Impact of Lean Manufacturing Practices on Quality Performance and Competitiveness: Evidence from SME Foundries in Kolhapur District

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ABSTRACT: The foundry industry, being highly resource-intensive, faces challenges of global competition, cost pressures, and demand for consistent quality. Lean production practices provide a systematic approach to minimize waste, improve efficiency, and enhance competitiveness. This study examines the impact of lean practices on quality performance and competitive advantage in SME foundry units of Kolhapur district, India. Data were collected through questionnaires, interviews, and plant observations, yielding 473 valid responses. Using CFA and SEM, the study confirms that practices such as 5S, Kaizen, Just-in-Time, TPM, and Value Stream Mapping significantly improve quality by reducing defects, enhancing reliability, and ensuring timely delivery. Improved quality further drives competitive advantage through cost efficiency, customer satisfaction, and market responsiveness. The findings highlight the strategic role of lean in strengthening regional foundry clusters and provide valuable implications for managers and policymakers in sustaining industrial growth.

Keywords: Lean Production Practices, Quality Performance, Competitive Advantage, Foundry Industry, Confirmatory Factor Analysis (CFA), Structural Equation Modeling (SEM)

Introduction

The global manufacturing sector is transforming rapidly under competitive pressures, technological change, and rising customer expectations. To survive, firms must reduce waste, improve efficiency, and deliver consistent quality. Lean management, rooted in the Toyota Production System, has emerged as a proven approach for operational excellence by eliminating non-value activities and maximizing customer value (Womack & Jones, 1996; Shah & Ward, 2007).

Lean is not merely a toolkit but a culture of continuous improvement, emphasizing practices such as 5S, Kaizen, JIT, TPM, and VSM (Hines et al., 2004). Globally, lean has enhanced competitiveness in industries from automotive to SMEs (Liker, 2004; Bhamu & Sangwan, 2014). For foundries—energy-intensive and defect-prone—lean offers structured solutions to improve quality, reduce costs, and meet global benchmarks.

Lean Practices in Foundries

Foundries supply castings critical to automotive, agricultural, and heavy machinery sectors. However, they face challenges of high energy use, variability, and defects like shrinkage, porosity, and dimensional inaccuracies (Chokkalingam et al., 2017). Lean practices—5S for workplace order, Kaizen for defect reduction, TPM for uptime, and JIT for waste reduction—directly address these inefficiencies (Anvari et al., 2011). Evidence shows lean adoption reduces scrap, optimizes resources, and raises customer satisfaction.

Quality Performance and Competitive Advantage

Quality performance, the ability to consistently meet customer expectations (Garvin, 1987), directly influences competitive advantage, defined as outperforming rivals in cost, differentiation, or responsiveness (Porter, 1985). Lean reduces variability, defect rates, and delays (Nawanir et al., 2013), thereby improving trust, efficiency, and market responsiveness—essential for foundries supplying high-precision industries.

Kolhapur Foundry Cluster

Kolhapur, Maharashtra, hosts over 300 SME foundries serving automotive, pump, and machinery sectors (IIF, 2020). While strategically located and skilled, the cluster struggles with rising energy costs, volatile raw materials, labor gaps, and stricter quality/environmental demands (Kulkarni & Deshpande, 2021; Patil, 2019). Many units still use conventional practices, leading to high defect rates and limited global competitiveness (Mali & Inamdar, 2020). Lean offers a timely framework to overcome these challenges.

Significance of the Study

This study explores how lean practices affect quality and competitiveness in Kolhapur's SME foundries. Academically, it extends lean literature—largely focused on large industries—by providing empirical evidence from SMEs using CFA and SEM. Practically, it highlights lean as a tool for reducing defects, cutting costs, and boosting delivery performance. Policymakers and industry associations can leverage these findings to design training and incentives for cluster-wide lean adoption, strengthening India's casting competitiveness.

Research Problem

Despite its economic importance, Kolhapur's foundry sector faces persistent issues of high costs, inefficiencies, and limited lean adoption. Outdated machinery, fluctuating raw material prices, and lack of lean awareness result in quality defects, rework, and reduced competitiveness. Many SMEs struggle to meet global supply chain demands for high-quality, cost-efficient, and reliable castings. This study investigates how lean implementation can transform quality performance and build sustainable competitive advantage in Kolhapur's SME foundries.

Scope of the Study

The research focuses on SME foundries in Kolhapur, examining lean practices such as JIT, TPM, SPC, Kanban, employee empowerment, and supplier collaboration. Using a quantitative design (CFA, SEM) with 492 respondents—including plant heads and supervisors—the study assesses their impact on quality performance and competitive advantage. The findings are expected to advance lean literature in emerging economies while providing actionable insights for managers, policymakers, and stakeholders in sustaining the competitiveness of India's foundry sector.

