Journal of Innovations in Business and Industry

Vol. 04, No. 04 (2026) 437-446, DOI: 10.61552/JIBI.2026.04.007 - http://jibi.aspur.rs

A SEQUENTIAL ANALYTICAL FRAMEWORK FOR DEFECT DIAGNOSIS IN DIRECT INJECTION PROCESS MANUFACTURING: APPLICATION IN THE FOOTWEAR INDUSTRY OF BANGLADESH

Syed Tahmid Jamil
Md. Sarfuddin Anowar Khan [1]
Md Tasfiq Alam
Md Jahid Hasan
Mohammed Jubaed

Received 11.06.2026.
Revised 29.07.2026.
Accepted 31.08.2026.

Keywords:

Trend analysis; Chi-square; Cramér's V; Machine attribution; Pareto analysis.

Original research

A B S T R A C T

In the growing footwear industry of Bangladesh, defect management in Direct Injection Process (DIP) production is still a challenge, especially in manufacturing production areas where data availability is limited and defect logs are the only means to get quality information. This study suggests a sequential analytical framework for systematic diagnosis of defect sources based on log-only production data, which includes Pareto analysis, machine-wise defect attribution, chi-square test of independence to determine the significant influences, Cramér's V effect size estimation to measure the influence size, and linear regression-based trend analysis. Applied across five injection machines over a 47-week observation period, with 39 weeks containing usable defect records. The four priority defect types determined were Short Injection, Spew, Cavity, and Upper Cut, which covered 78.3% of all recorded failures. The highest contribution of defects was from machine MC_3 with a statistically significant but negligible machine-defect association (Cramér's V = 0.077), suggesting that the machine identity is not a significant contributor to the defect variation, and the variation is due to the process-level variables. The slope of defect volumes as a function of time was determined and was found to be positive but not significant; this indicates that defect volumes are being driven up and should continue to be monitored. As defect counts were analyzed without production volume denominators, the framework is scoped to distribution diagnosis rather than rate estimation. The proposed framework offers a reproducible, data-driven diagnostic tool for quality improvement in manufacturing environments where comprehensive process data are unavailable.

1. INTRODUCTION

Bangladesh's footwear industry is steadily expanding as a major segment of the country's manufacturing sector. As the industry grows, managing defects in production processes becomes increasingly critical to maintaining quality standards and operational efficiency. Despite its growing export potential, the footwear industry in

[1] Corresponding author: Md. Sarfuddin Anowar Khan
Email: md.sarfuddin.siam@gmail.com

Bangladesh faces significant challenges related to process inefficiencies and suboptimal resource utilization (Ahmed et al., 2023). Analyzing rejection patterns in the production process is essential for enhancing quality control and overall efficiency in footwear production (Sufian et al., 2023). According to (Jagadeesan & Umasankar, 2022) defects in direct injection manufacturing are strongly influenced by variations in process parameters, material behavior, and mould design. Also, integrating historical and real-time production data enables early defect prediction and classification in manufacturing processes (Burmeister et al., 2023). Using Structured analytical frameworks combined with traditional quality approaches, process variables that cause defects can be better identified (Gonzalez Santacruz et al., 2025). However, large-scale production environments generate extensive data, which complicates the identification of defect sources. Machine attribution analysis provides an accurate mapping of defects to individual machines and their operating conditions (Lyu et al., 2020). In addition, statistical analysis shows that variations in process parameters are statistically significantly correlated with various types of defects. Through Statistical measures such as chi-square and Cramér's V, the relationships between process variables and defect types can be both identified and quantified (Guachamín-Chicaiza et al., 2025).

While these advances are made, many manufacturing environments face a lack of data availability: Data from the production volume or about the process is missing or only sporadically kept, and there is often no monitoring data from the sensors. Therefore, defect logs are often used as the sole source of quality information. But there is little existing research available to guide systematic defect diagnosis based on log-only data. This creates a practical gap between advanced quality methodologies and the realities of data-constrained manufacturing environments. In order to address this, a sequential analytical framework for defect diagnosis in a manufacturing process is proposed for a log-only manufacturing environment. The framework uses Pareto analysis to prioritize defects, machine-wise attribution to detect defect concentration patterns, Chi-sqaure analysis and Cramér's V analysis to analyze defect patterns across the machines and trend analysis to investigate defect behavior over time. The framework is illustrated in a direct injection footwear manufacturing environment in Bangladesh, and offers a practical solution to improve product quality, where only defect-log records exist.

Specifically, this study addresses the following research questions:

RQ1: Using only log-only production data, without production-volume denominators, which defect categories are the primary contributors to DIP failures?

RQ2: Within this log-only constraint, is defect-type occurrence significantly associated with machine identity, and is the effect large enough to justify machine-targeted intervention?

RQ3: Within this log-only constraint, do defect volumes show a statistically significant trend over time, and can process change be distinguished from shifts in production volume without volume data?

