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A Diagnostic Approach Using Statistical Quality Control Tools for Root Cause Identification of Ceramic Glaze Defects

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Abstract

This study applies statistical quality control (SQC) tools to address glaze defects and strengthen process stability in the production of artisan ceramic mugs at Artisan Mugs Inc., with particular focus on the "Midnight Blue" product line. A Pareto analysis of 300 defective units identified glaze imperfections as the most frequent issue (54%), followed by handle cracks (21.7%). Root cause analysis using a fishbone diagram revealed multiple contributing factors spanning materials (e.g., elevated glaze viscosity), manpower (e.g., insufficient operator training), methods, machinery, measurement practices, and environmental conditions. To evaluate process stability, $\bar{X}$ and R control charts were constructed from 25 production batches. Both charts demonstrated statistical control with no evidence of assignable causes, further validated by runs tests ($p > 0.05$). Process capability analysis indicated adequate but improvable performance, with indices of $C_p = 1.23$ and $C_{pk} = 1.14$ for means, and $C_p = 1.24$ and $C_{pk} = 0.76$ for ranges. These findings confirm that the process is stable, yet improvements are needed in centering and reducing variability.

1. INTRODUCTION

The global ceramic industry has become a fundamental pillar of contemporary manufacturing, supplying products that span from traditional tableware and construction materials to highly specialized components used in aerospace and healthcare applications. Within this broad spectrum, the performance and visual appeal of the final product remain central to both consumer acceptance and commercial viability [1]. Among the many production stages, glazing is especially critical, as it involves the fusion of a glassy coating onto the ceramic body during firing. This layer not only enhances durability and impermeability but also provides the defining decorative finish. However, flaws such as pinholes, crazing, crawling, or inconsistent glaze thickness can compromise both function and appearance, leading to costly rework, product rejection, and even reputational damage for manufacturers.

Managing the glazing process is inherently complex due to the number of variables that influence outcomes. The chemical formulation and flow properties of the glaze, the chosen method of application, surrounding atmospheric conditions, and the accuracy of the firing temperature curve all interact in ways that determine final quality [5]. In many production environments, quality control practices still rely heavily on operator experience and end-of-line inspection. While these methods can identify visible defects, they remain largely reactive, as they uncover issues only after significant resources have already been consumed. This shortcoming, frequently observed in dinnerware production, underscores the inefficiency of such approaches and the pressing need for systematic solutions that can proactively address process variability [8]. In this context, Statistical Quality Control (SQC) offers a structured and data-driven methodology for monitoring and improving industrial processes. Widely adopted across manufacturing sectors, SQC provides tools that help distinguish between normal process variation and anomalies that signal underlying problems, thereby enabling evidence-based decision-making [7]. Techniques such as Pareto analysis, cause-and-effect diagrams, and control charts transform raw data into meaningful insights, supporting targeted interventions and cultivating a culture of continuous improvement. With the integration of Industry 4.0 technologies, the relevance of SQC has expanded further, as it now underpins real-time monitoring and advanced analytics aimed at strengthening operational efficiency [9].

Evidence of the effectiveness of SQC extends across diverse industrial landscapes, including Nigeria, where its application has delivered tangible results. For example, studies have demonstrated how SQC improved quality and compliance within sachet water production and distribution [4], while also reducing variability and enhancing reliability in soap manufacturing [3]. These examples highlight the adaptability of SQC and reinforce its potential for addressing quality issues in contexts where consistent standards are vital. Despite these advances, research applying SQC specifically to ceramic glaze production remains limited. Although structured improvement frameworks such as DMAIC have shown success in related areas of ceramic manufacturing [2], studies that comprehensively deploy SQC to diagnose and resolve glaze defects remain scarce. While earlier work has addressed quality challenges in ceramic tiles [10], few efforts have integrated multiple SQC tools into a cohesive diagnostic model designed for high-volume tableware production. This lack of a consolidated framework represents a critical knowledge gap, as glaze defects often result from complex interdependencies within the production process that require more than isolated analysis to resolve.