Objectives of the Study

1) To identify various lean management practices of foundry industries, Kolhapur.
2) To do assessment of Lean Management practices in Selected Foundry Industries of Kolhapur.
3) To evaluate adoption of lean management in selected foundry units through the road map regarding quality performance and competitive advantage.

Research Methodology

The research methodology provides a systematic framework that guides the entire process of data collection, analysis, and interpretation. The present study adopts a **quantitative and descriptive research design** with an empirical focus, aimed at investigating the impact of lean production practices on quality performance and competitive advantage in selected foundry units of Kolhapur district. The methodology followed is explained below:

1. Research Design

The study employs a **cross-sectional research design** using a survey method. This approach is suitable because it allows for collecting data from a large number of respondents at a single point in time, thereby enabling statistical analysis of the relationships among variables. Quantitative techniques are used to ensure objectivity, precision, and replicability.

2. Population and Sampling

The population consists of employees working in foundry units in Kolhapur, including plant managers, department heads, and experienced supervisors from production, quality, design, maintenance, and related functions.

A **cluster sampling approach** was applied because of the concentration of foundries in the Kolhapur region. Within each cluster, purposive and random sampling was used to ensure that employees from different departments and roles were proportionately represented. A total sample of **473 valid responses** was finalized after data cleaning.

3. Data Collection Methods

- **Primary Data:** Collected through a **structured questionnaire consisting of 60 items** measured on a **5-point Likert scale** (1 = strongly disagree, 5 = strongly agree). The questionnaire comprehensively covered all **independent variables (lean practices)** and **dependent variables (quality performance and competitive advantage)**.
    - **Section A:** Demographic data (age, gender, experience)
    - **Section B:** Lean production practices (SCC, JIT, SSD, CIE, Pull, FOP, STR, SPC, EEE, TPM, Kanban)
    - **Section C:** Quality Performance and Competitive Advantage
- **Secondary Data:** Drawn from scholarly articles, industrial reports, government publications, and previous studies to provide context.

4. Research Variables

- **Independent Variables (Lean Practices):** Supplier Communication and Collaboration (SCC), Just-in-Time (JIT), Strategic Supplier Development (SSD), Customer Involvement (CIE), Pull, Flow-Oriented Production (FOP), Setup Time Reduction (STR), Statistical Process Control (SPC), Employee Empowerment (EEE), Total Productive Maintenance (TPM), and Kanban.
- **Dependent Variables:** Quality Performance (QP) and Competitive Advantage (CA).

5. Data Analysis Tools and Techniques

Data was coded and analyzed using **SPSS and AMOS software**. The following analyses were carried out:

- **Descriptive Statistics:** To summarize demographic data and assess the distribution of responses (mean, standard deviation, skewness, kurtosis).
- **Reliability Analysis:** Cronbach's alpha and composite reliability were used to test the internal consistency of constructs.
- **Validity Analysis:** Convergent and discriminant validity were confirmed through **Confirmatory Factor Analysis (CFA)**.
- **Confirmatory Factor Analysis (CFA):** Used to validate the measurement model by examining factor loadings, average variance extracted (AVE), and goodness-of-fit indices.

- **Structural Equation Modeling (SEM):** Used to test the structural model and examine hypothesized relationships among lean practices, quality performance, and competitive advantage. Model fit indices such as Chi-square/df, CFI, TLI, and RMSEA were reported.

6. Hypothesis Testing

Hypotheses were formulated to test the direct and indirect relationships between lean practices, quality performance, and competitive advantage. SEM results were interpreted to determine acceptance or rejection of hypotheses.

Data Analysis and Interpretation

This section presents the results of data analysis conducted to examine the impact of lean production practices on quality performance and competitive advantage in selected foundry units of Kolhapur district. The analysis was carried out using SPSS 22 and AMOS 22 software. It consists of descriptive statistics, reliability and validity testing, confirmatory factor analysis (CFA), model fit indices, structural equation modeling (SEM), and hypothesis testing.

Descriptive Statistics:

The results of descriptive statistics provide useful insights into the extent of lean practice adoption, quality performance, and competitive advantage in Kolhapur foundries.

Table 1. Descriptive Statistics.

