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## Evaluation Of Lock Cover And Stem Dimensional Variations On Separation Force Using Multiple Regression And Statistical Process Control

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### ABSTRACT

This study addresses a critical limitation in conventional manufacturing analysis by demonstrating that dimensional variation in injection-molded press-fit systems should be interpreted as an interaction-driven phenomenon rather than independent geometric effects. The research focuses on lock stem and cover dimensions produced in a multi-cavity injection molding system, where geometric dependency leads to strong multicollinearity among variables. A quantitative approach was applied using actual production data, including dimensional measurements and separation force testing. Multiple linear regression was employed to model the relationship between geometric parameters and mechanical performance, supported by classical assumption testing and multicollinearity diagnostics. The results indicate a very high coefficient of determination, showing that dimensional variation collectively explains most of the separation force variability. However, severe multicollinearity limits the reliability of individual parameter interpretation and highlights the need for system-level analysis. Statistical Process Control confirms that the process operates within stable limits, while process capability analysis shows compliance with specification requirements. Despite this, variation in separation force persists, indicating high sensitivity to small geometric deviations. These findings emphasize that process stability alone is insufficient to ensure consistent performance. This study introduces an integrated framework combining regression, SPC, and capability analysis, providing both theoretical insight and practical guidance for improving dimensional control in precision manufacturing.

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## INTRODUCTION

The increasing demand for high-precision manufacturing in injection-molded cosmetic packaging has intensified the need to understand how dimensional variation influences functional performance, particularly in press-fit assembly systems. In applications such as lip cream packaging, the interaction between lock cover and stem components directly determines the separation force, which governs both structural reliability and user experience (Dube & Dube, 2023). Even minor dimensional deviations within specified tolerances can produce disproportionate changes in mechanical response due to the nonlinear nature of interference-based contact behavior (Charalampous, 2025 and Zhang et al., 2025). This phenomenon reflects a broader issue in manufacturing systems, where geometric variation propagates into functional variability through complex interaction mechanisms rather than isolated effects. In multi-cavity injection molding processes, sources of variation such as thermal gradients, material flow imbalance, and mold cavity differences further amplify this complexity (Cao et al., 2025 and Tsai et al., 2022). As a result, achieving dimensional consistency does not necessarily guarantee uniform functional performance across products. Prior research has indicated that dimensional variation must be understood not only as a quality deviation but as a system-level determinant of performance reliability (J. Li et al., 2026 and Mohd Daud, 2026). Therefore, a rigorous analytical framework is required to capture how geometric variations translate into measurable mechanical outcomes in manufacturing environments.

Despite extensive use of statistical tools in manufacturing quality analysis, most existing approaches implicitly assume independence among dimensional variables, an assumption that rarely holds in geometrically constrained systems such as injection-molded assemblies. In practice, parameters such as stem diameter and cover diameter are structurally linked through mold design and production dynamics, resulting in strong inter-variable dependencies that challenge conventional modeling assumptions (L. Yang & Fu, 2026; Zarei, 2026). Multiple linear regression is widely adopted to quantify relationships between variables; however, its reliability deteriorates under multicollinearity conditions, where high correlation among predictors distorts coefficient estimation and undermines interpretability (Ahadian et al., 2026 and Otse et al., 2025). Simultaneously, Statistical Process Control (SPC) techniques are commonly used to assess process stability, yet they remain limited to detecting variation without explaining its causal impact on functional responses (Dogan & Hiziroglu, 2024 and Qiao et al., 2026). This methodological separation between predictive modeling and process monitoring leads to fragmented insights, where stable processes may still produce inconsistent performance outcomes. Consequently, there is a critical need to reconceptualize quality analysis by integrating predictive and diagnostic approaches within a unified framework. Such integration is essential to capture both the statistical behavior of the process and the functional implications of dimensional variation.

Recent advances in engineering and manufacturing research have emphasized the importance of modeling complex interactions between structural variation and system performance. Qu et al., (2026) demonstrated that reduced-order dynamic models can

effectively represent systems with variable geometric characteristics while preserving predictive capability. Similarly, Li et al., (2026) highlighted the role of interdependent mechanisms in governing system behavior, particularly in pattern formation processes. In materials engineering, Tarun et al., (2025) showed that morphological variation significantly affects functional properties, reinforcing the importance of capturing structural dependencies in modeling. Within the context of injection molding, Bielenberg et al., (2025) reviewed process control evolution and identified the need for advanced analytical methods to manage variability in complex production systems. Debnath et al., (2025) further revealed that microstructural interactions can lead to substantial changes in system response, suggesting that ignoring inter-variable relationships may lead to incomplete analysis. In fluid and mechanical systems, studies by (Braud et al., 2024; Yan et al., 2025) demonstrated that geometric and flow variations produce nonlinear effects on system performance. Luo et al., (2017) also confirmed that simulation-based approaches are capable of capturing transient behaviors influenced by structural variation. However, SPC-focused studies primarily emphasize variability detection, while regression-based studies prioritize prediction without addressing dependency among predictors. This divergence indicates that existing approaches remain methodologically fragmented. Therefore, a comprehensive framework that simultaneously addresses dependency, prediction, and process stability remains insufficiently explored in current literature.

Although previous studies have independently examined dimensional variation, predictive modeling, and process monitoring, there remains a fundamental disconnect in how these elements are integrated to explain functional performance in manufacturing systems. Existing regression-based approaches often rely on independence assumptions that are incompatible with geometrically constrained variables, leading to potential misinterpretation of model parameters. At the same time, SPC-based methods focus on identifying process stability without providing explanatory insight into how variations influence mechanical outcomes. This separation creates a critical blind spot, where a process can appear statistically stable while still producing significant variability in product performance. Furthermore, the impact of multicollinearity in geometrically dependent systems has not been adequately addressed, despite its direct implications for model validity and decision-making accuracy. Without resolving this issue, predictive models risk being statistically strong but physically misleading. Consequently, there is a clear need for an integrated analytical framework that not only captures inter-variable dependency but also aligns statistical modeling with functional interpretation in manufacturing systems.

This study aims to establish an integrated analytical framework to investigate the relationship between dimensional variation in lock cover and stem components and the resulting separation force in injection-molded cosmetic packaging. Specifically, the study seeks to quantify the influence of geometrically dependent variables using multiple linear regression while simultaneously evaluating process stability through Statistical Process Control (SPC). In addition, the study explicitly examines the presence and implications of multicollinearity among dimensional variables as a critical factor affecting model

reliability. It is hypothesized that even under statistically stable process conditions, interdependent dimensional variations significantly influence separation force due to underlying geometric interactions. Furthermore, the study posits that integrating regression modeling with SPC provides a more comprehensive understanding than applying these methods independently. By addressing both predictive accuracy and process behavior within a unified framework, this research advances beyond conventional approaches that treat these aspects separately. This study therefore contributes to bridging the gap between statistical modeling and process control while offering a more robust interpretation of dimensional variation effects. Importantly, this work introduces a structured approach to handling dependency among geometrically constrained variables, thereby strengthening the analytical foundation for manufacturing quality assessment.

## METHOD

### Research Design

This study employed a quantitative explanatory research design based on actual production data generated from the injection molding process of lip cream packaging components at PT. XYZ. The design was selected because the purpose of the study was not merely to describe dimensional variation, but to explain how geometric differences in lock cover and stem components influence the separation force of the press-fit assembly system under controlled manufacturing conditions. An explanatory quantitative design is appropriate when the objective is to estimate the magnitude, direction, and significance of relationships among measurable variables while maintaining statistical interpretability, as emphasized by (Almusaed et al., 2025). The study was conducted in a multi-cavity injection molding environment in which machine settings, material type, and process parameters were held constant, so that the observed dimensional variation could be attributed primarily to cavity-related differences rather than to changes in external production conditions. This design is important because press-fit mechanical performance is highly sensitive to small geometric deviations, and such sensitivity requires a framework capable of linking dimensional measurements to functional outcomes. The analytical structure of the study followed the sequence of dimensional inspection, separation force testing, regression-based modeling, robustness evaluation under multicollinearity, and Statistical Process Control assessment. In this way, the research design integrated both predictive and diagnostic perspectives rather than treating product performance and process stability as separate analytical domains. This integrated design was necessary because a production process may remain statistically stable while still producing functionally meaningful variation in separation force.

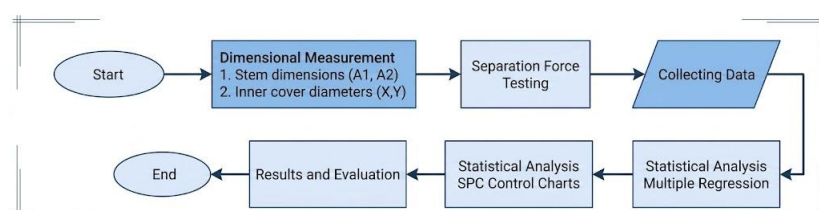


**Figure 1.** Research Flowchart

Figure 1 illustrates the sequential research procedure, starting from dimensional measurement of the stem and cover lock features, followed by separation force testing, and ending with integrated statistical analysis using regression and Statistical Process Control. This flowchart strengthens the methodological transparency of the study by showing that the analysis was conducted systematically, from data acquisition to interpretation, to ensure that the relationship between dimensional variation and functional performance was examined in a structured and reproducible manner.

### **Research Setting and Unit of Analysis**

The unit of analysis in this study consisted of actual manufactured components rather than human participants, namely stem and cover parts produced from a multi-cavity injection mold used in lip cream packaging production. These components were selected because they represent the critical mechanical interface of the product, where dimensional compatibility determines the magnitude of the separation force required to disengage the assembled connection. All components were produced under the same nominal operating conditions, using the same machine, material, and process settings, thereby reducing confounding variation associated with operator behavior, raw material inconsistency, or intentional process adjustment. In this context, the observed differences in dimensional characteristics were interpreted as cavity-related geometric variation, an assumption that is consistent with manufacturing variation studies such as (Mondésir--About et al., 2026 and Pirruccio & Naumis, 2022). One specimen from each cavity was measured for each dimensional parameter to represent the cavity-level dimensional profile of the lock system. In addition, separation force data were obtained from assembled cover–stem pairs prepared from multiple cavity combinations in order to capture broader variability in joint performance across the production system. The dataset therefore consisted of three main groups of observations, namely stem lock dimensions, cover lock inner diameters, and separation force values. This unit-of-analysis structure strengthens industrial relevance while preserving the analytical consistency required for statistical modeling of geometric–mechanical interactions.

