < .001$) and Quality Management ($\beta = 0.364$, $B = 0.361$, $SE = 0.048$, $t = 7.527$, $p < .001$). VIF values ranged from 1.057 to 1.089, indicating no serious multicollinearity concern among the reported predictors.



Figure 5. Standardized regression coefficients reported in the study

Data verification note: the source report contains one item-level descriptive row with a maximum value of 6 even though the stated Likert scale ranges from 1 to 5. No silent recoding has been assumed in this short paper. In addition, the inferential outputs use a variable labelled Production Performance Score, but the source report does not separately document its item-level construction. The inferential statistics are therefore retained exactly as reported and the underlying scoring method should be verified before final journal submission.

V. RESULT AND DISCUSSION

The descriptive findings show that respondents did not express strong agreement with the measured workplace practices. Construct means remained close to the neutral point, with Workforce Training receiving the highest mean and Quality Management the lowest. This pattern suggests that respondents may recognise the relevance of these practices while perceiving room for improvement in their actual implementation. The result is consistent with the broader manufacturing literature, which treats employee capability and

operational systems as continuing organisational requirements rather than one-time interventions (Kipper et al., 2021; Mittal et al., 2020).

Workforce Training showed the strongest relationship with the reported Production Performance Score in both correlation and standardized regression results. The finding is plausible in a manufacturing context because employees require technical knowledge, confidence, machine understanding, and problem-solving ability to complete tasks efficiently and reduce production errors. Human-centric manufacturing literature supports this interpretation by emphasising that technological systems still depend on human judgement and adaptability (Lu et al., 2021). Industry 4.0 competency research also highlights the need for continuous skill development as manufacturing processes become more digital and complex (Kipper et al., 2021).

Quality Management was also positively associated with the reported production-performance outcome. Quality practices such as maintaining standards, inspection, early identification of problems, and defect control can reduce rework and improve operational consistency. Javaid et al. (2021) describe Quality 4.0 as a shift toward more systematic and data-supported quality management, while Abbas (2020) shows that quality management is strengthened when knowledge is embedded in organisational processes. The present findings are therefore consistent with the view that quality discipline can support production effectiveness when it is integrated into everyday operations.

Continuous Improvement produced a positive relationship with the reported Production Performance Score and remained significant in the regression model. Continuous improvement activities—employee feedback, teamwork, waste reduction, and management encouragement—are closely related to lean manufacturing and operational excellence. Kamble et al. (2020) found that lean practices and Industry 4.0 can jointly support sustainable organisational performance. The current result similarly suggests that improvement-oriented routines may complement workforce capability and quality practices rather than functioning as an isolated initiative.

An important feature of the results is the contrast between moderate descriptive means and comparatively strong inferential relationships. These findings are not necessarily contradictory. A sample can report only moderate levels of a practice while still showing that respondents who report relatively higher

levels of that practice also report higher production performance. The correlation and regression coefficients describe variation among respondents; they do not require the average level of each practice to be high. At the same time, the cross-sectional design, convenience sampling, weak overall reliability, and unresolved construction of Production Performance Score limit the strength of causal conclusions. The results are best interpreted as evidence of significant associations within the study sample rather than proof that the three practices independently cause production improvements across the manufacturing sector.

VI. RECOMMENDATION

Manufacturing organisations should conduct regular skill-based training that is linked directly to production requirements. Training should address machine operation, new technologies, quality standards, problem solving, and error prevention rather than relying only on general classroom sessions. Periodic skill-gap assessment can help managers identify where training resources will have the greatest operational value.

Quality management should be treated as a daily production discipline rather than only as a final inspection activity. Clear standards, early problem detection, process monitoring, and corrective action can help reduce defects, rework, and unnecessary cost. Employees should understand why quality procedures are required and how deviations affect downstream production performance.

Continuous improvement should be supported through simple mechanisms for employee feedback and team-based problem solving. Workers, technicians, supervisors, and quality personnel are close to production processes and may identify practical opportunities to reduce wastage, improve workflow, or prevent recurring errors. Management should provide visible support for improvement suggestions and communicate the actions taken in response.