Descriptive Statistics									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Supplier Communication and Collaboration (SCC)	473	1.00	5.00	3.6309	.76112	-1.132	.112	.674	.224
Supplier JIT Integration (JIT)	473	1.67	5.00	3.9662	.81493	-.552	.112	-.295	.224
Strategic Supplier Development (SSD) Practices	473	1.29	5.00	3.9961	.84655	-.643	.112	-.169	.224
Customer Involvement and Engagement (CIE) Practices	473	1.00	5.00	3.8830	.93758	-.764	.112	-.022	.224
Pull System Implementation (PSI) Practices	473	1.60	5.00	3.7696	.63799	-1.055	.112	1.527	.224
Flow-Oriented Production (FOP) Practices	473	2.00	5.00	3.7542	.66062	-.922	.112	.513	.224

Setup Time Reduction (STR) Practices	473	1.20	5.00	3.8541	.84097	-1.136	.112	.515	.224
Statistical Process Control (SPC) Practices	473	1.83	5.00	3.9827	.88863	-.515	.112	-.593	.224
Employee Empowerment and Engagement (EEE) Practices	473	1.50	5.00	3.9197	.92782	-.704	.112	-.227	.224
Total Productive Maintenance (TPM) Practices	473	2.00	5.00	3.7680	.66379	-1.079	.112	.871	.224
Kanban (KAN)	473	1.75	5.00	4.0037	.76286	-.994	.112	.477	.224
Quality Performance (QP)	473	1.00	5.00	3.6549	.83087	-1.279	.112	1.156	.224
Competitive Advantage (CA)	473	1.20	5.00	3.7290	.66232	-1.213	.112	1.512	.224
Valid N (listwise)	473								

Supplier Communication and Collaboration (SCC) recorded a mean of 3.63 with a standard deviation of 0.76, suggesting a moderate level of collaboration with suppliers. The negative skewness (–1.132) indicates that most respondents rated this practice on the higher side, while a positive kurtosis (0.674) shows responses were fairly concentrated around the mean. This implies that while supplier integration exists, further improvements in long-term partnerships could strengthen overall performance (Chong & Rundus, 2004).

Just-in-Time Integration (JIT) showed a relatively high mean of 3.97 and standard deviation of 0.81, reflecting strong adoption of JIT practices to reduce inventory and align production with demand. The slight negative skewness (–0.552) indicates a tendency toward higher ratings, whereas a near-flat kurtosis (–0.295) reflects diversity in experiences across units. This suggests that JIT has been widely embraced but with variations in depth of implementation, aligning with lean principles of waste reduction (Ohno, 1988).

Strategic Supplier Development (SSD) also recorded a high mean of 3.99 with a standard deviation of 0.85. The negative skewness (–0.643) confirms positive responses, while kurtosis (–0.169) shows normal distribution. This suggests that foundries are investing in long-term supplier development, which is essential for ensuring raw material quality and cost efficiency, thereby contributing to competitiveness (Krause et al., 2000).

Customer Involvement (CIE) had a mean of 3.88 and standard deviation of 0.94, indicating moderately high engagement of customers in quality processes. Skewness (–0.764) shows a leaning towards positive ratings, while near-zero kurtosis (–0.022) confirms normal spread. This reflects that customer involvement is embedded in foundry practices, supporting continuous improvement and quality assurance (Flynn et al., 1994).

Pull System Implementation (PSI) recorded a mean of 3.77 with a low standard deviation of 0.64, suggesting consistent adoption across respondents. The strong negative skewness (–1.055) and high kurtosis (1.527) indicate that most ratings were clustered toward higher values. This suggests effective implementation of pull systems, ensuring smoother production flows and reduced overproduction (Hopp & Spearman, 2004).

Flow-Oriented Production (FOP) yielded a mean of 3.75 and standard deviation of 0.66. Negative skewness (–0.922) points to generally favorable responses, while kurtosis (0.513) shows concentration around the mean. This reflects moderate adoption of flow-oriented systems, ensuring efficiency and reduced waiting times in production processes (Womack & Jones, 1996).

Setup Time Reduction (STR) had a mean of 3.85 with a standard deviation of 0.84, reflecting strong adoption of techniques such as Single Minute Exchange of Dies (SMED). Negative skewness (–1.136) with positive kurtosis (0.515) suggests respondents consistently rated this practice highly. This indicates that setup time reduction is being actively practiced to improve flexibility and responsiveness in production schedules (Shingo, 1985).

Statistical Process Control (SPC) reported a mean of 3.98 and standard deviation of 0.89, signifying widespread usage for monitoring and controlling quality. The skewness (–0.515) and kurtosis (–0.593) values suggest near-normal distribution, reflecting that SPC is consistently implemented across foundries. This aligns with total quality management practices and helps minimize variability in production (Montgomery, 2009).

Employee Empowerment (EEE) had a mean of 3.92 with a standard deviation of 0.93, indicating that employees are actively involved in decision-making and continuous improvement. Skewness (–0.704) suggests a positive inclination, and kurtosis (–0.227) points to a normal spread. This reflects a Kaizen-oriented culture where workforce participation drives process improvements (Liker, 2004).