2. LITERATURE REVIEW

Structured methodologies for quality improvement have been extensively used in manufacturing to minimize defect rates and stabilize manufacturing processes in footwear manufacturing. The DMAIC methodology of six sigma and Seven QC tools is found to be effective in different productions situation (Klochkov et al., 2019; Hadi Hashim & Oudah Sabeeh, 2021). For the specific case of footwear manufacturing, (Fatimah & Wahyuni, 2023) used the DMAIC methodology to improve leather shoe production and (Silmi et al., 2024)) found that there were skin defects that overlapped in the leather shoes, which reached 13%, the process sigma level was 3.71, and preventive maintenance, enforcement of SOP, and training for the workforce were recommended. It is observed that controlling the mold temperature and optimizing the mold parameters greatly affect the defect formation during the DIM-based manufacturing (Correia et al., 2020).

DMAIC has been used to improve defect management, with the help of risk prioritization tools. Critical failure points in cutting and molding machines have been identified using Process Failure Mode and Effects Analysis (PFMEA). The results of (Dimyati et al., 2020) demonstrated that the use of SPC combined with FMEA using control chart, Pareto diagram, and Risk Priority Number (RPN) makes the process of monitoring the variability better, as well as the prioritization of actions. To reduce the process variation and to keep the process means near to the target range specifications, (Ravichandran, 2016) suggested Six Sigma based X-bar control chart. (Díaz-Ruiz & Trujillo-Gallego, 2022) extended this statistical approach by integrating DMAIC with multivariate control techniques to reduce coating defects in tin-plating operations. More recently, (Ávila et al., 2026) proposed the MAPIC methodology as a proactive improvement framework incorporating pre-implementation validation and continuous improvement mechanisms.

Statistical association testing offers a complementary analytical pathway for categorical quality data. (Mayr & Himmelbauer, 2020) demonstrated that the chi-square test statistic is effective in detecting anomalies in production quality time series, outperforming standard outlier methods for categorical failure-rate data. While chi-square identifies whether an association between categorical variables is statistically significant, it does not quantify the strength of that association. Therefore, an effect-size measure such as Cramér's V is required (Ben-Shachar et al., 2023). In another study, (Anacleto Filho et al., 2024) chi-square tests and Cramér's V to examine associations between job type and musculoskeletal complaints in a needle manufacturing industry. They reported a moderate association between job type and ankle/foot complaints (Cramér's V = 0.261).

Although effective, DMAIC, SPC-FMEA, Lean Six Sigma, multivariate control, and MAPIC are typically applied in data-rich manufacturing environments. Limited studies provide an integrated framework for defect diagnosis conducted exclusively from defect log records. This represents a significant gap between established quality methods and the operational reality of data-constrained manufacturing environments, especially in developing economies where defect logs are often only consistent source of quality information available.

3. METHODOLOGY

This research employs a quantitative analytical approach, which is used to analyze the quality failure of Direct Injection Process in Footwear Production. Data were gathered from a single DIP footwear factory in Bangladesh, where production log books are kept. The dataset includes 13,599 defect pair records from 5 injection machines (MC_1 to MC_5) in a single production floor, from week 1 to week 47 in 2025. The dataset is missing 8 weeks of production recordings and 8 weeks of source log recordings (weeks 9-15 and week 24), leaving 39 weeks of usable recordings. The date, machine ID, defect type and number of defect pairs are recorded for each log entry. This did not permit the use of production-volume data, thus imposing a "log-only constraint" that frames the analytical structure described in the following subsections.

3.1 Pareto Analysis

Pareto analysis was used to analyze the DIP failure in order to find the relative importance of each type of failure. The goal was to determine the most significant category of defects to overall production losses. Pareto analysis is based on the Pareto principle, which is commonly used to prioritize a small number of causes that account for a large proportion of an observed outcome. Most of the nonconformances in the field of quality engineering are likely to occur due to a few defects. This allows the practitioners to focus on the major categories of defects and not on all the categories (Lestyánszka Škůrková et al., 2023). Pareto analysis was chosen as the prioritisation method, rather than other methods like failure mode ranking or cost-weighted scoring, as it is only based on count data. The benefits of a log-only environment. It is a technique that does not need any volume normalization, and yields an image which is easy to understand and understand at the process level. Ranking of the types of defects was done by decreasing frequencies and the cumulative percentages were determined. Then, the intersection of the distribution at its "natural frequency" was set as a threshold between the two peaks of the distribution. All defects were considered priority defects and were analysed on a machine by machine basis and statistically.

3.2 Machine-Wise Defect Attribution

There are two complementary analyses that were done directly from the raw data in the DIP observation log to examine the distribution of defect generation across individual injection machines. First, all-defect totals per machine were added together to calculate the overall defect burden each machine is carrying. Each machine was analysed as a categorical machine (MC_1 to MC_5) and a percentage contribution to the total number of defects pairs (DIP) for each machine was calculated on a consistent basis, based on the grand total of all DIP defect pairs for which a machine identifier had been recorded. Second, the Pareto analysis four priority defects were broken down by machine. This resulted in a Machine × Defect Type matrix which allowed the assessment of whether there was disproportionate association of particular defect categories with particular machines. It is similar to what has been done in previous defect diagnosis, which is to isolate the unit-level contributors to the overall failure load and then proceed to the inferential testing (Lyu et al., 2020; Dimyati et al., 2020).