The present study seeks to close this gap by proposing a systematic diagnostic framework grounded in SQC. Focusing on a ceramic mug production line, the research aims to identify prevalent defects through Pareto analysis, investigate their underlying causes using structured problem-solving tools such as cause-and-effect diagrams and Failure Mode and Effects Analysis (FMEA), and establish ongoing process stability through the application of control charts. The ultimate objective is to move quality assurance from a reactive model to a proactive and preventive strategy, thereby reducing defect rates, enhancing process consistency, and improving operational performance. By addressing glaze defects with a structured, data-oriented approach, this study not only advances academic understanding of quality management in ceramics but also provides industry practitioners with a replicable model for risk evaluation and process improvement. The anticipated outcomes will demonstrate the value of SQC as a diagnostic tool in complex manufacturing environments and contribute practical insights to the wider field of quality engineering [6].

2. METHOD

This study focused on all Midnight Blue ceramic mugs produced by Artisan Mugs Inc. in August 2024, using purposive sampling to ensure data captured was directly relevant to quality assessment. Defect analysis drew on records from 300 flawed mugs, classified according to the type of imperfection, while glaze consistency was evaluated through 125 measurements taken from five mugs in each of 25 selected production batches. The following analytical procedures were employed:

2.1 Pareto Chart

The Pareto chart will be used as the initial analytical tool because it will allow defects to be prioritized according to their frequency, highlighting the “vital few” issues that account for the majority of losses. This approach will be guided by the Pareto principle (80/20 rule), which states that a small number of causes usually contribute to most of the problems.

The construction procedure will involve the following steps:

1. Tabulation of Defects: All defective mugs recorded in the month of August (n = 300) will be classified into six distinct categories: glaze imperfections, handle cracks, color mismatch, lip chips, base wobble, and logo smudge. The absolute frequency of each defect type will be documented.
2. Ranking and Ordering: The defects will be arranged in descending order of frequency. For example, glaze imperfections, which will account for the largest share, will be ranked first, while logo smudges, which will be least frequent, will be ranked last.
3. Cumulative Frequency Calculation: The defect counts will be added successively to obtain cumulative totals. This will help determine the contribution of each successive defect category to the overall number of defects.
4. Percentage Conversion: Each defect type will be expressed as a percentage of the total number of defects ($f \div 300 \times 100$). Cumulative percentages will also be computed to illustrate the proportion of total defects accounted for by the leading categories.
5. Chart Plotting: A dual-axis Pareto chart will then be constructed.
   a. The x-axis will represent the defect categories.
   b. The left y-axis will display absolute frequencies, represented by vertical bars.
   c. The right y-axis will display cumulative percentages, represented by a line graph.
6. Interpretation: The completed chart will be analyzed to identify the “vital few” defect categories.

2.2 Fishbone Diagram

To investigate the root causes of glaze imperfections highlighted by the Pareto analysis, a fishbone (Ishikawa) diagram will be applied as a structured tool for diagnosis. The steps are below listed:

1. Problem Statement Definition: The central issues, high frequency of glaze defects in Midnight Blue mugs will be placed at the “fish head,” ensuring all causes remain focused on this problem.
2. Category Identification: Contributing factors will be organized under the 4M framework:
   i. Machine: equipment used for spraying, drying, and firing.
   ii. Method: process variations and deviations from standard procedures.
   iii. Material: glaze, clay, and compressed air quality.
   iv. Manpower: operator skill, training, and fatigue.
3. Brainstorming of Contributing Factors: Input from quality officers, kiln operators, and supervisors will identify specific issues. Examples include clogged spray nozzles, kiln temperature shifts, overcrowding in firing, excessive glaze viscosity, inconsistent clay supply, and worker fatigue from extended shifts.
4. Diagram Drafting: These causes will be arranged into branches of the fishbone diagram, visually mapping direct and indirect pathways that may explain glaze imperfections.

2.3 Control Chart

Assessing the stability of glaze thickness and confirm whether the process remains under statistical control, both $\overline{X}$ and R control charts were developed. These tools distinguished between natural process variation and unusual shifts that may point to special causes.