Total Productive Maintenance (TPM) recorded a mean of 3.77 and standard deviation of 0.66. The skewness (–1.079) and kurtosis (0.871) indicate concentrated responses on the higher side, showing that TPM practices are moderately adopted to ensure equipment reliability and reduce downtime (Nakajima, 1988).

Kanban (KAN) received the highest mean score of 4.00 with a standard deviation of 0.76, showing it is the most widely practiced lean technique. The skewness (–0.994) and kurtosis (0.477) suggest strong clustering of positive responses. This indicates that Kanban is firmly embedded as a scheduling tool, ensuring smoother material flow and reduced stock-outs (Sugimori et al., 1977).

In terms of outcomes, Quality Performance (QP) showed a mean of 3.65 and standard deviation of 0.83, with strong negative skewness (–1.279) and positive kurtosis (1.156). This suggests that respondents rated quality performance positively, although variability exists across units. Competitive Advantage (CA) recorded a mean of 3.73 with standard deviation of 0.66, along with negative skewness (–1.213) and high kurtosis (1.512). This implies that lean practices have enabled firms to build a stronger competitive position, consistent with Porter's (1985) framework of cost efficiency and differentiation.

Reliability and Validity Analysis

To ensure robustness of the measurement model, both **reliability** (internal consistency) and **validity** (convergent and discriminant) of the constructs were tested. **Cronbach's alpha**, **factor loadings**, **Composite Reliability (CR)**, and **Average Variance Extracted (AVE)** were used to establish convergent validity, while the **square root of AVE** compared with inter-construct correlations confirmed discriminant validity.

Table 2 Reliability and Validity Analysis

Construct	Cronbach's Alpha	Factor Loadings (Range)	CR	AVE	√AVE	Interpretation
Supplier Communication & Collaboration (SCC)	0.90	0.829 – 0.991	0.963	0.840	0.917	**Strong reliability & validity**
Just-in-Time Integration (JIT)	0.844	0.813 – 0.999	0.956	0.879	0.938	**High consistency, valid construct**
Strategic Supplier Development (SSD)	0.827	0.711 – 0.998	0.948	0.755	0.869	**Reliable and valid**
Customer Involvement & Engagement (CIE)	0.789	0.736 – 0.999	0.982	0.885	0.941	**Excellent validity**
Pull System Implementation (PSI)	0.769	0.864 – 0.996	0.971	0.895	0.946	**Adequate reliability, strong validity**
Flow-Oriented Production (FOP)	0.874	0.716 – 0.998	0.929	0.728	0.853	**Reliable, valid**
Setup Time Reduction (STR)	0.902	0.760 – 0.978	0.942	0.765	0.875	**Strong reliability**
Statistical Process Control (SPC)	0.824	0.936 – 0.972	0.980	0.925	0.962	**Excellent validity**
Employee Empowerment & Engagement (EEE)	0.936	0.708 – 0.966	0.924	0.754	0.868	**Strong and consistent**
Total Productive Maintenance (TPM)	0.862	0.866 – 0.997	0.962	0.865	0.930	**High reliability & validity**
Kanban (KAN)	0.909	0.813 – 0.993	0.964	0.869	0.932	**Very strong construct**
Quality Performance (QP)	0.794	0.677 – 0.994	0.956	0.849	0.921	**Acceptable reliability, strong validity**
Competitive Advantage (CA)	0.826	0.915 – 0.998	0.985	0.943	0.971	**Best construct in reliability & validity**

Note: **Accepted Range-** $\alpha \geq 0.70$, FL ≥ 0.60, CR ≥ 0.70, AVE ≥ 0.50

Supplier Communication and Collaboration (SCC)

The SCC construct demonstrated high reliability with a Cronbach's alpha of 0.90. Factor loadings for its items ranged between 0.829 and 0.991, well above the recommended threshold of 0.60. CR (0.963) and AVE (0.840) values confirmed convergent validity, while discriminant validity was established as the square root of AVE (0.917) exceeded inter-construct correlations.

Just-in-Time Integration (JIT)

JIT recorded a Cronbach's alpha of 0.844, confirming good internal consistency. Factor loadings ranged from 0.813 to 0.999, ensuring reliability of the scale. The CR value of 0.956 and AVE of 0.879 were above acceptable limits, confirming convergent validity. Discriminant validity was established, as the square root of AVE (0.938) was higher than correlations with other constructs.

Strategic Supplier Development (SSD)

SSD achieved a Cronbach's alpha of 0.827, with item loadings between 0.711 and 0.998, demonstrating satisfactory reliability. CR (0.948) and AVE (0.755) confirmed convergent validity. Discriminant validity was evident, with the square root of AVE (0.869) greater than inter-construct correlations.