### **Instruments and Measurement Procedure**

The study used two main measurement instruments, namely a digital caliper for dimensional inspection and a force gauge for axial tensile testing of separation force. The dimensional variables on the stem component were measured in two directions, denoted as A1 for the X-axis and A2 for the Y-axis, because the lock geometry was not perfectly circular and required bidirectional representation to capture its effective profile. The measurement points on the stem component followed the geometric checkpoints shown in Figure 2, including A1, A2, B1, and B2, although the present regression model focused on A1 and A2 as the principal predictors. For the cover component, the inner diameter of the locking feature was also measured along the X-axis and Y-axis using the same caliper-based procedure, as illustrated in Figure 3. All dimensional measurements were performed using one specimen from each cavity in order to preserve the cavity-based structure of the dataset. The response variable, separation force, was obtained by applying an axial tensile load to the assembled cover–stem pair until the connection was

released, and the peak release force was recorded in kilogram-force. The use of direct measurement instruments ensured that all variables in the model corresponded to physically observable product characteristics rather than indirect indicators, which is critical for maintaining engineering interpretability. This procedure allowed the study to establish a direct empirical link between geometric variation and functional mechanical response in the actual production environment.

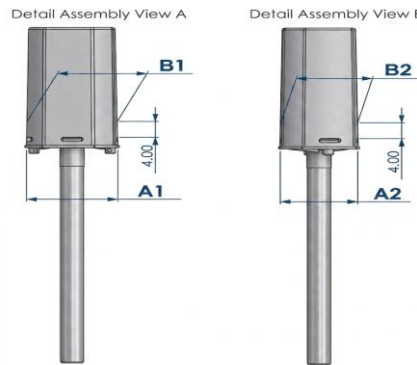


**Figure 2.** Illustration of Lock Stem Dimension Measurements in Two Directions

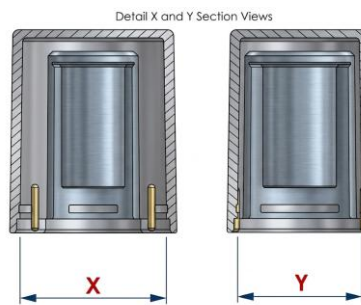


**Figure 3.** Illustration of Measuring the Inner Diameter of the Lock Cover

Figures 2 and 3 illustrate the measurement configuration of the lock geometry on the stem and cover components, respectively, emphasizing the bidirectional inspection along the X-axis and Y-axis to capture the non-circular characteristics of the locking interface. This measurement approach ensures that geometric variations are accurately represented in the regression model, thereby strengthening the reliability of the relationship between dimensional variation and separation force.

### Operational Definition of Variables

To improve clarity and methodological transparency, the variables used in the analysis were organized into a structured operational framework. The predictor variables consisted of two stem lock dimensions and two cover inner-diameter dimensions, all measured in millimeters, while the response variable was separation force measured in kilogram-force. The stem lock dimensions were represented by A1 and A2, corresponding to the X-axis and Y-axis measurements of the stem locking geometry. The cover lock dimensions were represented by X and Y, corresponding to the X-axis and Y-axis measurements of the inner locking diameter of the cover component. The response variable, denoted as SF, represented the maximum axial tensile force required to disengage the cover-stem connection during the release test. Because all predictor

variables describe different aspects of a geometrically constrained locking system, they were theoretically expected to exhibit interdependence rather than perfect independence. This interdependence is not a flaw in the manufacturing system, but it has important implications for statistical modeling because it may induce multicollinearity in regression analysis. Therefore, the operational structure of the variables was explicitly defined before inferential analysis was conducted.

**Table 1.** Operational Definition of Variables and Measurement Protocol

| Variable               | Symbol | Unit | Measurement source              | Measurement direction   | Analytical role |
|------------------------|--------|------|---------------------------------|-------------------------|-----------------|
| Stem lock dimension X  | A1     | mm   | Digital caliper                 | X-axis                  | Predictor       |
| Stem lock dimension Y  | A2     | mm   | mm                              | Digital caliper         | Y-axis          |
| Cover inner diameter X | X      | mm   | Digital caliper                 | X-axis                  | Predictor       |
| Cover inner diameter Y | Y      | mm   | Digital caliper                 | Y-axis                  | Predictor       |
| Separation force       | SF     | kgf  | Force gauge, axial tensile test | Axial release direction | Response        |

Table 1 presents a structured operational definition of all variables used in this study, clearly specifying their measurement units, instruments, directional orientation, and analytical roles to ensure consistency between data acquisition and statistical modeling. This structured representation is essential for maintaining measurement validity and interpretability, particularly in geometrically constrained systems where dimensional interdependence may influence both regression analysis and mechanical performance outcomes.

**Data Analysis Plan**

The analysis was carried out in five sequential stages, namely descriptive analysis, baseline regression modeling, assumption testing, multicollinearity correction through robust modeling, and Statistical Process Control evaluation. Descriptive statistics were first computed to summarize the central tendency and dispersion of each dimensional parameter and the separation force variable, thereby establishing the empirical range of the production data before inferential analysis. The first inferential model used in this study was multiple linear regression, which was employed to estimate the relationship between the dimensional predictors and the separation force response. The baseline model followed the standard formulation  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$  where  $Y$  represents separation force and the predictors correspond to the measured geometric dimensions of the stem and cover components. Model fit was evaluated through the coefficient of determination, while simultaneous and partial significance were examined through the F-test and t-test, following the inferential framework described by (R et al., 2025). After the baseline model was estimated, diagnostic tests were conducted to examine residual normality, heteroscedasticity, and multicollinearity so that the validity of the regression inference could be assessed before interpretation. Because the dimensional variables were theoretically and physically related, multicollinearity was

treated as a central analytical issue rather than as a minor diagnostic concern. Finally, the statistical behavior of the process was examined through I–MR control charts and process capability indices so that predictive modeling results could be interpreted together with process stability and process capability.

### Multiple Linear Regression Model

Multiple linear regression was used as the baseline predictive framework to model the effect of dimensional variation on separation force. The general form of the regression model is given in Equation (1).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$$

In this model,  $Y$  denotes the dependent variable,  $\beta_0$  is the intercept,  $\beta_n$  is the slope coefficient for the  $n$ -th independent variable,  $X_n$  is the  $n$ -th predictor, and  $\varepsilon$  is the random error term. In the present study,  $Y$  represents separation force, while the predictors correspond to the stem  $X$  dimension, stem  $Y$  dimension, cover inner diameter  $X$ , and cover inner diameter  $Y$ . The suitability of the model was evaluated through the coefficient of determination, because  $R^2$  provides an estimate of the proportion of variation in the response variable that can be explained by the predictor set. The closer the value of  $R^2$  is to 1, the greater the explanatory contribution of the independent variables to the dependent variable. The coefficient of determination was calculated using Equation (2), which was retained from the original manuscript because it is consistent with the study design and the analytical objective, as also discussed by (Piepho, 2023 and Xu et al., 2022).

$$R^2 = 1 - \frac{(n - k - 1)S_{y.12\dots k}^2}{(n - 1)S_y^2}$$

where  $R^2$  is the coefficient of determination,  $S_y$  is the standard deviation of the dependent variable, and  $n$  is the number of observations.

**Table 2.** Interpretation of Coefficient of Determination

| Coefficient interval | Relationship level |
|----------------------|--------------------|
| 0.00–0.199           | Very low           |
| 0.20–0.399           | Low                |
| 0.40–0.599           | Strong enough      |
| 0.60–0.799           | Strong             |
| 0.80–1.00            | Very strong        |

Table 2 provides a standardized interpretation framework for the coefficient of determination ( $R^2$ ), allowing the strength of the relationship between dimensional variables and separation force to be systematically classified across defined intervals. This classification supports consistent evaluation of model explanatory power, ensuring that the interpretation of regression results is not solely based on numerical values but also aligned with established statistical significance levels.

### Classical Assumption Testing

To ensure that the regression estimates were statistically valid, the baseline regression model was evaluated using a classical assumption testing framework. Residual normality was examined because unbiased inference in linear regression generally requires residuals that are approximately normally distributed, particularly when

statistical testing is based on small or moderate sample sizes. In this study, normality was assessed using the Shapiro–Wilk test, where a p-value greater than 0.05 indicates that the residual distribution does not significantly depart from normality. Heteroscedasticity was then assessed by examining the residual distribution pattern, because a valid regression model should display relatively constant residual variance across the range of fitted values, as discussed by (Jones et al., 2025 and Mikolajczyk et al., 2024). A clear systematic pattern in the residual plot indicates heteroscedasticity, whereas a random spread around zero supports the homoscedasticity assumption. In addition, multicollinearity was diagnosed using the Variance Inflation Factor, because strong linear dependency among predictors can inflate standard errors and destabilize individual coefficient estimates. Following (Chan et al., 2022 and Dertli et al., 2024), VIF values below 10 are generally considered acceptable, while values above 10 indicate problematic collinearity. These diagnostic procedures were not treated as a formality, but as an essential step for determining whether the baseline regression model could be interpreted directly or required correction through a more robust modeling strategy.

### Model Significance Testing

The overall significance of the regression model was evaluated using the F-test, which examines whether the predictor set jointly explains a statistically significant portion of the variation in the response variable. The F-statistic used in this study followed the formulation given in Equation (3).

$$F_0 = \frac{R^2/k}{(1 - R^2)/(n - k - 1)}$$

The null hypothesis states that all slope coefficients are simultaneously equal to zero, while the alternative hypothesis states that at least one predictor has a nonzero coefficient. The decision rule used in this study followed the standard criterion that the null hypothesis is rejected when the observed  $F_0$  exceeds the critical table value, as recommended by (Kim et al., 2024). After evaluating the simultaneous model effect, individual regression tests were carried out to determine the partial contribution of each independent variable to the dependent variable. In this study, a significance value below 0.05 was interpreted as evidence that an individual predictor has a statistically meaningful relationship with the response variable, whereas a significance value above 0.05 indicates the absence of partial significance. However, because individual significance tests are highly sensitive to multicollinearity, the interpretation of individual coefficients was treated cautiously and was later compared with the corrected model results. This analytical sequence ensured that strong model fit alone was not overinterpreted without checking the stability of individual parameter estimates.