3.3 Chi-Square Test of Independence

A chi-square test of independence was implemented to determine if there is a statistically significant relationship between type of defect and machine unit. Also known as a non-parametric test, it is used when the data is categorical, and no assumptions are made regarding distribution other than that there are adequate cell frequencies (Field, 2018). These were the following hypotheses to be specified:

H_0: The type of defect and the identity of the machine are independent, that is, the probability of observing type of defect i does not depend on the identity of the machine m that made it.

H_1: The distribution of defects is not equal on the machines; i.e., there are systematic relationships between the machines and failure modes.

The expected cell frequencies in the test were all >5.0, which ensured the validity of the test (Field, 2018). The significance of the statistical results was calculated at the level of the conventional $\alpha = 0.05$. To some extent, manufacturing quality research is a phenomenon of establishing an association between process variables and defect categories through the use of a chi-square testing, as mentioned by (Guachamín-Chicaiza et al., 2025; Lyu et al., 2020). Then standardised Pearson residuals were calculated in each cell of the contingency tables and the ones that do not fall within the limits of -2.0 and +2.0 were marked as statistically significant deviations from independence. A heatmap was created to visualize these residuals and determine machine-defect combinations to be investigated in operation.

It should be noted that with N exceeding 10,000 observations, statistical significance at $\alpha = 0.05$ is a near-certain outcome for any non-zero association. At this sample size, even trivially small departures from independence will produce a significant chi-square statistic. Consequently, the p-value alone provides limited inferential value in this context, and the primary interpretive weight was placed on the effect size measure described in section 3.4.

3.4 Cramér's V - Effect Size Estimation

Cramér's V was calculated as a supplementary effect size measure following the chi-square test. The chi-square statistic has known limitations in conveying the practical magnitude of an association, as its value is directly influenced by sample size (Cohen, 1988). Reporting effect size alongside statistical significance addresses this limitation and reflects established practice in quantitative quality research (Díaz-Ruiz & Trujillo-Gallego, 2022; Hadi Hashim & Oudah Sabeeh, 2021). The interpretive thresholds for **5 × 4** contingency table applied in this study follow the conventions established by (Cohen, 1988):

Table 1. Cramér's V Thresholds

Effect	Cramér's V
Small	0.06
Medium	0.17
Large	0.29

Together, the chi-square test and Cramér's V provided a two-level interpretation: the former confirmed whether the association is statistically significant, and the latter quantified its practical strength. This dual reporting approach would mitigate the potential for misunderstanding the relationship between the machine and defects if no supporting effect size findings were provided.

3.5 Trend Analysis

As a complementary temporal diagnostic, to those performed at the machine level described in section 3.3 and 3.4, weekly trend analysis was carried out independently. This step is not a continuation of the cross-sectional analysis but rather a separate question: Do the overall defect process have any stability, improvement or deterioration during the observation window? Linear regression was chosen as the method to use because it was easily interpreted and explained, and it provided an interpretable estimate of the rate of change in the volume of defects in each week, given the time-ordered data of defect counts. More formal time-series models, such as ARIMA, generally require appropriately specified time intervals and treatment of missing observations and non-stationarity. Because the observation series contained eight missing weeks and the objective was descriptive trend estimation rather than forecasting, ordinary least-squares regression was used as a first-order temporal diagnostic (Hyndman & Athanasopoulos, 2021). There were a number of weeks missing, so the fitted regression model was not used as a forecasting model, but rather as a first-order approximation to the data. Although imperfect, OLS regression on a gapped series gives an explicit estimate of the slope and the uncertainty of this estimate is explicitly reported by the p-value and R2 (Montgomery, 2009). The data on the number of defects were summarized by production week as a series of defect pairs. Overall process behaviour was represented by calculating the weekly mean, peak week and the minimum week before fitting the regression model. The weekly bar chart was smoothed by applying a 13-week rolling average trajectory (Montgomery, 2009) to a third of the 39 points available (39/13). Two-tailed t-test at α = 0.05 was used for the statistical significance of the trend slope.

4. RESULT & DISCUSSION

4.1 Interpretation of Pareto Analysis

Pareto analysis was used to analyse a total of 13,599 defect pairs that were recorded from 25 different defect categories from the DIP observation log.