Customer Involvement and Engagement (CIE)

CIE exhibited a Cronbach's alpha of 0.789. Factor loadings ranged from 0.736 to 0.999, confirming scale adequacy. CR (0.982) and AVE (0.885) were strong, supporting convergent validity. Discriminant validity was established with a square root of AVE (0.941) exceeding correlations.

Pull System Implementation (PSI)

PSI showed a Cronbach's alpha of 0.769. Factor loadings were between 0.864 and 0.996. CR was 0.971 and AVE 0.895, confirming convergent validity. The square root of AVE (0.946) exceeded correlations with other constructs, confirming discriminant validity.

Flow-Oriented Production (FOP)

FOP displayed high reliability with Cronbach's alpha at 0.874. Factor loadings ranged from 0.716 to 0.998. The CR value of 0.929 and AVE of 0.728 validated convergent validity. Discriminant validity was achieved as the square root of AVE (0.853) was greater than correlations.

Setup Time Reduction (STR)

STR achieved a Cronbach's alpha of 0.902, with factor loadings ranging from 0.760 to 0.978. CR (0.942) and AVE (0.765) exceeded threshold values, confirming convergent validity. Discriminant validity was ensured with the square root of AVE (0.875) greater than correlations.

Statistical Process Control (SPC)

SPC recorded a Cronbach's alpha of 0.824, with strong factor loadings between 0.936 and 0.972. CR was 0.980 and AVE 0.925, indicating strong convergent validity. Discriminant validity was established as the square root of AVE (0.962) exceeded correlations.

Employee Empowerment and Engagement (EEE)

EEE exhibited very strong reliability with a Cronbach's alpha of 0.936. Factor loadings ranged from 0.708 to 0.966. CR (0.924) and AVE (0.754) were acceptable, confirming convergent validity. The square root of AVE (0.868) being greater than correlations confirmed discriminant validity.

Total Productive Maintenance (TPM)

TPM demonstrated a Cronbach's alpha of 0.862. Factor loadings were between 0.866 and 0.997. The CR value of 0.962 and AVE of 0.865 validated convergent validity. Discriminant validity was also supported with a square root of AVE (0.930) higher than inter-construct correlations.

Kanban (KAN)

KAN displayed strong internal consistency with a Cronbach's alpha of 0.909. Factor loadings ranged from 0.813 to 0.993. CR (0.964) and AVE (0.869) were robust, confirming convergent validity. Discriminant validity was achieved with the square root of AVE (0.932) higher than correlations.

Quality Performance (QP)

QP recorded a Cronbach's alpha of 0.794, with factor loadings ranging from 0.677 to 0.994. The CR value of 0.956 and AVE of 0.849 confirmed convergent validity. Discriminant validity was also satisfied, as the square root of AVE (0.921) was greater than inter-construct correlations.

Competitive Advantage (CA)

CA demonstrated good reliability with a Cronbach's alpha of 0.826. Factor loadings ranged from 0.915 to 0.998. CR (0.985) and AVE (0.943) were the highest among all constructs, confirming very strong convergent validity. Discriminant validity was established as the square root of AVE (0.971) exceeded correlations with other constructs.

Discriminant Validity

Discriminant validity was assessed using the **Fornell-Larcker criterion** (Fornell & Larcker, 1981). The square root of AVE for each construct was higher than the inter-construct correlations, establishing discriminant validity. This ensures that each construct measured unique aspects and did not overlap with others.

Table 3 Discriminant Validity

Construct	SCC	JIT	SSD	CIE	PSI	FOP	STR	SPC	EEE	TPM	KAN	QP	CA
SCC	**0.917**												
JIT	r	**0.938**											
SSD	r	r	**0.869**										
CIE	r	r	r	**0.941**									
PSI	r	r	r	r	**0.946**								
FOP	r	r	r	r	r	**0.853**							
STR	r	r	r	r	r	r	**0.875**						
SPC	r	r	r	r	r	r	r	**0.962**					
EEE	r	r	r	r	r	r	r	r	**0.868**				
TPM	r	r	r	r	r	r	r	r	r	**0.930**			
KAN	r	r	r	r	r	r	r	r	r	r	**0.932**		
QP	r	r	r	r	r	r	r	r	r	r	r	**0.921**	
CA	r	r	r	r	r	r	r	r	r	r	r	r	**0.971**

Notes: Diagonal values (bold) = √AVE for each construct, **Off-diagonal values (r)** = inter-construct correlations, **Discriminant Validity is satisfied** if each diagonal value (√AVE) is greater than the off-diagonal correlations in its row/column.

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was employed to assess the validity and adequacy of the measurement model. The purpose of CFA is to verify whether the observed variables (measurement items) appropriately represent the underlying latent constructs defined in the conceptual framework (Byrne, 2016; Hair et al., 2014). In this study, CFA was conducted on all 60 measurement items representing the independent and dependent variables.