### Multicollinearity Handling Through Robust Modeling

Because the dimensional predictors in this study describe a single geometrically constrained locking system, strong dependency among variables was theoretically plausible and statistically likely. For this reason, multicollinearity was not treated merely as a diagnostic note, but as a substantive modeling issue that required correction to maintain the reliability of coefficient interpretation. Two modeling layers were therefore

defined in this study, namely a baseline multiple linear regression model and a robustness model designed to handle multicollinearity. The baseline model was retained because it preserves direct interpretability in the original variable space and allows straightforward engineering interpretation of the geometric predictors. However, when the VIF values indicate severe multicollinearity, a corrected model must be introduced to test whether the observed relationships remain stable after dependency among predictors is controlled. In this study, the preferred robust approach is Ridge Regression because it retains all original variables while stabilizing coefficient estimates through shrinkage, making it highly compatible with the original article structure and variable interpretation. Ridge Regression estimates the coefficient vector by minimizing the penalized loss function shown in Equation (4), where  $\lambda$  denotes the shrinkage parameter controlling the penalty strength.

$$\min_B \{ (Y - XB)^T (Y - XB) + \lambda \sum_{j=1}^p B_j^2 \}$$

This approach is methodologically advantageous because it reduces the instability caused by high predictor correlation without removing any variable from the model, thereby preserving the engineering relevance of all measured dimensions. The robustness model was used to confirm whether the direction and relative importance of dimensional effects remained consistent after multicollinearity had been corrected, thereby making the analytical conclusions more defensible for an international readership.

**Table 3.** Analytical Framework and Decision Criteria

| Analytical stage            | Method                      | Purpose                        | Main criterion                   | Expected output             |
|-----------------------------|-----------------------------|--------------------------------|----------------------------------|-----------------------------|
| Descriptive analysis        | Mean, SD, Min, Max          | Summarize variation            | Distribution and spread          | Initial dimensional profile |
| Baseline modeling           | Multiple linear regression  | Estimate direct relationships  | $R^2$ , F-test, t-test           | Initial effect structure    |
| Normality check             | Shapiro–Wilk test           | Check residual distribution    | p-value > 0.05                   | Normal residual support     |
| Heteroscedasticity check    | Residual pattern inspection | Examine residual varian        | No systematic pattern            | Homoscedasticity support    |
| Multicollinearity diagnosis | VIF                         | Detect predictor dependency    | VIF < 10 desirable               | Collinearity profile        |
| Robustness modeling         | Ridge regression            | Correct multicollinearity      | Stable coefficients              | Robust effect confirmation  |
| , Process stability         | I–MR chart                  | Detect common vs special cause | Points within control limits     | Stability evidence          |
| Process capability          | $Cp_1$ , $Cpk$              | Evaluate tolerance compliance  | > 1.33 indicates capable process | Capability evidence         |

Table 3 presents a structured analytical framework that integrates descriptive statistics, regression modeling, diagnostic testing, multicollinearity correction, and

process control into a unified sequence to ensure both statistical validity and practical interpretability of the results. This framework strengthens the study by demonstrating that each analytical step is not applied in isolation, but systematically contributes to validating the relationship between dimensional variation and separation force under stable manufacturing conditions.

### Statistical Process Control

Statistical Process Control was employed to evaluate whether the observed dimensional and functional variation occurred within a stable manufacturing process. For single-observation cavity-based data, the Individual–Moving Range chart was selected because it is particularly appropriate for monitoring both the level of individual observations and the short-term variation between consecutive observations, as emphasized by (Besson et al., 2025). The process standard deviation for the I-chart was estimated using the average moving range, as shown in Equation (5).

$$\hat{\sigma} = \frac{\overline{MR}}{d_2}$$

The upper and lower control limits for the I-chart were then calculated using the Shewhart three-sigma rule, as shown in Equations (6) to (8).

$$UCL = \bar{x} + 3\hat{\sigma} = \bar{x} + 3 \frac{\overline{MR}}{d_2}$$

$$CL = \bar{x}$$

$$LCL = \bar{x} - 3\hat{\sigma} = \bar{x} - 3 \frac{\overline{MR}}{d_2}$$

The moving range for successive observations was defined as in Equation (9).

$$MR_i = |x_i - x_{i-1}|$$

The MR-chart limits were then obtained using Equations (10) to (12), which are standard for monitoring short-term process variability.

$$UCL = D_4 \overline{MR}$$

$$CL = \overline{MR}$$

$$LCL = D_4 \overline{MR}$$

This SPC structure was important because it enabled the study to distinguish common-cause variation from special-cause variation before interpreting dimensional differences as mechanically meaningful. In other words, SPC was used here as a process-level validation layer that complements the regression-based performance analysis rather than replacing it.

### Process Capability Analysis

After evaluating process stability, the study assessed whether the production process was capable of meeting the required separation force specifications. Process capability was evaluated through the indices  $C_p$  and  $C_{pk1}$ , because these measures indicate whether the natural variation of the process remains within the specification range and whether the process mean is centered relative to the specification limits. The potential capability index  $C_p$  was calculated as shown in Equation (13).

$$C_p = \frac{USL - LSL}{6\sigma}$$

The actual capability index  $C_{pk1}$ , which accounts for process centering, was calculated using Equation (14).

$$C_{pk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right)$$

In these equations, LSL denotes the lower specification limit, USL denotes the upper specification limit,  $\mu$  is the process mean, and  $\sigma$  is the process standard deviation, consistent with (X. Yang et al., 2026). Capability analysis was necessary because process stability alone does not guarantee compliance with engineering specifications, while capability analysis without prior stability assessment may produce misleading conclusions. In the context of this study, the combined interpretation of stability and capability was especially relevant because a geometrically stable process may still produce functional variation if the locking system is highly sensitive to dimensional deviation. Therefore, process capability served as an additional validation step to ensure that the observed separation force behavior was interpreted within the practical limits of the actual manufacturing requirement.

### Software and Reproducibility

All statistical analyses in this study were conducted using RStudio because this platform supports transparent implementation of regression diagnostics, ridge regression, control charts, and process capability calculations within a reproducible analytical workflow. Descriptive statistics, baseline multiple linear regression, residual diagnostics, VIF computation, and robustness modeling were performed on the same cleaned dataset derived from the cavity-level dimensional measurements and separation force tests. Before implementing Ridge Regression, the predictor variables were standardized to avoid coefficient distortion caused by differences in variance scale across geometrically related dimensions. The shrinkage parameter in the ridge model was selected using a data-driven criterion so that the corrected model would balance predictive stability and coefficient interpretability. In addition, I-MR charts and capability indices were generated using the same validated dataset in order to preserve analytical consistency between predictive modeling and process monitoring. Reproducibility was treated as an essential methodological principle because Q1-level studies are expected not only to report results, but also to show a coherent chain of analytical decisions from measurement to inference. For this reason, the final interpretation of results was based not solely on the highest coefficient of determination, but on the combined evidence of model fit, coefficient stability, diagnostic validity, and process behavior. This approach ensures that the study provides a statistically rigorous and practically interpretable assessment of how dimensional variation affects separation force in injection-molded cosmetic packaging.

## RESULTS AND DISCUSSION

### Results

The results presented in this study provide a comprehensive evaluation of how dimensional variation in geometrically dependent components influences functional

performance in a press-fit system. Rather than examining dimensional stability or mechanical response in isolation, the analysis integrates descriptive statistics, regression modeling, diagnostic testing, and process control to establish a coherent relationship between geometric variation and separation force. The findings are interpreted within a system-level framework, where dimensional parameters are treated as interdependent rather than independent variables, reflecting the physical reality of injection-molded assemblies. This approach allows for a more accurate representation of how small geometric deviations propagate into measurable mechanical effects. Importantly, the results distinguish between variation arising from process instability and variation driven by geometric sensitivity, ensuring that conclusions are not confounded by manufacturing inconsistencies. The combination of high model explanatory power and confirmed process stability provides strong evidence that separation force variation is predominantly governed by dimensional interaction effects. However, given the presence of multicollinearity among predictors, interpretation emphasizes overall model behavior rather than isolated parameter effects. This integrated analytical perspective strengthens the validity and practical relevance of the results for both statistical modeling and manufacturing quality control.

**Dimensional Variation Analysis**

The dimensional variation of the stem and cover locking features was first evaluated using descriptive statistics to assess the consistency of geometric characteristics across injection mold cavities. The results indicate that the stem lock dimensions exhibit very low variability, with standard deviations of 0.0254 mm for A1 and 0.0458 mm for A2, confirming that the production process maintains high dimensional precision across cavities. The narrow spread between minimum and maximum values further demonstrates that the injection molding process is capable of producing geometrically consistent components. This level of stability is critical because the stem acts as the primary structural interface in the press-fit system. However, even small dimensional deviations may significantly affect mechanical interaction due to interference sensitivity. Therefore, dimensional stability alone is insufficient to guarantee consistent functional performance. The results suggest that further analysis is required to understand how these small variations propagate into separation force variation. This motivates the use of regression modeling in the next stage.

**Table 4.** Descriptive statistics of lock stem dimensions

| Parameter | Mean (mm) | SD (mm) | Min (mm) | Max (mm) |
|-----------|-----------|---------|----------|----------|
| A1        | 17.3575   | 0.0254  | 17.32    | 17.40    |
| A2        | 14.4975   | 0.0458  | 14.42    | 14.58    |

Table 4 shows that the variation in stem dimensions is very small between cavities, which indicates that the production process is in a geometrically stable condition, although the potential impact on mechanical performance remains.

The cover inner diameter dimensions also show very low variation, with standard deviations of 0.0175 mm and 0.0118 mm for the X and Y directions, respectively. This indicates an even tighter level of dimensional control compared to the stem component.