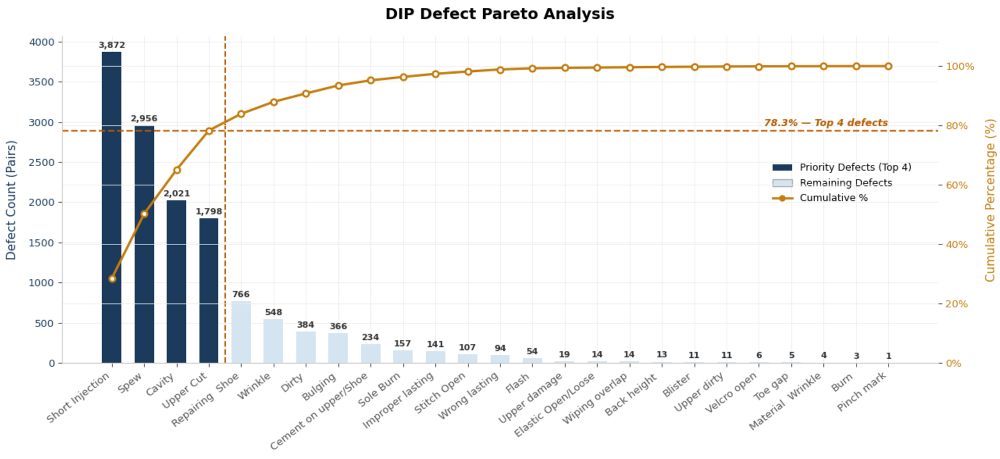

Figure 1. Pareto analysis

The Pareto analysis indicates that four defect types namely Short Injection, Spew, Cavity and Upper Cut account for 78.3% of all DIP failures in Figure 1. The concentration is not a coincidence but is attributable to a statistically uneven failure mode distribution.
The first four defect categories accounted for 78.3% of all recorded failures and were therefore selected as priority defects for subsequent machine-wise and statistical analysis.

4.2 Machine-Wise Defect Attribution

The defects of each of the five injection machines are presented in Figure 2 using a single denominator. Of the 13,599 pairs of DIP defects reported, 13,552 pairs (99.7%) had machine identifiers. The most defects were found by MC_3 (3611 defect pairs). There were 2,776 and 2,686 defect pairs for MC_2 and MC_1, respectively. The smallest number of defect pairs were found in MC_5 (2,249) and MC_4 (2,230). There was very little difference between the two machines, suggesting similar defect loads. The observed distribution indicates that there are differences in the incidence of defects in the five machines. The results give a preliminary impression of the difference in defect distribution between the machines and serve as a foundation for the statistical evaluation of the machine-defect relationship in the future.

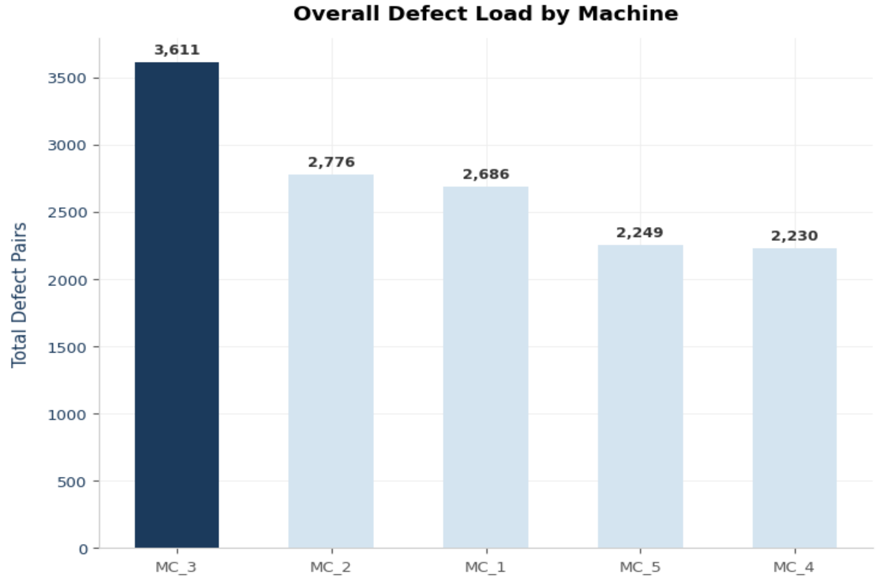

Figure 2. Machine Attribution

The grouped bar chart in Figure 3. further describes the distribution of the four dominant defect categories for each individual machine. Short Injection defects were very strongly clustered in machine MC_3 with 1,082 defect pairs, much more than the other machines. The MC_2 group had the highest number of spew defects (750 defect pairs) whereas the Cavity defects demonstrated relatively higher frequencies in MC_3 and MC_4. The distribution was somewhat more even for Upper Cut defects with MC_2 having the largest contribution in this category.