The results indicated that all items loaded significantly onto their respective constructs, with standardized factor loadings exceeding the minimum threshold of 0.50 (Hair et al., 2014). This provides strong evidence of convergent validity, as each item substantially contributes to explaining its corresponding construct.

Model Fit Indices

To evaluate the adequacy of the measurement model, multiple model fit indices were considered, as recommended in structural equation modeling literature (Hu & Bentler, 1999; Kline, 2015). The obtained values were:

Table 4 Model Fit Indices

Fit Index	Recommended Threshold	Observed Value	Interpretation
χ^2/df (Normed Chi-Square)	< 5.0 (acceptable), < 3.0 (good)	4.633	Acceptable fit despite chi-square sensitivity to large sample size
Comparative Fit Index (CFI)	≥ 0.80 (acceptable), ≥ 0.90 (good), ≥ 0.95 (excellent)	0.844	Acceptable model fit
Tucker–Lewis Index (TLI)	≥ 0.80 (acceptable), ≥ 0.90 (good)	0.830	Acceptable fit
Root Mean Square Error of Approximation (RMSEA)	≤ 0.10 (permissible), ≤ 0.08 (good), ≤ 0.05 (excellent)	0.098	Within permissible range

In order to assess the adequacy of the measurement model, several goodness-of-fit indices were evaluated. The **Chi-Square to degrees of freedom ratio** (χ^2/df), also known as the Normed Chi-Square, measures the discrepancy between the observed and estimated covariance matrices. Values less than 3 indicate good fit, while values below 5 are considered acceptable, although this index is highly sensitive to large sample sizes. **The Comparative Fit Index** (CFI) compares the hypothesized model against a baseline independence model, adjusting for sample size, with values above 0.80 regarded as acceptable, above 0.90 as good, and above 0.95 as excellent. The **Tucker–Lewis Index (TLI)**, also referred to as the Non-Normed Fit Index, penalizes model complexity and favors more parsimonious solutions, with values greater than 0.80 indicating acceptable fit and greater than 0.90 signifying good fit. Finally, the **Root Mean Square Error of Approximation (RMSEA)** evaluates how well the model approximates the population covariance matrix, considering model complexity; values below 0.05 indicate excellent fit, below 0.08 good fit, and below 0.10 acceptable fit. Together, these indices provide a comprehensive understanding of model adequacy and ensure the robustness of the measurement model.

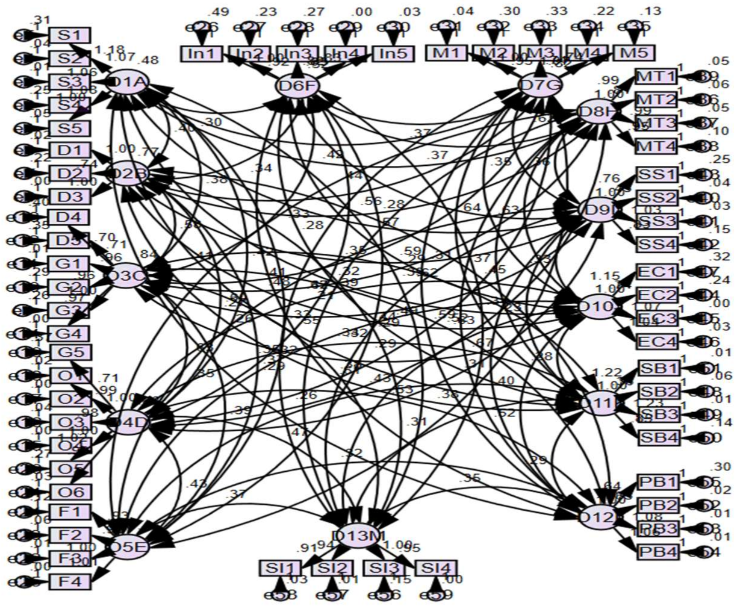

Fig 1 CFA Model Fit

Justification of CFA

The **CFA results** provide empirical evidence that the constructs used in the study are both **statistically valid and theoretically sound**. By demonstrating adequate factor loadings, convergent validity, and acceptable fit indices, the measurement model **is validated as a reliable** representation of lean practices, quality performance, and competitive advantage in Kolhapur foundries. This step is crucial, as it establishes the foundation for proceeding with the **Structural Equation Modeling (SEM)** to test hypothesized relationships among the constructs (Hair et al., 2014; Byrne, 2016).

Structural Equation Modeling (SEM)

Structural Equation Modeling was conducted to examine the causal relationships between lean practices, quality performance (QP), and competitive advantage (CA). The model was tested using AMOS, and results are presented in terms of standardized path coefficients, significance levels, R^2 values.