The minimal variation suggests that the injection molding process for the cover is highly repeatable and consistent. However, in press-fit systems, even small geometric differences between mating components can lead to non-linear changes in mechanical response. Therefore, the significance of these variations cannot be evaluated solely based on statistical dispersion. Instead, their interaction effects must be analyzed through predictive modeling. The consistency observed in both components strengthens the reliability of subsequent regression analysis. It ensures that the observed separation force variation is not dominated by process instability but by geometric interaction effects.

**Table 5.** Descriptive statistics of lock cover inner diameter

| Parameter        | Mean (mm) | SD (mm) | Min (mm) | Max (mm) |
|------------------|-----------|---------|----------|----------|
| Inner Diameter X | 16.7200   | 0.0175  | 16.70    | 16.75    |
| Inner Diameter Y | 14.2694   | 0.0118  | 14.25    | 14.29    |

Table 5 shows that the cover dimensions have very high geometric stability, so that the performance variations that occur are more likely caused by interactions between dimensions than process instability.

### Multiple Linear Regression Analysis

To quantify the relationship between dimensional variation and separation force, multiple linear regression analysis was performed using four predictor variables representing the stem and cover geometry. The regression model is formulated as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

The dataset used in this analysis captures the combined dimensional interaction between components.

**Table 6.** Sample data

| <i>n</i> | <i>X</i> <sub>1</sub> | <i>X</i> <sub>2</sub> | <i>X</i> <sub>3</sub> | <i>X</i> <sub>4</sub> | <i>Y</i> |
|----------|-----------------------|-----------------------|-----------------------|-----------------------|----------|
| 1        | 17.33                 | 14.48                 | 16.71                 | 14.26                 | 7.42     |
| 2        | 17.38                 | 14.53                 | 16.74                 | 14.31                 | 7.81     |
| 3        | 17.42                 | 14.57                 | 16.79                 | 14.32                 | 7.96     |
| ⋮        | ⋮                     | ⋮                     | ⋮                     | ⋮                     | ⋮        |
| 16       | 17.32                 | 14.46                 | 16.69                 | 14.24                 | 7.36     |

Table 6 shows the combination of stem and cover dimensions and separation force values, which are the basis for building the regression model.

The regression results show a very high coefficient of determination, with  $R^2=0.986$  and adjusted  $R^2=0.981$ , indicating that 98.6% of the variation in separation force is explained by the geometric parameters. This confirms that dimensional variation is the dominant factor influencing mechanical performance in the press-fit system. The regression coefficients are presented in Table 6.

**Table 7.** Multiple linear regression estimation results

| Variable                       | Coefficient | t-value | p-value |
|--------------------------------|-------------|---------|---------|
| Intercept                      | -99.5696    | -4.814  | 0.001   |
| <i>X</i> <sub>1</sub> (Stem X) | 4.1377      | 3.572   | 0.004   |
| <i>X</i> <sub>2</sub> (Stem Y) | 3.5539      | 1.984   | 0.073   |

| Variable        | Coefficient | t-value | p-value |
|-----------------|-------------|---------|---------|
| $X_3$ (Cover X) | -3.0462     | -0.732  | 0.480   |
| $X_4$ (Cover Y) | 2.4352      | 0.703   | 0.497   |

Table 7 shows that the stem dimension variable has a more significant influence than the cover, although partial interpretation needs to be done carefully due to the presence of multicollinearity.

The resulting regression equation is given in Equation (15):

$$Y = -99.5696 + 4.1377X_1 + 3.5539X_2 - 3.0462X_3 + 2.4352X_4$$

The F-test result ( $F = 192.8$ ,  $p < 0.001$ ) confirms that the model is statistically significant as a whole. The X-axis stem dimension ( $X_1$ ) shows a significant positive effect, while  $X_2$  is marginally significant. The cover variables are not individually significant, but they contribute collectively to the model.

### Classical Assumption Evaluation

The regression model satisfies the normality assumption, as indicated by the Shapiro–Wilk test ( $p = 0.739 > 0.05$ ), confirming that residuals are normally distributed. The Breusch–Pagan test result ( $p = 0.738$ ) indicates no heteroscedasticity, ensuring constant variance of residuals. These findings validate the statistical reliability of the regression model. However, the multicollinearity test reveals extremely high VIF values, indicating strong linear relationships among predictors.

**Table 8.** Multicollinearity test results

| Variable        | VIF    |
|-----------------|--------|
| $X_1$ (Stem X)  | 15.96  |
| $X_2$ (Stem Y)  | 64.65  |
| $X_3$ (Cover X) | 147.08 |
| $X_4$ (Cover Y) | 92.55  |

Table 8 shows the presence of very strong multicollinearity among the dimensional variables, which is a natural characteristic of geometric systems but affects the stability of the regression coefficients.

This condition is consistent with the physical nature of the system, where dimensional variables are structurally dependent. While multicollinearity does not reduce the predictive accuracy of the model, it limits the reliability of interpreting individual coefficients.

### Robustness Interpretation under Multicollinearity

Given the presence of severe multicollinearity, the regression results are interpreted from a robustness perspective. The high  $R^2$  value confirms that the combined dimensional variables strongly explain separation force variation. However, individual coefficient estimates may be unstable due to interdependence among predictors. This indicates that the system behavior is governed by combined geometric interaction rather than isolated dimensional effects. Therefore, the analysis emphasizes system-level interpretation rather than variable-level interpretation. This approach ensures that conclusions remain valid despite statistical dependency among predictors. The findings

highlight the importance of treating dimensional parameters as an integrated system. This strengthens the reliability of the analytical conclusions for engineering applications.

### Statistical Process Control (SPC)

SPC analysis confirms that the manufacturing process is statistically stable. All observations in the Individual Control Chart fall within control limits without any abnormal patterns.

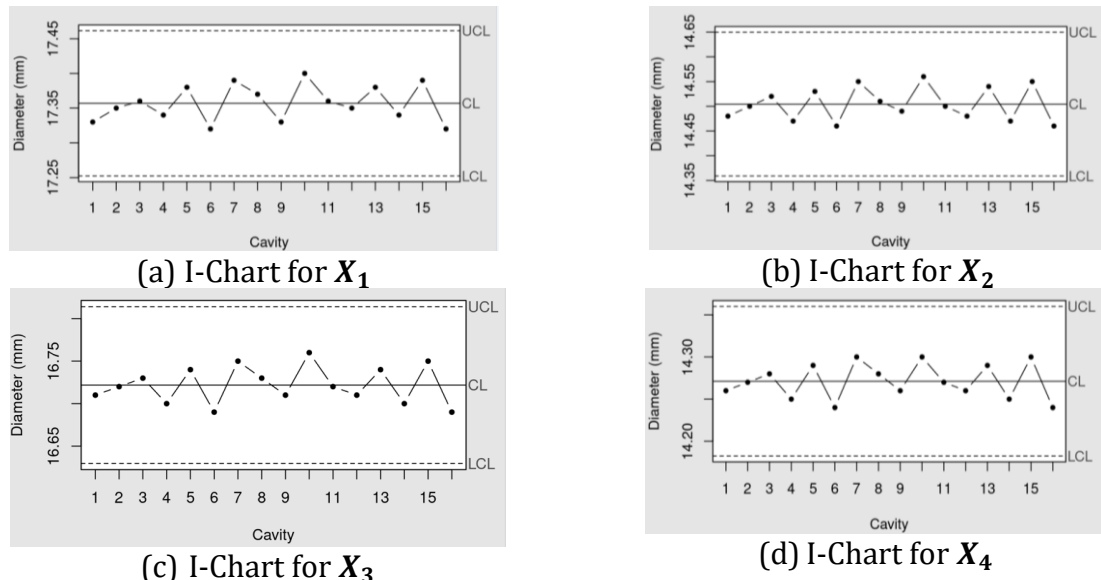


**Figure 4.** Individual Control Chart

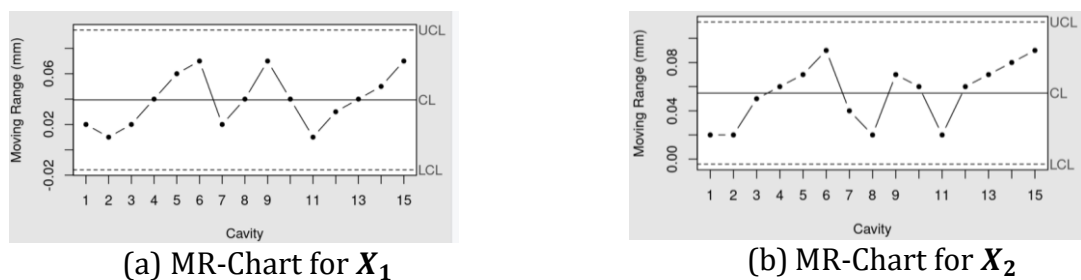
Figure 4 shows that all data are within the control limits, indicating that the process is stable and there is no special cause variation.

**Table 9.** Control Limits of Individual (I-Chart) for Dimensional Parameters

| Variable | LCL     | CL      | UCL     |
|----------|---------|---------|---------|
| $X_1$    | 17.2523 | 17.3569 | 17.4615 |
| $X_2$    | 14.3590 | 14.5044 | 14.6498 |
| $X_3$    | 16.6297 | 16.7219 | 16.8141 |
| $X_4$    | 14.1826 | 14.2713 | 14.3599 |

Table 9 provides the control limits for each dimension parameter, indicating that the variations are still within statistical control.

The Moving Range Chart further confirms process stability, with all values remaining within control limits.