1. Data Grouping: Glaze thickness values collected in August will be organized into 25 subgroups, each representing a production batch. Five mugs per batch (n = 5) will provide the basis for analysis.
2. Subgroup Calculations: For each batch, two statistics will be calculated: the mean thickness ($\overline{X}$), representing the average for that subgroup, and the range (R), reflecting the difference between the highest and lowest measurement.
3. Overall Averages: After all subgroups are analyzed, the grand mean ($\overline{\overline{X}}$), the average of subgroup means and the average range ($\overline{R}$), the mean of subgroup ranges will be computed to serve as central reference values.
4. Establishment of Control Limits: Control limits will be determined using standard statistical constants (A_2, D_3, and D_4) applicable to subgroup size n = 5. The formulas applied will be:
   a. For the **$\overline{X}$ chart**:

$$\mathrm{UCL} = \overline{\overline{X}} + A_2\overline{R} \tag{1}$$
$$\mathrm{CL} = \overline{\overline{X}} \tag{2}$$
$$\mathrm{LCL} = \overline{\overline{X}} - A_2\overline{R} \tag{3}$$

   b. For the **R chart**:

$$\mathrm{UCL} = D_4\overline{R} \tag{4}$$
$$\mathrm{CL} = \overline{R} \tag{5}$$
$$\mathrm{LCL} = D_3\overline{R} \tag{6}$$

   where 〖A〗_2, D_3, and D_4 are tabulated constants in statistical quality control literature.
5. Chart Construction
   a. The $\overline{X}$ chart will display subgroup means plotted against batch numbers on the x-axis, with the grand mean and calculated control limits serving as reference lines.
   b. The R chart will present subgroup ranges against batch numbers, evaluated against the average range ($\overline{R}$) and its corresponding limits.
6. Interpretation of Results
   Once constructed, the charts will be reviewed for signs of process instability, including:
   a. Data points lying beyond the control limits.
   b. Sustained upward or downward shifts in plotted values.
   c. Repeated cyclical patterns or clustering of points near the control boundaries.

Once the control limits are defined, any point that lies outside them signals the need for immediate investigation to uncover potential causes. A process can be regarded as stable only when all observations remain within the limits and display a random, pattern-free distribution, reflecting the presence of common cause variation alone.

2.4 Process Capability Indices

Process capability indices provide a simple way to judge whether a stable process can consistently meet customer requirements. Unlike control limits, which come from process data, specification limits are set externally, based on business and customer needs. These indices compare natural process variation with the tolerance range, turning complex behavior into clear numerical measures.

Process Capability (C_p):

C_p shows the potential of a process by comparing the specification width to six times the standard deviation (6σ):

$$C_P = \frac{(USL - LSL)}{6\sigma} \tag{7}$$

If $C_p < 1$, the process variation is too wide to meet specifications. If $C_p > 1$, the process has enough potential, though this measure does not reflect whether it is centered.

Process Capability with Centering (C_{pk}):

C_{pk} accounts for how close the process mean is to the specification limits:

$$\begin{aligned} C_{Pk} &= C_P(1-k) \\ &= Minimum(C_{Pu}, C_{Pl}) \end{aligned} \tag{8}$$

If $C_{pk} \geq 1$, the process is capable of meeting specifications most of the time. If $C_{pk} < 1$, it suggests too much variation or that the process is off-center, increasing the risk of defects.

3. RESULTS AND DISCUSSION

3.1 Identification of the Predominant Defects in the Mug Production Line

A record of production flaws was compiled for the mug line to understand the main sources of quality problems. Table 1 outlines the different defect types and their frequency, while the accompanying Pareto chart visually ranks them, setting the stage for identifying which defects occur most often and warrant closer investigation.