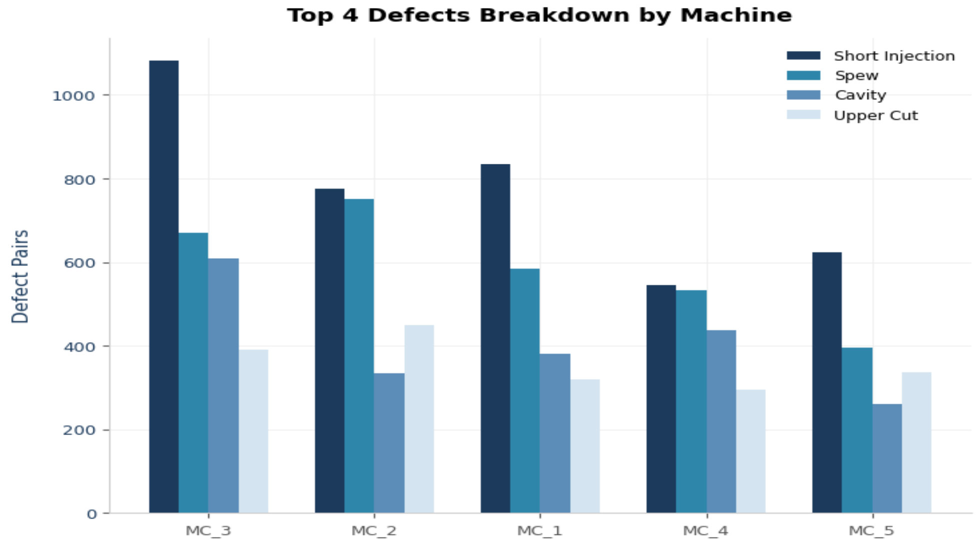

Figure 3. Top 4 defect breakdown

A cross-tabulation analysis is used to demonstrate that the four priorities defect types were not distributed evenly among machines. However, machine-targeted intervention should not be based on the fact that the higher raw load of MC_3 exists. The machine identity accounts for a very small percentage of the variation in defect as shown by the chi-square analysis of Section 4.3. The absolute defect burden for MC_3 is the most, however, the effect size is very small, therefore machine targeted intervention is not statistically justified and there is a higher likelihood of success if targeting variables related to the process, rather than a particular machine, such as the injection parameters, material batch quality, and operator quality. The above cross-sectional results, therefore, support the need for formal statistical evaluation as presented in the next section.

4.3 Statistical Interpretation of Chi-Square and Cramér's V Findings

The chi-square test was used for the 5 x 4 contingency table for Machine x Defect Type for 10,608 valid observations in the 4 priority defect categories. The chi-square value for the test was χ^2 (12) = 189.55 and the p-value was less than 0.001, so the null hypothesis of independence was rejected. This result validates the hypothesis that the distribution of defect types over machines is not random: some machines have a higher number of some types of defects than others, if they were random. The minimum value for the expected cell frequency was 273.01, which is greater than the minimum value of 5.0 for the validity assumption of chi-square inference (Field, 2018).

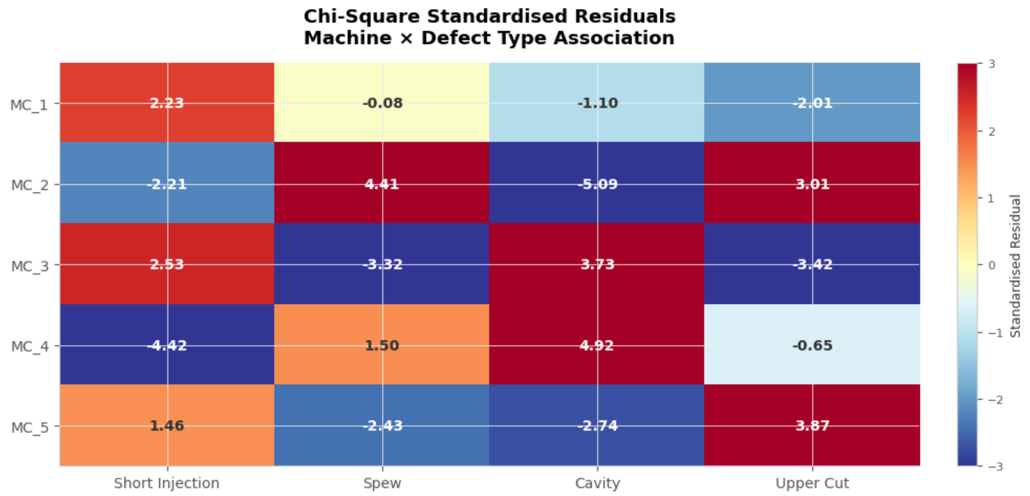

Figure 4. Residual heatmap

But it should be noted that, with 10,608 observations, the results of this association are statistically significant at $\alpha = 0.05$ for any non-zero association; at this size of the sample, it is virtually sure to be statistically significant, regardless of the strength of the association. As a result, in this context, the p-value in its own right has little inferential value, with the focus instead being on the measure of effect size reported in section 4.4. The standardized Pearson residuals heatmap is shown in Figure 4. Cells with values greater than +2.0 are cells in which the frequency actually observed is significantly greater than the frequency expected if cells were independent, and cells with values less than -2.0 represent the reverse. The heatmap shows that there are certain high positive residual cells: Short Injection-MC_3 and Cavity-MC_3 are the highest positive deviations, while Short Injection-MC_4 and Cavity-MC_1 are the highest negative deviations. It is important to bear in mind that these residual patterns are found in the small-N context of this study, with less than about 10,600 observations, and that even small deviations of the cell absolute counts from expected counts results in standardized residuals that exceed the threshold of ±2.0 but that do not imply any practically meaningful specialization of the machine. The use of the heatmap is thus more on the nature of a hypothesis generator, pointing to combinations of heat and machine to be closely monitored during operation, and not as a means to identify systematic failure modes for the machine.