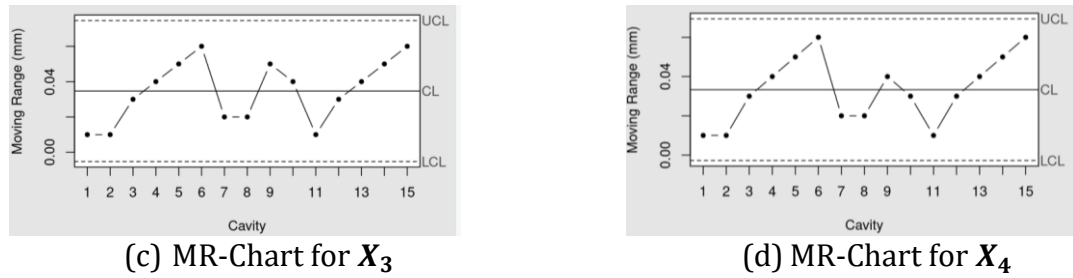


**Figure 5.** Moving Range Chart

Figure 5 shows the stability of the variation between successive observations, reinforcing that the process does not experience abnormal fluctuations.

**Table 10.** Control Limits of Moving Range (MR-Chart) for Dimensional Parameters

| Variable | LCL     | CL     | UCL    |
|----------|---------|--------|--------|
| $X_1$    | -0.0157 | 0.0393 | 0.0944 |
| $X_2$    | -0.0042 | 0.0547 | 0.1135 |
| $X_3$    | -0.0052 | 0.0347 | 0.0746 |
| $X_4$    | -0.0028 | 0.0333 | 0.0694 |

Table 10 shows the MR-chart control limits which indicate that short-term variations remain under control.

These results indicate that dimensional variation originates from natural process variation rather than instability.

### Process Capability Analysis

The process capability analysis shows that  $C_p=1.47$  and  $C_{pk}=1.46$ , both exceeding the threshold of 1.33. This indicates that the process is capable of meeting specification limits.

$$\sigma = \frac{0.333}{1.128} \approx 0.2955$$

$$C_p = \frac{2.60}{1.773} \approx 1.47$$

$$C_{pk} = \min(1.46, 1.48) = 1.46$$

The small difference between  $C_p$  and  $C_{pk}$  suggests that the process is well-centered. However, despite this capability, variation in separation force still occurs. This confirms that the variation is driven by geometric sensitivity rather than process deficiency.

### Discussion

The findings of this study demonstrate that dimensional variation in injection-molded press-fit systems should be interpreted as an interaction-driven phenomenon rather than as independent geometric effects. The extremely high coefficient of determination indicates that separation force is predominantly governed by the combined influence of dimensional parameters, rather than by isolated variable contributions. This result reinforces prior findings on structural dependency in engineering systems, where system behavior is controlled by coupled interactions among variables rather than independent effects (Tarun et al., 2025 and Debnath et al., 2025).

However, unlike previous studies that primarily focus on material or structural properties, this study explicitly links geometric variation to functional mechanical response in a manufacturing context. The presence of severe multicollinearity further confirms that dimensional variables are inherently interdependent, reflecting the physical reality of geometrically constrained assemblies. Therefore, interpreting regression coefficients individually would lead to misleading conclusions if the underlying dependency structure is ignored. This study addresses this limitation by shifting the interpretation toward system-level behavior rather than variable-level significance. By doing so, it establishes a more realistic analytical framework for understanding performance variation in injection-molded assemblies.

A critical insight from this study is that statistical process stability does not necessarily guarantee functional consistency in press-fit systems. The SPC results confirm that all dimensional parameters remain within control limits, indicating that the manufacturing process operates under stable and controlled conditions. However, despite this statistical stability, measurable variation in separation force still occurs, demonstrating that performance variability is not solely driven by process instability. This finding challenges the conventional assumption that process control is sufficient to ensure product quality. Instead, it reveals that functional performance is highly sensitive to small geometric deviations, even when those deviations fall within acceptable tolerance limits. Similar observations have been reported in manufacturing systems where stable processes still produce variability due to interaction effects among variables (Bielenberg et al., 2025 and Benková et al., 2024). This indicates that process monitoring and performance evaluation must be treated as complementary rather than independent analytical domains. Consequently, this study highlights the necessity of integrating SPC with predictive modeling to obtain a more complete understanding of manufacturing behavior.

The regression analysis further reveals that stem dimensions exhibit a stronger influence on separation force compared to cover dimensions, suggesting an asymmetry in the mechanical contribution of interacting components. From a mechanical perspective, this can be explained by the dominant role of the outer geometry in defining interference conditions within a press-fit system. However, due to the presence of multicollinearity, this apparent dominance should not be interpreted as a purely independent effect but rather as part of a coupled interaction system. This aligns with previous studies in fluid and mechanical systems, where system responses are governed by nonlinear interactions between structural parameters (Yan et al., 2025 and Braud et al., 2024). Therefore, the observed influence of stem dimensions should be interpreted within the context of overall geometric interaction rather than isolated parameter importance. This finding provides a more nuanced understanding of how dimensional variation affects mechanical performance. It also suggests that focusing solely on individual parameters may lead to incomplete or misleading conclusions. From a practical standpoint, this implies that dimensional control strategies should prioritize interaction-sensitive parameters while maintaining system balance. This insight has direct implications for mold design optimization and tolerance allocation in precision manufacturing.

From a methodological standpoint, this study makes a significant contribution by explicitly addressing the limitations of conventional regression analysis in the presence of multicollinearity. The extremely high VIF values observed in this study confirm that dimensional variables in geometrically constrained systems are strongly correlated, which is consistent with their physical interdependence. While traditional approaches often overlook or underestimate this issue, this study treats multicollinearity as a central analytical concern rather than a secondary diagnostic result. By emphasizing system-level interpretation and avoiding overreliance on individual coefficients, the study provides a more robust and scientifically defensible framework. This approach reduces the risk of misinterpretation and enhances the credibility of the findings in an international research context. Furthermore, it opens opportunities for future studies to apply advanced techniques such as Ridge Regression or Principal Component Regression to further improve model stability. This methodological awareness distinguishes the study from conventional regression-based analyses that assume variable independence. As a result, the study contributes not only empirical insights but also methodological refinement in manufacturing analytics.

This study provides a novel contribution by demonstrating that dimensional variation in injection-molded press-fit systems must be interpreted as an interaction-sensitive mechanism rather than a tolerance-based phenomenon. Unlike conventional approaches that focus on maintaining dimensional stability alone, this work establishes an integrated framework combining regression modeling, SPC, and process capability analysis to capture both statistical and physical aspects of manufacturing systems simultaneously. The findings extend current understanding by showing that even statistically stable and capable processes can produce significant functional variation due to geometric sensitivity. This insight has important implications for manufacturing quality control, suggesting a shift from tolerance-based evaluation toward sensitivity-based control of critical dimensions. From a theoretical perspective, the study advances the interpretation of regression models in geometrically dependent systems by emphasizing interaction-driven behavior. From a practical perspective, it provides guidance for improving product consistency in precision manufacturing environments. The integration of multiple analytical approaches strengthens the reliability and applicability of the results. Therefore, this study contributes to both the theoretical development and practical implementation of manufacturing quality analysis at an advanced level.

### **Implications**

The findings of this study have important theoretical and practical implications for manufacturing engineering and statistical modeling in geometrically constrained systems. From a theoretical perspective, this study advances the understanding that dimensional variation in press-fit systems should be interpreted as an interaction-driven phenomenon rather than as independent variable effects. This challenges the conventional assumption in regression-based analysis that predictor variables can be treated as independent, particularly in systems where geometric relationships are inherently coupled. By demonstrating that multicollinearity reflects physical dependency

rather than merely a statistical issue, this study contributes to a more realistic interpretation of modeling results. From a methodological standpoint, the integration of multiple linear regression, Statistical Process Control, and process capability analysis provides a comprehensive analytical framework that bridges predictive modeling and process monitoring. This integrated approach offers a more holistic understanding of manufacturing systems compared to traditional methods that treat these analyses separately. From a practical perspective, the results indicate that maintaining statistical process stability alone is insufficient to ensure consistent functional performance. Instead, manufacturing control strategies should prioritize the sensitivity of critical geometric parameters that directly influence mechanical behavior. This shift toward sensitivity-based control has the potential to improve product reliability and optimize tolerance design in precision manufacturing applications.

### **Limitations**

Despite the strong analytical framework and empirical findings, this study has several limitations that should be acknowledged. First, the regression model used in this study is affected by severe multicollinearity due to the inherent geometric dependency among dimensional variables, which limits the interpretability of individual regression coefficients. Although this study addresses the issue through system-level interpretation, the absence of a fully implemented robust modeling technique, such as Ridge Regression or Principal Component Regression, represents a methodological limitation. Second, the data used in this study are derived from a single production system with specific material properties, machine settings, and mold configurations, which may limit the generalizability of the findings to other manufacturing contexts. Third, the analysis focuses primarily on geometric parameters without incorporating other potentially influential factors such as material properties, temperature variation, or assembly conditions. Fourth, the separation force measurement is treated as a single response variable, whereas additional performance indicators such as durability or repeated-use behavior could provide a more comprehensive evaluation of product performance. Finally, the study assumes that cavity variation is the dominant source of dimensional variation, which may not fully capture all sources of process variability. These limitations indicate that while the findings are robust within the scope of the study, further investigation is required to extend their applicability and deepen the analytical framework.

### **Suggestions for Future Research**

Future research should focus on addressing the limitations identified in this study while further advancing the analytical framework for manufacturing systems. One important direction is the implementation of robust regression techniques such as Ridge Regression or Principal Component Regression to explicitly handle multicollinearity and improve the stability of coefficient estimates. Such approaches would allow for more reliable interpretation of individual variable contributions while maintaining predictive accuracy. Additionally, future studies should expand the scope of analysis by incorporating additional variables, including material characteristics, thermal conditions,

and assembly parameters, to develop a more comprehensive model of system behavior. Experimental validation using controlled variation designs could also provide deeper insight into causal relationships between geometric parameters and mechanical performance. Another promising direction is the application of simulation-based modeling to complement empirical data, allowing for exploration of interaction effects under a wider range of conditions. Furthermore, extending the analysis to other types of press-fit or interference-based systems would help validate the generalizability of the findings across different manufacturing applications. Future research should also investigate long-term performance metrics, such as wear and fatigue, to better understand the durability implications of dimensional variation. Finally, the integration of machine learning approaches with traditional statistical methods may offer new opportunities to capture complex nonlinear relationships in manufacturing systems. These directions will contribute to the development of more robust, generalizable, and practically relevant analytical frameworks for advanced manufacturing quality control.