Table 1. Detailed Defect Log

Defect Type	Description	Frequency (f)	Cumulative (f)	Percentage (%)	Cumulative %
Glaze Imperfection	Bumps, pits, or uneven coating in the final glaze.	**162**	162	54.0%	54.0%
Handle Crack	Micro-cracks near where the handle joins the mug body.	**65**	227	21.7%	75.7%
Colour Mismatch	Final colour is outside the acceptable "Midnight Blue" range.	**31**	258	10.3%	86.0%
Lip Chip	Small chips or rough spots on the rim of the mug.	**18**	276	6.0%	92.0%
Base Wobble	The mug does not sit flat on a level surface.	**15**	291	5.0%	97.0%
Logo Smudge	The company logo printed on the base is smeared.	**9**	300	3.0%	100.0%

Total	**300**	**100.0%**

Table 1 outlines the range of defects identified in the mug production line, with glaze imperfections emerging as the most common issue at 54 percent, followed by handle cracks at 21.7 percent. Combined, these two categories represent over three-quarters of all recorded defects, whereas issues like colour mismatch, rim chips, base instability, and logo smudges appeared only occasionally.

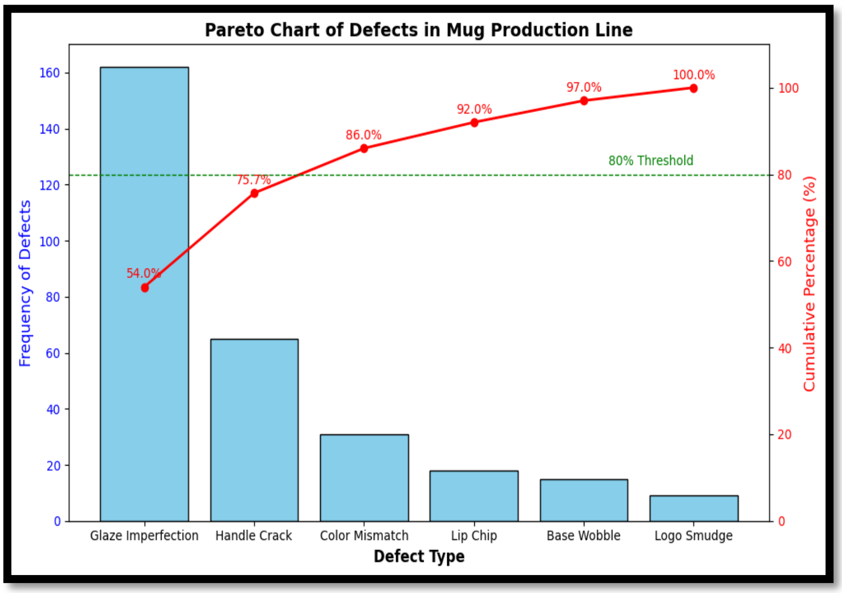

Figure 1. Pareto Chart of Defects in Mug Production Line

The Pareto analysis shows that defects were unevenly distributed, with glaze flaws as the dominant issue, representing nearly 60% of all cases. Handle cracks followed at 21.7%, and together they accounted for over three-quarters of rejections. The cumulative curve passed 80% after the second category, confirming their impact. Since glaze defects had the greatest influence, corrective action in this area is expected to yield the largest quality improvements. Minor issues like color mismatch, lip chips, base wobble, and logo smudge were far less significant.