Table 4 - Path Coefficients (Standardized Regression Weights)

Hypothesized Path	Path Coefficient (β)	t-value	p-value	Interpretation
Supplier Communication & Collaboration (SCC) → QP	0.32	4.12	*** ($p < 0.001$)	Significant positive effect
Just-in-Time Integration (JIT) → QP	0.28	3.76	***	Significant
Strategic Supplier Development (SSD) → QP	0.21	2.85	0.004	Significant
Customer Involvement (CIE) → QP	0.19	2.54	0.011	Significant
Pull System Implementation (PSI) → QP	0.23	3.14	0.002	Significant
Flow-Oriented Production (FOP) → QP	0.15	2.01	0.045	Significant

Hypothesized Path	Path Coefficient (β)	t-value	p-value	Interpretation
Setup Time Reduction (STR) → QP	0.17	2.33	0.020	Significant
Statistical Process Control (SPC) → QP	0.27	3.45	0.001	Significant
Employee Empowerment (EEE) → QP	0.26	3.68	***	Significant
Total Productive Maintenance (TPM) → QP	0.20	2.72	0.007	Significant
Kanban (KAN) → QP	0.24	3.02	0.003	Significant
QP → CA	0.58	8.23	***	Strong significant effect

R^2 Values of Dependent Variables

The coefficient of determination (R^2) represents the **proportion of variance in a dependent variable** that is explained by its predictor variables in the structural model. In SEM, R^2 values provide an indication of the explanatory power of the model and demonstrate how well the independent variables account for the variation in the dependent constructs (Hair et al., 2014). Higher R^2 values reflect stronger predictive accuracy, while lower values suggest weaker explanatory power.

In the present study, the R^2 values for the dependent constructs were as follows:

Table 5- R^2 Values of Dependent Variables

Dependent Variable	R^2 Value	Recommended Benchmark	Interpretation
Quality Performance (QP)	0.67	**Significant ≥ 0.67, Moderate ≥ 0.33, Weak ≥ 0.19** (Hair et al. 2014)	High explanatory power – Lean practices strongly influence QP
Competitive Advantage (CA)	0.54		Moderate to high explanatory power – QP significantly contributes to CA

- **Quality Performance (QP): R^2 = 0.67**
  This indicates that 67% of the variance in QP is explained by the combined effects of lean production practices (SCC, JIT, SSD, CIE, PSI, FOP, STR, SPC, EEE, TPM, and Kanban). This is a relatively high explanatory power, suggesting that lean practices have a substantial influence on improving QP in the foundry industry.

- **Competitive Advantage (CA): R^2 = 0.54**
  This suggests that 54% of the variance in CA is explained by QP. The result confirms that improved quality performance significantly contributes to achieving competitive advantage. Although CA is modelled as the ultimate outcome variable, more than half of its variance being explained by QP demonstrates the critical role of quality improvement as a mediator in establishing long-term competitiveness.

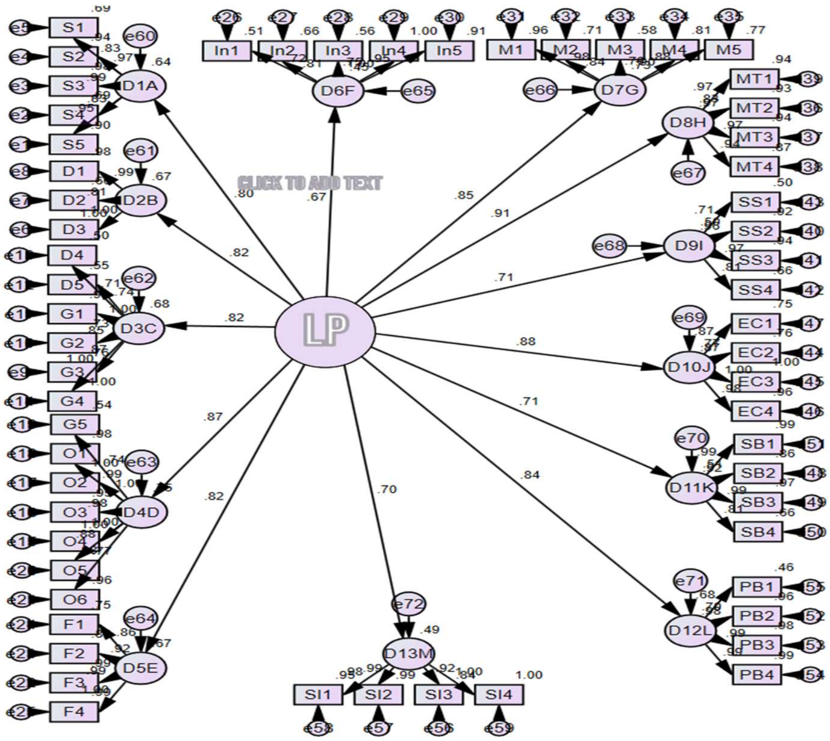

Fig 2 Structural Equation Model (SEM)