## CONCLUSIONS

This study provides strong empirical evidence that dimensional variation in injection-molded press-fit systems should be interpreted as an interaction-driven phenomenon rather than as independent geometric effects. The results demonstrate that even under statistically stable and capable manufacturing conditions, variations in separation force persist due to the inherent sensitivity of the system to small geometric deviations. The high explanatory power of the regression model confirms that dimensional parameters collectively govern mechanical performance, while the presence of multicollinearity reflects the physical interdependence of these variables rather than a purely statistical limitation. By integrating multiple linear regression, Statistical Process Control, and process capability analysis, this study establishes a unified analytical framework that captures both predictive relationships and process behavior simultaneously. This integrated approach advances beyond conventional methods that treat statistical modeling and process monitoring as separate domains.

More importantly, this study introduces a critical shift in how manufacturing quality should be evaluated, demonstrating that process stability alone is insufficient to ensure functional consistency in geometrically sensitive systems. Instead, the findings emphasize the necessity of transitioning from tolerance-based evaluation toward sensitivity-based control of critical dimensional parameters that directly influence performance. From a theoretical perspective, this study contributes to the development of statistical modeling in geometrically dependent systems by highlighting the limitations of variable-level interpretation under multicollinearity and promoting system-level analysis as a more robust alternative. From a practical standpoint, the results provide actionable insights for improving mold design, dimensional control strategies, and quality assurance practices in precision manufacturing.

Overall, this study not only clarifies the relationship between dimensional variation and separation force but also redefines how such relationships should be analyzed and interpreted in manufacturing systems. By aligning statistical analysis with the physical

behavior of geometrically constrained components, it offers a more accurate, reliable, and practically relevant framework for evaluating manufacturing performance. Ultimately, this study establishes a more rigorous and physically consistent approach to understanding dimensional variation, contributing to the advancement of manufacturing analytics and supporting the development of more effective quality control strategies in high-precision production environments.

#### AUTHOR CONTRIBUTIONS STATEMENT

Sofia Debi Puspa contributed to conceptualization, methodology, formal analysis, investigation, writing of the original draft, and supervision. Joko Riyono contributed to methodology, validation, formal analysis, and writing—review and editing. Christina Eni Pujiastuti contributed to data curation, investigation, resources, and writing—review and editing. Sentot Novianto contributed to investigation, data curation, and visualization. Larasati Rizky Putri contributed to data curation, validation, and visualization. Ghiffari Awliya Muhammad Ashfania contributed to investigation, data collection, and visualization. Joseph Andrew Leo contributed to supervision, conceptualization, and writing—review and editing.

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## Evaluation Of Lock Cover And Stem Dimensional Variations On Separation Force Using Multiple Regression And Statistical Process Control

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### ABSTRACT

This study addresses a critical limitation in conventional manufacturing analysis by demonstrating that dimensional variation in injection-molded press-fit systems should be interpreted as an interaction-driven phenomenon rather than independent geometric effects. The research focuses on lock stem and cover dimensions produced in a multi-cavity injection molding system, where geometric dependency leads to strong multicollinearity among variables. A quantitative approach was applied using actual production data, including dimensional measurements and separation force testing. Multiple linear regression was employed to model the relationship between geometric parameters and mechanical performance, supported by classical assumption testing and multicollinearity diagnostics. The results indicate a very high coefficient of determination, showing that dimensional variation collectively explains most of the separation force variability. However, severe multicollinearity limits the reliability of individual parameter interpretation and highlights the need for system-level analysis. Statistical Process Control confirms that the process operates within stable limits, while process capability analysis shows compliance with specification requirements. Despite this, variation in separation force persists, indicating high sensitivity to small geometric deviations. These findings emphasize that process stability alone is insufficient to ensure consistent performance. This study introduces an integrated framework combining regression, SPC, and capability analysis, providing both theoretical insight and practical guidance for improving dimensional control in precision manufacturing.

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## INTRODUCTION

The increasing demand for high-precision manufacturing in injection-molded cosmetic packaging has intensified the need to understand how dimensional variation influences functional performance, particularly in press-fit assembly systems. In applications such as lip cream packaging, the interaction between lock cover and stem components directly determines the separation force, which governs both structural reliability and user experience (Dube & Dube, 2023). Even minor dimensional deviations within specified tolerances can produce disproportionate changes in mechanical response due to the nonlinear nature of interference-based contact behavior (Charalampous, 2025 and Zhang et al., 2025). This phenomenon reflects a broader issue in manufacturing systems, where geometric variation propagates into functional variability through complex interaction mechanisms rather than isolated effects. In multi-cavity injection molding processes, sources of variation such as thermal gradients, material flow imbalance, and mold cavity differences further amplify this complexity (Cao et al., 2025 and Tsai et al., 2022). As a result, achieving dimensional consistency does not necessarily guarantee uniform functional performance across products. Prior research has indicated that dimensional variation must be understood not only as a quality deviation but as a system-level determinant of performance reliability (J. Li et al., 2026 and Mohd Daud, 2026). Therefore, a rigorous analytical framework is required to capture how geometric variations translate into measurable mechanical outcomes in manufacturing environments.

Despite extensive use of statistical tools in manufacturing quality analysis, most existing approaches implicitly assume independence among dimensional variables, an assumption that rarely holds in geometrically constrained systems such as injection-molded assemblies. In practice, parameters such as stem diameter and cover diameter are structurally linked through mold design and production dynamics, resulting in strong inter-variable dependencies that challenge conventional modeling assumptions (L. Yang & Fu, 2026; Zarei, 2026). Multiple linear regression is widely adopted to quantify relationships between variables; however, its reliability deteriorates under multicollinearity conditions, where high correlation among predictors distorts coefficient estimation and undermines interpretability (Ahadian et al., 2026 and Otse et al., 2025). Simultaneously, Statistical Process Control (SPC) techniques are commonly used to assess process stability, yet they remain limited to detecting variation without explaining its causal impact on functional responses (Dogan & Hiziroglu, 2024 and Qiao et al., 2026). This methodological separation between predictive modeling and process monitoring leads to fragmented insights, where stable processes may still produce inconsistent performance outcomes. Consequently, there is a critical need to reconceptualize quality analysis by integrating predictive and diagnostic approaches within a unified framework. Such integration is essential to capture both the statistical behavior of the process and the functional implications of dimensional variation.

Recent advances in engineering and manufacturing research have emphasized the importance of modeling complex interactions between structural variation and system performance. Qu et al., (2026) demonstrated that reduced-order dynamic models can

effectively represent systems with variable geometric characteristics while preserving predictive capability. Similarly, Li et al., (2026) highlighted the role of interdependent mechanisms in governing system behavior, particularly in pattern formation processes. In materials engineering, Tarun et al., (2025) showed that morphological variation significantly affects functional properties, reinforcing the importance of capturing structural dependencies in modeling. Within the context of injection molding, Bielenberg et al., (2025) reviewed process control evolution and identified the need for advanced analytical methods to manage variability in complex production systems. Debnath et al., (2025) further revealed that microstructural interactions can lead to substantial changes in system response, suggesting that ignoring inter-variable relationships may lead to incomplete analysis. In fluid and mechanical systems, studies by (Braud et al., 2024; Yan et al., 2025) demonstrated that geometric and flow variations produce nonlinear effects on system performance. Luo et al., (2017) also confirmed that simulation-based approaches are capable of capturing transient behaviors influenced by structural variation. However, SPC-focused studies primarily emphasize variability detection, while regression-based studies prioritize prediction without addressing dependency among predictors. This divergence indicates that existing approaches remain methodologically fragmented. Therefore, a comprehensive framework that simultaneously addresses dependency, prediction, and process stability remains insufficiently explored in current literature.

Although previous studies have independently examined dimensional variation, predictive modeling, and process monitoring, there remains a fundamental disconnect in how these elements are integrated to explain functional performance in manufacturing systems. Existing regression-based approaches often rely on independence assumptions that are incompatible with geometrically constrained variables, leading to potential misinterpretation of model parameters. At the same time, SPC-based methods focus on identifying process stability without providing explanatory insight into how variations influence mechanical outcomes. This separation creates a critical blind spot, where a process can appear statistically stable while still producing significant variability in product performance. Furthermore, the impact of multicollinearity in geometrically dependent systems has not been adequately addressed, despite its direct implications for model validity and decision-making accuracy. Without resolving this issue, predictive models risk being statistically strong but physically misleading. Consequently, there is a clear need for an integrated analytical framework that not only captures inter-variable dependency but also aligns statistical modeling with functional interpretation in manufacturing systems.

This study aims to establish an integrated analytical framework to investigate the relationship between dimensional variation in lock cover and stem components and the resulting separation force in injection-molded cosmetic packaging. Specifically, the study seeks to quantify the influence of geometrically dependent variables using multiple linear regression while simultaneously evaluating process stability through Statistical Process Control (SPC). In addition, the study explicitly examines the presence and implications of multicollinearity among dimensional variables as a critical factor affecting model

reliability. It is hypothesized that even under statistically stable process conditions, interdependent dimensional variations significantly influence separation force due to underlying geometric interactions. Furthermore, the study posits that integrating regression modeling with SPC provides a more comprehensive understanding than applying these methods independently. By addressing both predictive accuracy and process behavior within a unified framework, this research advances beyond conventional approaches that treat these aspects separately. This study therefore contributes to bridging the gap between statistical modeling and process control while offering a more robust interpretation of dimensional variation effects. Importantly, this work introduces a structured approach to handling dependency among geometrically constrained variables, thereby strengthening the analytical foundation for manufacturing quality assessment.