3.2 Analysis of the Root Causes of Glaze Imperfections

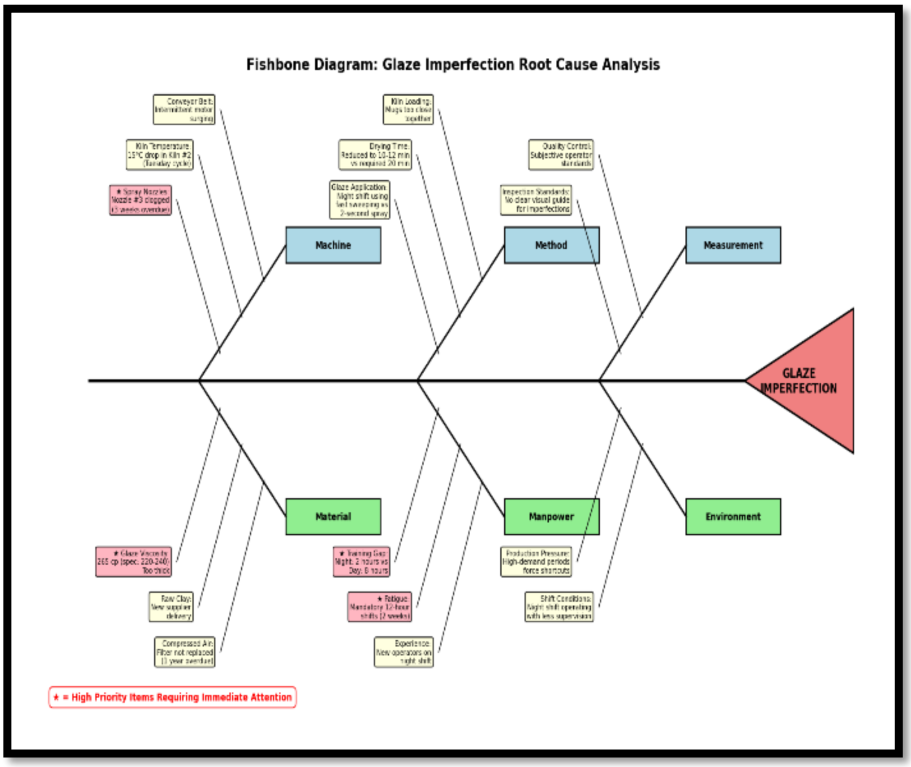

Figure 2. Fishbone Diagram: Glaze Imperfection Root Cause Analysis

Figure 2 shows a fishbone diagram created to trace the main causes of glaze defects in ceramic mug production. The possible factors were grouped into six areas: Machine, Method, Material, Manpower, Measurement, and Environment, giving a structured view of the process. Machine issues included unstable kiln temperatures and spray nozzles that were not cleaned on time, especially Nozzle 3. Material concerns were also present since glaze viscosity was measured at 265 centipoise, higher than the recommended 220 to 240 range and the compressed air filter had not been serviced for more than a year, increasing the chance of contamination.

Human and procedural factors were significant as well. Workers on the night shift had only two hours of training compared with eight for the day shift and were required to work twelve hour shifts, leading to fatigue. These conditions contributed to problems such as uneven glaze coating and shortened drying times during periods of high demand. Measurement practices also showed gaps because inspection standards were not consistent, which caused variations in how glaze defects were judged.

3.3 Monitoring Glaze Thickness Using Control Charts to Ensure Process Stability and Promote Long-Term Quality Improvement

Table 2. Glaze Thickness

Batch	Mug 1	Mug 2	Mug 3	Mug 4	Mug 5	Average ($\bar{X}$)	Range (R)
1	81	79	80	82	80	80.4	3
2	78	80	81	83	79	80.2	5
3	80	79	81	83	82	81.0	3
4	79	82	81	80	81	80.6	3
5	80	79	81	80	82	80.4	3
6	82	78	80	81	76	79.2	6
7	81	80	83	79	80	80.6	4
8	79	80	80	81	82	80.4	3
9	82	81	79	80	80	80.4	3
10	78	79	81	80	81	79.8	3
11	80	81	82	80	79	80.4	3
12	83	81	80	79	81	80.8	4
13	79	79	80	81	80	79.8	2

14	81	82	78	80	79	80.0	4
15	80	81	80	82	81	80.8	2
16	78	79	81	81	80	79.8	3
17	82	83	80	81	81	81.4	3
18	80	80	79	80	81	80.0	2
19	81	79	82	80	80	80.4	3
20	79	81	81	82	78	80.2	4
21	80	80	81	81	82	80.8	2
22	81	78	79	80	80	79.6	3
23	82	80	81	80	79	80.4	3
24	80	81	79	81	81	80.4	2
25	79	81	80	82	81	80.6	3
Totals						2023.2	85

Control charts for monitoring the Glaze thickness were constructed using $\bar{X}$ and R charts. Based on the data from Tables 2, these charts were generated in Google Colab and are presented in Figures 3 and 4 respectively.