4.4 Cramér's V - Strength of Association

The practical strength of the association of machine-defects was calculated through the chi-square test and then Cramér's V was calculated. The calculated value was: V = 0.077. This indicates that there is not much relation between machine identification and defect type (Cohen, 1988). As the result of the chi-square test, there is a statistically significant relationship between the variables ($p < 0.001$); however, the value of the Cramér's V correlation did not exceed 0.10, which suggests that the practical significance of the correlation is not high. The change in the number of defects from one stage of production to another cannot be expressed in terms of the number of the machine alone. This is consistent with this framework, which can only be revealed on logs, and no difference in machines is revealed except by real difference in defect rates – except by difference in machine output volume. The results show that machine effects are not the only ones that can explain a large part of the defect variance and that process-level variables such as injection parameter settings, material quality and operator proficiency are likely to.These results suggest that process-level variables, such as injection parameter settings, material quality and operator proficiency which cannot be distinguished from machine effects using count data should be included in future investigations.

4.5 Trend Analysis

The weekly trend for DIP defect is shown in Figure 5 throughout the entire period of observation. The chart includes individual weekly bar values, a line of the rolling average, and the fitted line of linear regression trend.

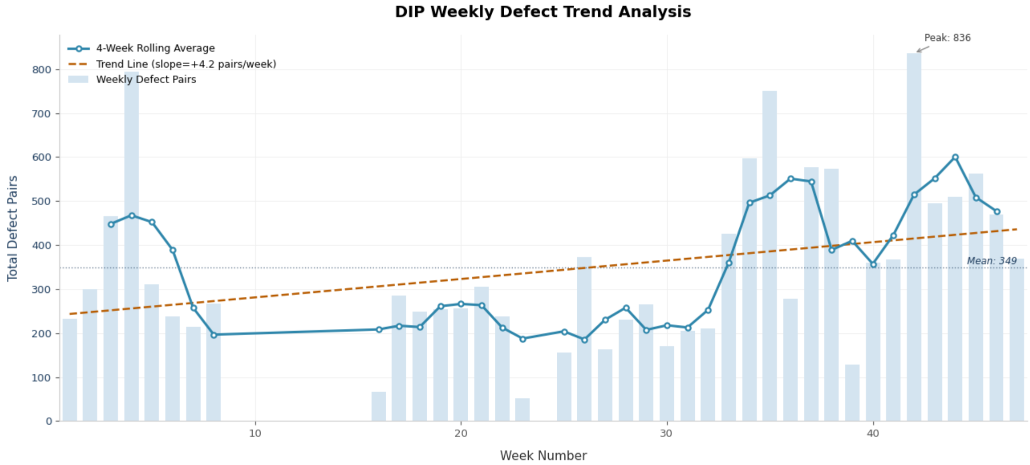

Figure 5. Trend analysis

Absolute failure numbers, which are not defect rates per number of parts produced, are used in this analysis. Therefore, an increasing number of people in a week may be interpreted as a deterioration of the process or more people are being produced in that week. Without volume data, these two explanations can't be differentiated.

The overall trend analysis shows that there is no statistically significant evidence of deterioration or improvement throughout the 39-week observation period (β_1 = +4.19 pairs/week, R^2 = 0.095, p = 0.057). The p-value of 0.057 does not provide sufficient evidence of a statistically significant linear trend at α = 0.05. The positive estimated slope and the increase observed in the rolling average during the later weeks nevertheless indicate a pattern that warrants continued monitoring. Given the missing observations and absence of production-volume denominators, this pattern should not be interpreted as evidence of process deterioration. The production log actually contains 47 weeks, but with the absence of 8 observation weeks (week 9 to 15 and week 24), the OLS model was therefore fitted to 39 non-consecutive observation weeks. Without these observations, there is uncertainty in the estimated trend because their values are not known. Consequently, the magnitude and direction of their potential impact on the slope estimate and statistical significance is unknown. It is therefore advisable to interpret the borderline result with caution and consider it as inconclusive and not as evidence of a worsening trend or process stability. The pattern of weekly defect volumes, therefore, should be monitored to see if the trend toward an increase in the last half of the series persists with time. From a manufacturing standpoint, the concentration of higher weekly volumes in the final observation quarter suggests that the concentration of higher weekly defect volumes in the final observation period warrants further investigation using production-volume, maintenance, material-batch and process-parameter records, and these should be examined against the maintenance and procurement records for the corresponding period. These findings support the need for systematic weekly defect logging with production-volume denominators from the next observation cycle. Such records would enable this framework to be extended to proportion-based trend analysis, specifically a p-chart fitted to weekly defect rates, yielding a rate-adjusted conclusion not achievable under the present log-only constraint (Montgomery, 2009; Ravichandran, 2016).