## METHOD

### Research Design

This study employed a quantitative explanatory research design based on actual production data generated from the injection molding process of lip cream packaging components at PT. XYZ. The design was selected because the purpose of the study was not merely to describe dimensional variation, but to explain how geometric differences in lock cover and stem components influence the separation force of the press-fit assembly system under controlled manufacturing conditions. An explanatory quantitative design is appropriate when the objective is to estimate the magnitude, direction, and significance of relationships among measurable variables while maintaining statistical interpretability, as emphasized by (Almusaed et al., 2025). The study was conducted in a multi-cavity injection molding environment in which machine settings, material type, and process parameters were held constant, so that the observed dimensional variation could be attributed primarily to cavity-related differences rather than to changes in external production conditions. This design is important because press-fit mechanical performance is highly sensitive to small geometric deviations, and such sensitivity requires a framework capable of linking dimensional measurements to functional outcomes. The analytical structure of the study followed the sequence of dimensional inspection, separation force testing, regression-based modeling, robustness evaluation under multicollinearity, and Statistical Process Control assessment. In this way, the research design integrated both predictive and diagnostic perspectives rather than treating product performance and process stability as separate analytical domains. This integrated design was necessary because a production process may remain statistically stable while still producing functionally meaningful variation in separation force.

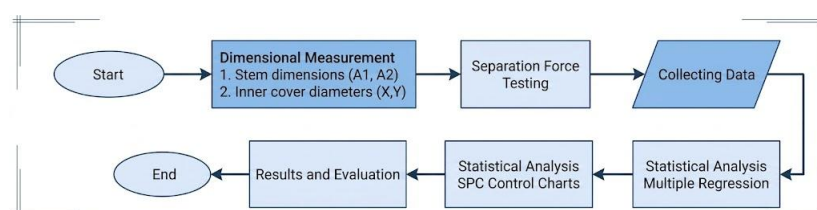


**Figure 1.** Research Flowchart

Figure 1 illustrates the sequential research procedure, starting from dimensional measurement of the stem and cover lock features, followed by separation force testing, and ending with integrated statistical analysis using regression and Statistical Process Control. This flowchart strengthens the methodological transparency of the study by showing that the analysis was conducted systematically, from data acquisition to interpretation, to ensure that the relationship between dimensional variation and functional performance was examined in a structured and reproducible manner.

### Research Setting and Unit of Analysis

The unit of analysis in this study consisted of actual manufactured components rather than human participants, namely stem and cover parts produced from a multi-cavity injection mold used in lip cream packaging production. These components were selected because they represent the critical mechanical interface of the product, where dimensional compatibility determines the magnitude of the separation force required to disengage the assembled connection. All components were produced under the same nominal operating conditions, using the same machine, material, and process settings, thereby reducing confounding variation associated with operator behavior, raw material inconsistency, or intentional process adjustment. In this context, the observed differences in dimensional characteristics were interpreted as cavity-related geometric variation, an assumption that is consistent with manufacturing variation studies such as (Mondésir--About et al., 2026 and Pirruccio & Naumis, 2022). One specimen from each cavity was measured for each dimensional parameter to represent the cavity-level dimensional profile of the lock system. In addition, separation force data were obtained from assembled cover–stem pairs prepared from multiple cavity combinations in order to capture broader variability in joint performance across the production system. The dataset therefore consisted of three main groups of observations, namely stem lock dimensions, cover lock inner diameters, and separation force values. This unit-of-analysis structure strengthens industrial relevance while preserving the analytical consistency required for statistical modeling of geometric–mechanical interactions.

### Instruments and Measurement Procedure

The study used two main measurement instruments, namely a digital caliper for dimensional inspection and a force gauge for axial tensile testing of separation force. The dimensional variables on the stem component were measured in two directions, denoted as A1 for the X-axis and A2 for the Y-axis, because the lock geometry was not perfectly circular and required bidirectional representation to capture its effective profile. The measurement points on the stem component followed the geometric checkpoints shown in Figure 2, including A1, A2, B1, and B2, although the present regression model focused on A1 and A2 as the principal predictors. For the cover component, the inner diameter of the locking feature was also measured along the X-axis and Y-axis using the same caliper-based procedure, as illustrated in Figure 3. All dimensional measurements were performed using one specimen from each cavity in order to preserve the cavity-based structure of the dataset. The response variable, separation force, was obtained by applying an axial tensile load to the assembled cover–stem pair until the connection was

released, and the peak release force was recorded in kilogram-force. The use of direct measurement instruments ensured that all variables in the model corresponded to physically observable product characteristics rather than indirect indicators, which is critical for maintaining engineering interpretability. This procedure allowed the study to establish a direct empirical link between geometric variation and functional mechanical response in the actual production environment.

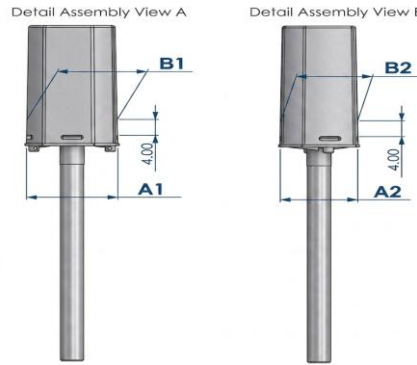


**Figure 2.** Illustration of Lock Stem Dimension Measurements in Two Directions

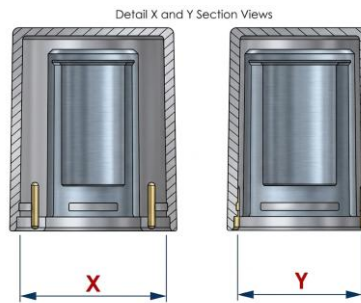


**Figure 3.** Illustration of Measuring the Inner Diameter of the Lock Cover

Figures 2 and 3 illustrate the measurement configuration of the lock geometry on the stem and cover components, respectively, emphasizing the bidirectional inspection along the X-axis and Y-axis to capture the non-circular characteristics of the locking interface. This measurement approach ensures that geometric variations are accurately represented in the regression model, thereby strengthening the reliability of the relationship between dimensional variation and separation force.

### Operational Definition of Variables

To improve clarity and methodological transparency, the variables used in the analysis were organized into a structured operational framework. The predictor variables consisted of two stem lock dimensions and two cover inner-diameter dimensions, all measured in millimeters, while the response variable was separation force measured in kilogram-force. The stem lock dimensions were represented by A1 and A2, corresponding to the X-axis and Y-axis measurements of the stem locking geometry. The cover lock dimensions were represented by X and Y, corresponding to the X-axis and Y-axis measurements of the inner locking diameter of the cover component. The response variable, denoted as SF, represented the maximum axial tensile force required to disengage the cover-stem connection during the release test. Because all predictor

variables describe different aspects of a geometrically constrained locking system, they were theoretically expected to exhibit interdependence rather than perfect independence. This interdependence is not a flaw in the manufacturing system, but it has important implications for statistical modeling because it may induce multicollinearity in regression analysis. Therefore, the operational structure of the variables was explicitly defined before inferential analysis was conducted.

**Table 1.** Operational Definition of Variables and Measurement Protocol

| Variable               | Symbol | Unit | Measurement source              | Measurement direction   | Analytical role |
|------------------------|--------|------|---------------------------------|-------------------------|-----------------|
| Stem lock dimension X  | A1     | mm   | Digital caliper                 | X-axis                  | Predictor       |
| Stem lock dimension Y  | A2     | mm   | mm                              | Digital caliper         | Y-axis          |
| Cover inner diameter X | X      | mm   | Digital caliper                 | X-axis                  | Predictor       |
| Cover inner diameter Y | Y      | mm   | Digital caliper                 | Y-axis                  | Predictor       |
| Separation force       | SF     | kgf  | Force gauge, axial tensile test | Axial release direction | Response        |

Table 1 presents a structured operational definition of all variables used in this study, clearly specifying their measurement units, instruments, directional orientation, and analytical roles to ensure consistency between data acquisition and statistical modeling. This structured representation is essential for maintaining measurement validity and interpretability, particularly in geometrically constrained systems where dimensional interdependence may influence both regression analysis and mechanical performance outcomes.

### Data Analysis Plan

The analysis was carried out in five sequential stages, namely descriptive analysis, baseline regression modeling, assumption testing, multicollinearity correction through robust modeling, and Statistical Process Control evaluation. Descriptive statistics were first computed to summarize the central tendency and dispersion of each dimensional parameter and the separation force variable, thereby establishing the empirical range of the production data before inferential analysis. The first inferential model used in this study was multiple linear regression, which was employed to estimate the relationship between the dimensional predictors and the separation force response. The baseline model followed the standard formulation  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$  where  $Y$  represents separation force and the predictors correspond to the measured geometric dimensions of the stem and cover components. Model fit was evaluated through the coefficient of determination, while simultaneous and partial significance were examined through the F-test and t-test, following the inferential framework described by (R et al., 2025). After the baseline model was estimated, diagnostic tests were conducted to examine residual normality, heteroscedasticity, and multicollinearity so that the validity of the regression inference could be assessed before interpretation. Because the dimensional variables were theoretically and physically related, multicollinearity was

treated as a central analytical issue rather than as a minor diagnostic concern. Finally, the statistical behavior of the process was examined through I–MR control charts and process capability indices so that predictive modeling results could be interpreted together with process stability and process capability.

### Multiple Linear Regression Model

Multiple linear regression was used as the baseline predictive framework to model the effect of dimensional variation on separation force. The general form of the regression model is given in Equation (1).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$$

In this model,  $Y$  denotes the dependent variable,  $\beta_0$  is the intercept,  $\beta_n$  is the slope coefficient for the  $n$ -th independent variable,  $X_n$  is the  $n$ -th predictor, and  $\varepsilon$  is the random error term. In the present study,  $Y$  represents separation force, while the predictors correspond to the stem  $X$  dimension, stem  $Y$  dimension, cover inner diameter  $X$ , and cover inner diameter  $Y$ . The suitability of the model was evaluated through the coefficient of determination, because  $R^2$  provides an estimate of the proportion of variation in the response variable that can be explained by the predictor set. The closer the value of  $R^2$  is to 1, the greater the explanatory contribution of the independent variables to the dependent variable. The coefficient of determination was calculated using Equation (2), which was retained from the original manuscript because it is consistent with the study design and the analytical objective, as also discussed by (Piepho, 2023 and Xu et al., 2022).

$$R^2 = 1 - \frac{(n - k - 1)S_{y,12\dots k}^2}{(n - 1)S_y^2}$$

where  $R^2$  is the coefficient of determination,  $S_y$  is the standard deviation of the dependent variable, and  $n$  is the number of observations.