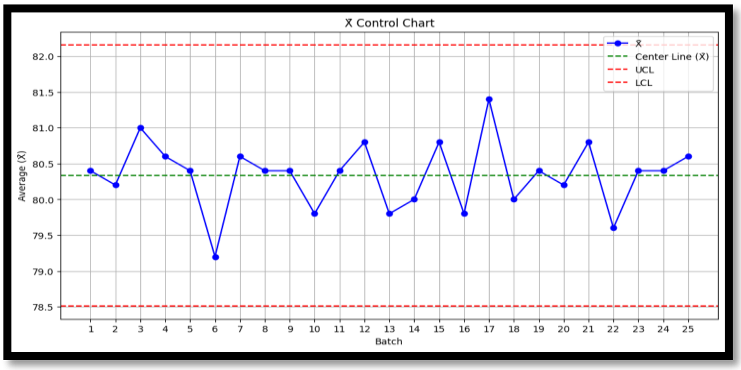

Figure 3. $\bar{X}$ *Chart for* Glaze Thickness

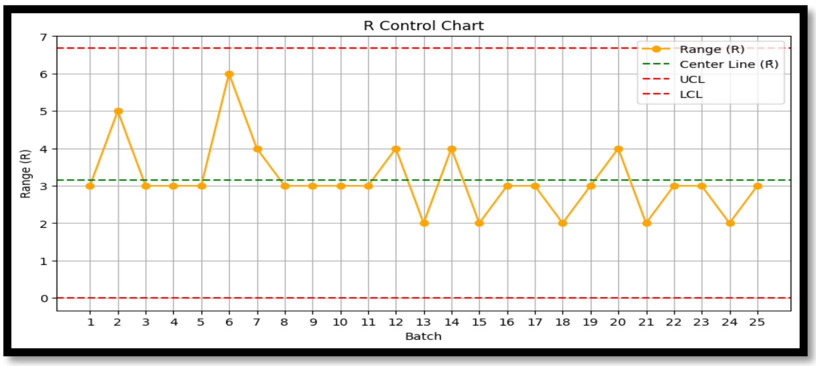

Figure 4. R *Chart for* Glaze Thickness

Table 3. Runs Test For: $\bar{X}$ *and R Chart*

Chart	Statistic	Z-Value	P-Value	Conclusion
$\bar{X}$	Runs above/below centerline	1.207	0.227	Random (fail to reject H_0)
R	Runs above/below centerline	0.279	0.781	Random (fail to reject H_0)

Review of the $\bar{X}$ and R charts, supported by the outcomes of the runs test, demonstrates that the process is operating under statistical control. In the $\bar{X}$ chart, every subgroup mean remains within the prescribed control boundaries, with values centered near 80.3 and ranging only from about 79.2 to 81.4, confirming a stable process average. The R chart also indicates consistency, as the variation within subgroups clusters around 3.2 and shows no evidence of points beyond the limits. Statistical testing provides further support: the $\bar{X}$ chart yielded $Z = 1.207$ with $p = 0.227$, while the

R chart produced Z = 0.279 with p = 0.781, both results signifying randomness in the pattern of plotted points. Since all variation arises from common causes rather than special ones, the process can be regarded as predictable, stable, and under effective statistical control.

3.4 Process Capability Analysis for Glaze Thickness

Since both the $\bar{X}$ and R charts confirm that the process is under statistical control, as shown by stable chart behavior and the absence of assignable cause variation, the appropriate next step in the quality evaluation is to conduct a process capability analysis. This assessment provides a quantitative measure of how effectively the process can consistently operate within the required tolerance limits over time, thereby reflecting its inherent ability to meet product specifications.