Training, quality management, and continuous improvement should be coordinated rather than implemented as separate programmes. New technologies should be accompanied by employee preparation and updated quality procedures, while improvement initiatives should use both operational data and employee experience. This integrated approach is more consistent with the human-centred direction of advanced manufacturing described in Industry 5.0 literature (Adel, 2022; Leng et al., 2022).

For future empirical work, the measurement model should be strengthened before publication-level inference. Construct-specific reliability should be assessed, the out-of-range Likert response should be checked against the raw dataset, and the exact construction of Production Performance Score should be documented. Larger probability-based samples and the inclusion of objective production indicators such as defect rates, output, downtime, rework, and wastage would further strengthen evidence on the relationships identified in this study.

VII. CONCLUSION

This study examined workforce training, quality management practices, and continuous improvement initiatives in relation to production performance using questionnaire responses from 164 manufacturing-related respondents. The descriptive findings showed moderate, near-neutral assessments of the three practice areas. However, each predictor was positively and significantly associated with the reported Production Performance Score, and the combined regression model explained a substantial proportion of its reported variance within the sample.

Workforce Training showed the largest standardized regression coefficient, followed by Continuous Improvement and Quality Management. The findings support the practical importance of employee capability, disciplined quality systems, and improvement-oriented work practices in manufacturing. They also reinforce the broader research view that technology and production systems depend on organisational capabilities and human participation for effective implementation. Because the study used convenience sampling and the source measurement contains issues requiring verification, the results should be interpreted cautiously. Even so, the study provides a useful basis for manufacturing organisations to consider training, quality discipline, and continuous improvement as connected components of production performance rather than isolated management practices.

REFERENCE

- Abbas, J. (2020). Impact of total quality management on corporate sustainability through the mediating effect of knowledge management. *Journal of Cleaner Production*, 244, 118806. <https://doi.org/10.1016/j.jclepro.2019.118806>
- Adel, A. (2022). Future of industry 5.0 in society: Human-centric solutions, challenges and prospective research areas. *Journal of Cloud*

Computing, 11, Article 40.
<https://doi.org/10.1186/s13677-022-00314-5>

- Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, 163, 120420. <https://doi.org/10.1016/j.techfore.2020.120420>
- Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, 229, 107776. <https://doi.org/10.1016/j.ijpe.2020.107776>
- Culot, G., Orzes, G., Sartor, M., & Nassimbeni, G. (2020). Behind the definition of Industry 4.0: Analysis and open questions. *International Journal of Production Economics*, 226, 107617. <https://doi.org/10.1016/j.ijpe.2020.107617>
- Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. *Journal of Cleaner Production*, 252, 119869. <https://doi.org/10.1016/j.jclepro.2019.119869>
- Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2021). Significance of Quality 4.0 towards comprehensive enhancement in manufacturing sector. *Sensors International*, 2, 100109. <https://doi.org/10.1016/j.sintl.2021.100109>
- Kamble, S. S., Gunasekaran, A., & Dhone, N. C. (2020). Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies. *International Journal of Production Research*, 58(5), 1319–1337. <https://doi.org/10.1080/00207543.2019.1630772>
- Kipper, L. M., Iepsen, S., Dal Forno, A. J., Frozza, R., Furstenau, L., Agnes, J., & Cossul, D. (2021). Scientific mapping to identify competencies required by Industry 4.0. *Technology in Society*, 64, 101454. <https://doi.org/10.1016/j.techsoc.2020.101454>
- Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., Wuest, T., Mourtzis, D., & Wang, L. (2022). Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*, 65, 279–295. <https://doi.org/10.1016/j.jmsy.2022.09.017>

- Lu, Y., Adrados, J. S., Chand, S. S., & Wang, L. (2021). Humans are not machines: Anthropocentric human-machine symbiosis for ultra-flexible smart manufacturing. *Engineering*, 7(6), 734–737. <https://doi.org/10.1016/j.eng.2021.03.018>
- Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2020). Smart manufacturing: Characteristics, technologies and enabling factors. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 234(5), 835–852. <https://doi.org/10.1177/0954405419886294>