5. CONCLUSION

This study presented a sequential diagnostic framework for defect analysis in direct injection footwear manufacturing. The framework was specifically developed for log-only environments where production-volume records are not available. Applied to a single DIP facility in Bangladesh, the framework combines Pareto analysis, machine-wise attribution, Chi-square testing, Cramér's V effect-size estimation, and linear regression-based trend analysis in a structured sequence covering the Define, Measure, and Analyse stages. Four defect types, namely Short Injection, Spew, Cavity, and Upper Cut, accounted for 78.3% of all recorded failures. Although MC_3 recorded the highest number of defects, a Cramér's V value of 0.077 indicated that machine identity had only a small association with defect-type distribution. This indicates that machine identity alone does not account for a substantial association with defect-type distribution. Other process-level factors may contribute, but these factors could not be evaluated using the available log-only data. However, the near-significant result and the visible increase in defects during the later observation period suggest that continued monitoring is warranted rather than concluding that the process remained stable throughout the study period. The main contribution of this study is methodological. The findings demonstrate that statistically supported defect diagnosis can be conducted using production defect logs alone. Under such conditions, a small effect size should be interpreted as a meaningful diagnostic result rather than a limitation of the analysis. The proposed framework can be reproduced in other manufacturing facilities and is not restricted to a specific production environment. Future extension of the framework to defect-rate analysis would require only the inclusion of production-volume data, representing a logical next step toward more comprehensive statistical process control.

There are some limitations of this study. Initially, the number of defects was examined without reference to production volume data. The upward trend could be due to an increase in production volume, not necessarily to a deterioration in the process; a downward trend could indicate that production decreased but the defect rate increased. Raw counts do not have a volume denominator and thus cannot be interpreted as defect rates per unit produced. This is exactly why the framework is limited to the diagnosis of distribution and not rate estimation. Future applications should include paired production volume records to allow for good monitoring of defect rates. Second, the production log does not contain eight of the 47 observation weeks. The magnitude and direction of their potential impact on the slope estimate and statistical significance is unknown, and the borderline p-value (0.057) should not be interpreted as evidence of stability of the process. Third, the data were collected in a single facility, and the numerical results were not generalizable. The thresholds of the Pareto and attributions for machines are context-dependent, as are the effect size estimates; the framework is transferable. The injection process parameters typically related to defect formation in direct injection manufacturing such as injection pressure, mold temperature, material batch quality, and operator proficiency were not available. This is reflected in the very small value of the Cramér's V (0.077) indicating that a large part of the variation of the defect is not accounted for by these unobserved factors but cannot be distinguished from the machine effects from the count data alone. The framework should be applied in other manufacturing environments in future studies and additional process data should be added to increase the diagnostic capability and generalizability of the framework.

References:

Ahmed, T., Begum, R., & Ahmed, S. (2023). Application of Six Sigma tools in footwear industry: An emerging economy case. *International Journal of Productivity and Quality Management, 38*(2), 211–242. DOI: 10.1504/IJPQM.2023.129607

Anacleto Filho, P. C., Braga, A. C., & Carneiro, P. (2024). Exploring musculoskeletal complaints in a needle manufacturing industry: A cross-sectional study. *International Journal of Environmental Research and Public Health, 21*(8), 996. DOI: 10.3390/ijerph21080996

Ávila, P., Monteiro, R., Mota, A., Castro, H., Pinto Ferreira, L., Bastos, J., Fernandes, N. O., Moreira, J., & Sá, J. (2026). MAPIC—A new comprehensive methodology for process improvement. *International Journal for Quality Research, 20*(1), 165–178. DOI: 10.24874/IJQR20.01-10

Ben-Shachar, M. S., Patil, I., Thériault, R., Wiernik, B. M., & Lüdecke, D. (2023). Phi, Fei, Fo, Fum: Effect sizes for categorical data that use the chi-squared statistic. *Mathematics, 11*(9), 1982. DOI: 10.3390/math11091982

Burmeister, N., Frederiksen, R. D., Høg, E., & Nielsen, P. (2023). Exploration of production data for predictive maintenance of industrial equipment: A case study. *IEEE Access, 11*, 102025–102037. DOI: 10.1109/ACCESS.2023.3315842

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Correia, L., Brito, A. M., Faria, L., Félix, M. J., Santos, G., Laranjeira, J., & Simoes, R. (2020). Dynamic temperature control influence on pressure during injection molding of plastic parts to improve part quality. *International Journal for Quality Research, 14*(2), 635–646. DOI: 10.24874/IJQR14.02-19

Díaz-Ruiz, G., & Trujillo-Gallego, M. (2022). A Six Sigma and system dynamic integration for process variability reduction in industrial processes. *International Journal for Quality Research, 16*(4), 1149–1178. DOI: 10.24874/IJQR16.04-13

Dimyati, Khadijah, A., & Kristiningrum, E. (2020). Defect analysis of shoes production processes using statistical process control and failure mode effect analysis method. *AIP Conference Proceedings, 2217*(1), 030130. DOI: 10.1063/5.0000725

Fatimah, S., & Wahyuni, H. C. (2023). Product Quality Control Using the Six Sigma method and Seven Tools in the PDL Shoe Industry. *Tibuana: Journal of Applied Industrial Engineering*, *6*(1), 12-22.. DOI: 10.36456/tibuana.6.1.6174.12-22

Field, A. (2018). Discovering statistics using IBM SPSS statistics (5th ed.). SAGE Publications.