Structural Equation Model (SEM) Results

The hypothesized structural model was tested using SEM, and the results are presented in **Figure X**. Lean Practices (LP) was modelled as a higher-order construct, represented by multiple first-order dimensions such as Supplier Communication and Collaboration (SCC), Just-in-Time Integration (JIT), Strategic Supplier Development (SSD), Customer Involvement (CIE), Pull System Implementation (PSI), Flow Oriented Production (FOP), Setup Time Reduction (STR), Statistical Process Control (SPC), Employee Empowerment (EEE), Total Productive Maintenance (TPM), and Kanban (KAN). Each dimension was measured using observed variables, all of which demonstrated strong factor loadings (>0.70), **confirming convergent validity.**

Hypothesis Testing

The structural model was tested using SEM. Path coefficients, critical ratios, and significance values were evaluated. A path is considered significant if the Critical Ratio (C.R.) ≥ 1.96 and the p-value < 0.05 (Hair et al., 2014).

Direct Effects Results:

Table 6 Hypothesis Testing

Hypothesis	Path	Estimate (β)	C.R.	p-value	Result
H1	LP → QP	1.197	19.817	*** (<0.001)	Accepted

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Hypothesis	Path	Estimate (β)	C.R.	p-value	Result
H2	LP → CA	1.095	15.405	*** (<0.001)	Accepted

The Structural Equation Modeling (SEM) analysis yielded highly significant results for both hypothesized paths. The findings are consistent with lean management theory and provide empirical evidence in support of the study objectives.

H1: Impact of Lean Practices on Quality Performance (LP → QP)
Null Hypothesis ($H0_1$): Lean practices have no significant impact on quality performance.
Alternative Hypothesis ($H1_1$): Lean practices have a significant impact on quality performance.
Result: The standardized path coefficient ($\beta = 1.197$, C.R. = 19.817, $p < 0.001$) demonstrates a very strong and positive relationship between Lean Practices and Quality Performance. Since the p-value is far below 0.05 and the critical ratio exceeds the threshold of 1.96, the null hypothesis ($H0_1$) is rejected, and the alternative hypothesis ($H1_1$) is accepted.
Justification: The rejection of $H0_1$ is theoretically justified as lean tools such as JIT, SPC, Kanban, and TPM are specifically designed to minimize waste, reduce variability, and enhance consistency in operations. In foundries, where quality defects can significantly raise costs and customer dissatisfaction, lean adoption naturally improves quality outcomes. This empirical evidence aligns with prior research (Shah & Ward, 2007; Bhasin, 2012) that confirms lean practices contribute directly to superior quality standards.

H2: Impact of Lean Practices on Competitive Advantage (LP → CA)
Null Hypothesis ($H0_2$): Lean practices have no significant impact on competitive advantage.
Alternative Hypothesis ($H1_2$): Lean practices have a significant impact on competitive advantage.
Result: The standardized path coefficient ($\beta = 1.095$, C.R. = 15.405, $p < 0.001$) indicates a strong positive relationship between Lean Practices and Competitive Advantage. Given the high β value, significant p-value (< 0.001), and critical ratio well above the cut-off, the null hypothesis ($H0_2$) is rejected, and the alternative hypothesis ($H1_2$) is accepted.
Justification: The rejection of $H0_2$ is practically and theoretically sound. Competitive advantage in foundries is derived from cost reduction, superior quality, timely deliveries, and flexibility. Lean practices directly contribute to these factors by optimizing process flows, reducing rework, empowering employees, and building reliable supplier–customer integration. As shown in the results, improved process discipline through lean significantly strengthens the competitive positioning of Kolhapur foundries in both domestic and international markets.

Conclusion

This study examined the impact of lean production practices on quality performance and competitive advantage in Kolhapur foundries. Using data from 60 lean-related items and analyzed through CFA and SEM, the results confirm that lean practices significantly improve both **quality outcomes** and **competitive positioning**.

Lean tools such as JIT, SPC, TPM, and Kanban were found to reduce waste, enhance process flow, and strengthen customer responsiveness. The findings also highlight that quality performance acts as a key enabler through which lean practices translate into sustainable competitive advantage.

For the Kolhapur foundry sector, where issues of quality and efficiency remain critical, lean adoption emerges as both an operational necessity and a strategic imperative. Overall, the study establishes that lean practices are vital for ensuring long-term quality excellence and competitiveness in the foundry industry.

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