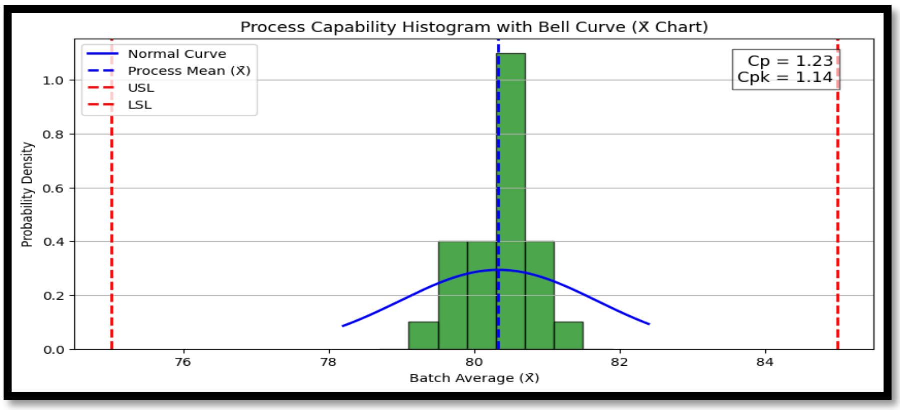

Figure 5. Process capability Analysis for Glaze Thickness $for\ \bar{X}$

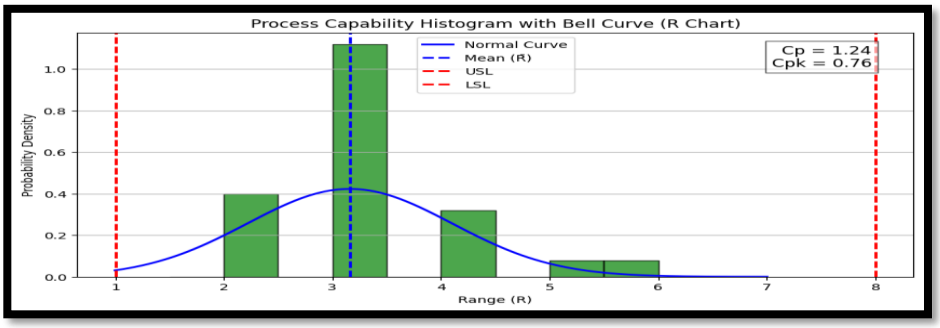

Figure 6. Process capability Analysis for Glaze Thickness $for\ \boldsymbol{R}$

Examination of the mean chart indicates that the average glaze thickness is close to 80.3 units, with subgroup means ranging between 79.2 and 81.4. All of these values remain well inside the specification limits of 75 and 85. The histogram, along with the fitted normal curve, shows a tight clustering around the process mean and relatively limited dispersion, pointing to a stable and predictable pattern. Process capability measures support this observation: a $C_p$of 1.23 suggests the spread is reasonably compatible with the tolerance range, while a C_{pk} of 1.14, being slightly lower, reflects that the mean is not exactly centered between the two boundaries. Although the shift is not extreme, further adjustment of centering could make the process more robust.

The range chart provides insight into within-group variability. The average range is 3.2 units, with values extending from 2 to 6, which falls inside the acceptable window of 1 to 8. The distribution of ranges is concentrated near the mean but displays a longer tail toward higher values, indicating that while many subgroups show moderate variation, a few demonstrate elevated dispersion. Capability results confirm this pattern: C_p is 1.24, consistent with the allowable tolerance, yet C_{pk} is only 0.76, showing that the distribution lacks balance and centering. This gap signals that excessive subgroup variation occasionally disrupts uniformity.

Taken together, the mean and range chart capability analysis demonstrates that glaze thickness is generally stable and capable of meeting requirements. However, the lower C_{pk} values highlight two key areas for refinement: bringing the process mean closer to the target and reducing variation within subgroups. Strengthening these aspects would improve both accuracy and consistency, thereby ensuring stronger adherence to glaze thickness specifications.

4. CONCLUSION

The use of statistical quality control in managing glaze thickness for handcrafted mugs shows that these methods can bring substantial value even in small production settings. Pareto analysis pointed to glaze defects as the primary issue, while the fishbone diagram revealed multiple underlying causes linked to materials, methods, workforce practices, equipment, and environmental conditions. Control charts verified that the process is under statistical control, with only common cause variation observed, ensuring consistent performance. Capability analysis confirmed general compliance with specifications but also highlighted opportunities to better align the process mean with the target and to reduce subgroup variability.

This study demonstrates that structured quality tools can reduce waste, improve product reliability, and strengthen the competitive position of artisan producers without diminishing the creative character of their work. Future research could explore the impact of targeted training programs for operators, advanced monitoring of glaze viscosity, or the use of digital process tracking to further enhance control. Comparative studies between artisan and industrial contexts may also provide insight into how small-scale operations can selectively adopt industrial practices for maximum benefit. In this way, the findings open avenues for refining craftsmanship with data-driven improvements while preserving its unique artistic value.

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