Gonzalez Santacruz, E., Romero, D., Noguez, J., & Wuest, T. (2025). Integrated Quality 4.0 framework for quality improvement based on Six Sigma and machine learning techniques towards zero-defect manufacturing. *The TQM Journal, 37*(4), 1115–1155. DOI: 10.1108/TQM-11-2023-0361

Guachamín-Chicaiza, C., Villota-González, F. H., & Zúñiga-Grajeda, V. (2025). Machine learning and probabilistic analysis strategies for defect reduction in windshield manufacturing. *International Journal of Information Management Data Insights, 5*(2), 100383. DOI: 10.1016/j.jjimei.2025.100383

Hadi Hashim, S. M., & Oudah Sabeeh, A. (2021). A study of using statistical methods to improves process performance. *International Journal for Quality Research, 15*(2), 643–664. DOI: 10.24874/IJQR15.02-18

Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: Principles and practice (3rd ed.). OTexts. https://otexts.com/fpp3/

Jagadeesan, S., & Umasankar, V. (2022). Cycle time reduction in multi-cavity injection mould through mould flow analysis and runner modification. *International Journal of Productivity and Quality Management, 37*(2), 180–215. DOI: 10.1504/IJPQM.2022.126330

Klochkov, Y., Gazizulina, A., & Muralidharan, K. (2019). Lean Six Sigma for sustainable business practices: A case study and standardisation. *International Journal for Quality Research, 13*(1), 47–74. DOI: 10.24874/IJQR13.01-04

Lestyánszka Škůrková, K., Fidlerová, H., Niciejewska, M., & Idzikowski, A. (2023). Quality improvement of the forging process using Pareto analysis and 8D methodology in automotive manufacturing: A case study. *Standards, 3*(1), 84–94. DOI: 10.3390/standards3010008

Lyu, J., Liang, C. W., & Chen, P.-S. (2020). A data-driven approach for identifying possible manufacturing processes and production parameters that cause product defects: A thin-film filter company case study. *IEEE Access, 8*, 49395–49411. DOI: 10.1109/ACCESS.2020.2974535

Mayr, M., & Himmelbauer, J. (2020). Detecting anomalies in production quality data using a method based on the chi-square test statistic. In M. Song, I.-Y. Song, G. Kotsis, I. Khalil, & A. M. Tjoa (Eds.), Big data analytics and knowledge discovery (Lecture Notes in Computer Science, Vol. 12393, pp. 348–363). Springer. DOI: 10.1007/978-3-030-59065-9_27

Montgomery, D. C. (2009). Introduction to statistical quality control (6th ed.). Wiley.

Ravichandran, J. (2016). Six Sigma-based X-bar control chart for continuous quality improvement. *International Journal for Quality Research, 10*(2), 257–266. DOI: 10.18421/IJQR10.02-02

Silmi, F. A., Sukmono, R. A., Sriyono, S., & Fitriyah, H. (2024). Optimizing footwear manufacturing through defect analysis and spare parts optimization. *Indonesian Journal of Innovation Studies, 25*(1). DOI: 10.21070/ijins.v25i1.1082

Sufian, M. A., Rahaman, M. Z., Ahmed, F., & Dewan, H. A. (2023). Analysis of rejection data in the lasting section of the footwear industry. *Australian Journal of Engineering and Innovative Technology, 5*(2), 35–57. DOI: 10.34104/ajeit.023.035057

Syed Tahmid Jamil
Department of Industrial Engineering, BGMEA University of Fashion & Technology, Dhaka-1230, Bangladesh
jamiltahmid@gmail.com
ORCID: 0009-0009-2074-6823

Md. Sarfuddin Anowar Khan
Department of Industrial Engineering, BGMEA University of Fashion & Technology, Dhaka-1230, Bangladesh
md.sarfuddin.siam@gmail.com
ORCID: 0009-0005-1329-0371

Md Tasfiq Alam
Department of Industrial Engineering, BGMEA University of Fashion & Technology, Dhaka-1230, Bangladesh
alamtasfiq65@gmail.com
ORCID: 0009-0005-0142-3800

Md Jahid Hasan
Department of Industrial Engineering, BGMEA University of Fashion & Technology, Dhaka-1230, Bangladesh
md.jahid.hsn7@gmail.com
ORCID: 0009-0006-8244-6330

Mohammed Jubaed
Department of Industrial Engineering, BGMEA University of Fashion & Technology, Dhaka-1230, Bangladesh
moh.jubaed@gmail.com
ORCID: 0009-0006-6216-7625