**Table 2.** Interpretation of Coefficient of Determination

| Coefficient interval | Relationship level |
|----------------------|--------------------|
| 0.00–0.199           | Very low           |
| 0.20–0.399           | Low                |
| 0.40–0.599           | Strong enough      |
| 0.60–0.799           | Strong             |
| 0.80–1.00            | Very strong        |

Table 2 provides a standardized interpretation framework for the coefficient of determination ( $R^2$ ), allowing the strength of the relationship between dimensional variables and separation force to be systematically classified across defined intervals. This classification supports consistent evaluation of model explanatory power, ensuring that the interpretation of regression results is not solely based on numerical values but also aligned with established statistical significance levels.

### Classical Assumption Testing

To ensure that the regression estimates were statistically valid, the baseline regression model was evaluated using a classical assumption testing framework. Residual normality was examined because unbiased inference in linear regression generally requires residuals that are approximately normally distributed, particularly when

statistical testing is based on small or moderate sample sizes. In this study, normality was assessed using the Shapiro–Wilk test, where a p-value greater than 0.05 indicates that the residual distribution does not significantly depart from normality. Heteroscedasticity was then assessed by examining the residual distribution pattern, because a valid regression model should display relatively constant residual variance across the range of fitted values, as discussed by (Jones et al., 2025 and Mikolajczyk et al., 2024). A clear systematic pattern in the residual plot indicates heteroscedasticity, whereas a random spread around zero supports the homoscedasticity assumption. In addition, multicollinearity was diagnosed using the Variance Inflation Factor, because strong linear dependency among predictors can inflate standard errors and destabilize individual coefficient estimates. Following (Chan et al., 2022 and Dertli et al., 2024), VIF values below 10 are generally considered acceptable, while values above 10 indicate problematic collinearity. These diagnostic procedures were not treated as a formality, but as an essential step for determining whether the baseline regression model could be interpreted directly or required correction through a more robust modeling strategy.

### Model Significance Testing

The overall significance of the regression model was evaluated using the F-test, which examines whether the predictor set jointly explains a statistically significant portion of the variation in the response variable. The F-statistic used in this study followed the formulation given in Equation (3).

$$F_0 = \frac{R^2/k}{(1 - R^2)/(n - k - 1)}$$

The null hypothesis states that all slope coefficients are simultaneously equal to zero, while the alternative hypothesis states that at least one predictor has a nonzero coefficient. The decision rule used in this study followed the standard criterion that the null hypothesis is rejected when the observed  $F_0$  exceeds the critical table value, as recommended by (Kim et al., 2024). After evaluating the simultaneous model effect, individual regression tests were carried out to determine the partial contribution of each independent variable to the dependent variable. In this study, a significance value below 0.05 was interpreted as evidence that an individual predictor has a statistically meaningful relationship with the response variable, whereas a significance value above 0.05 indicates the absence of partial significance. However, because individual significance tests are highly sensitive to multicollinearity, the interpretation of individual coefficients was treated cautiously and was later compared with the corrected model results. This analytical sequence ensured that strong model fit alone was not overinterpreted without checking the stability of individual parameter estimates.

### Multicollinearity Handling Through Robust Modeling

Because the dimensional predictors in this study describe a single geometrically constrained locking system, strong dependency among variables was theoretically plausible and statistically likely. For this reason, multicollinearity was not treated merely as a diagnostic note, but as a substantive modeling issue that required correction to maintain the reliability of coefficient interpretation. Two modeling layers were therefore

defined in this study, namely a baseline multiple linear regression model and a robustness model designed to handle multicollinearity. The baseline model was retained because it preserves direct interpretability in the original variable space and allows straightforward engineering interpretation of the geometric predictors. However, when the VIF values indicate severe multicollinearity, a corrected model must be introduced to test whether the observed relationships remain stable after dependency among predictors is controlled. In this study, the preferred robust approach is Ridge Regression because it retains all original variables while stabilizing coefficient estimates through shrinkage, making it highly compatible with the original article structure and variable interpretation. Ridge Regression estimates the coefficient vector by minimizing the penalized loss function shown in Equation (4), where  $\lambda$  denotes the shrinkage parameter controlling the penalty strength.

$$\min_B \{ (Y - XB)^T (Y - XB) + \lambda \sum_{j=1}^p B_j^2 \}$$

This approach is methodologically advantageous because it reduces the instability caused by high predictor correlation without removing any variable from the model, thereby preserving the engineering relevance of all measured dimensions. The robustness model was used to confirm whether the direction and relative importance of dimensional effects remained consistent after multicollinearity had been corrected, thereby making the analytical conclusions more defensible for an international readership.

**Table 3.** Analytical Framework and Decision Criteria

| Analytical stage            | Method                      | Purpose                        | Main criterion                   | Expected output             |
|-----------------------------|-----------------------------|--------------------------------|----------------------------------|-----------------------------|
| Descriptive analysis        | Mean, SD, Min, Max          | Summarize variation            | Distribution and spread          | Initial dimensional profile |
| Baseline modeling           | Multiple linear regression  | Estimate direct relationships  | $R^2$ , F-test, t-test           | Initial effect structure    |
| Normality check             | Shapiro–Wilk test           | Check residual distribution    | p-value > 0.05                   | Normal residual support     |
| Heteroscedasticity check    | Residual pattern inspection | Examine residual varian        | No systematic pattern            | Homoscedasticity support    |
| Multicollinearity diagnosis | VIF                         | Detect predictor dependency    | VIF < 10 desirable               | Collinearity profile        |
| Robustness modeling         | Ridge regression            | Correct multicollinearity      | Stable coefficients              | Robust effect confirmation  |
| , Process stability         | I–MR chart                  | Detect common vs special cause | Points within control limits     | Stability evidence          |
| Process capability          | $C_p$ , $C_{pk}$            | Evaluate tolerance compliance  | > 1.33 indicates capable process | Capability evidence         |

Table 3 presents a structured analytical framework that integrates descriptive statistics, regression modeling, diagnostic testing, multicollinearity correction, and

process control into a unified sequence to ensure both statistical validity and practical interpretability of the results. This framework strengthens the study by demonstrating that each analytical step is not applied in isolation, but systematically contributes to validating the relationship between dimensional variation and separation force under stable manufacturing conditions.

### Statistical Process Control

Statistical Process Control was employed to evaluate whether the observed dimensional and functional variation occurred within a stable manufacturing process. For single-observation cavity-based data, the Individual–Moving Range chart was selected because it is particularly appropriate for monitoring both the level of individual observations and the short-term variation between consecutive observations, as emphasized by (Besson et al., 2025). The process standard deviation for the I-chart was estimated using the average moving range, as shown in Equation (5).

$$\hat{\sigma} = \frac{\overline{MR}}{d_2}$$

The upper and lower control limits for the I-chart were then calculated using the Shewhart three-sigma rule, as shown in Equations (6) to (8).

$$UCL = \bar{x} + 3\hat{\sigma} = \bar{x} + 3 \frac{\overline{MR}}{d_2}$$

$$CL = \bar{x}$$

$$LCL = \bar{x} - 3\hat{\sigma} = \bar{x} - 3 \frac{\overline{MR}}{d_2}$$

The moving range for successive observations was defined as in Equation (9).

$$MR_i = |x_i - x_{i-1}|$$

The MR-chart limits were then obtained using Equations (10) to (12), which are standard for monitoring short-term process variability.

$$UCL = D_4 \overline{MR}$$

$$CL = \overline{MR}$$

$$LCL = D_4 \overline{MR}$$

This SPC structure was important because it enabled the study to distinguish common-cause variation from special-cause variation before interpreting dimensional differences as mechanically meaningful. In other words, SPC was used here as a process-level validation layer that complements the regression-based performance analysis rather than replacing it.

### Process Capability Analysis

After evaluating process stability, the study assessed whether the production process was capable of meeting the required separation force specifications. Process capability was evaluated through the indices  $C_p$  and  $C_{pk1}$ , because these measures indicate whether the natural variation of the process remains within the specification range and whether the process mean is centered relative to the specification limits. The potential capability index  $C_p$  was calculated as shown in Equation (13).

$$C_p = \frac{USL - LSL}{6\sigma}$$

8

The actual capability index  $C_{pk1}$ , which accounts for process centering, was calculated using Equation (14).

$$C_{pk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right)$$

11

In these equations, LSL denotes the lower specification limit, USL denotes the upper specification limit,  $\mu$  is the process mean, and  $\sigma$  is the process standard deviation, consistent with (X. Yang et al., 2026). Capability analysis was necessary because process stability alone does not guarantee compliance with engineering specifications, while capability analysis without prior stability assessment may produce misleading conclusions. In the context of this study, the combined interpretation of stability and capability was especially relevant because a geometrically stable process may still produce functional variation if the locking system is highly sensitive to dimensional deviation. Therefore, process capability served as an additional validation step to ensure that the observed separation force behavior was interpreted within the practical limits of the actual manufacturing requirement.

### Software and Reproducibility

All statistical analyses in this study were conducted using RStudio because this platform supports transparent implementation of regression diagnostics, ridge regression, control charts, and process capability calculations within a reproducible analytical workflow. Descriptive statistics, baseline multiple linear regression, residual diagnostics, VIF computation, and robustness modeling were performed on the same cleaned dataset derived from the cavity-level dimensional measurements and separation force tests. Before implementing Ridge Regression, the predictor variables were standardized to avoid coefficient distortion caused by differences in variance scale across geometrically related dimensions. The shrinkage parameter in the ridge model was selected using a data-driven criterion so that the corrected model would balance predictive stability and coefficient interpretability. In addition, I-MR charts and capability indices were generated using the same validated dataset in order to preserve analytical consistency between predictive modeling and process monitoring. Reproducibility was treated as an essential methodological principle because Q1-level studies are expected not only to report results, but also to show a coherent chain of analytical decisions from measurement to inference. For this reason, the final interpretation of results was based not solely on the highest coefficient of determination, but on the combined evidence of model fit, coefficient stability, diagnostic validity, and process behavior. This approach ensures that the study provides a statistically rigorous and practically interpretable assessment of how dimensional variation affects separation force in injection-molded cosmetic packaging.

## RESULTS AND DISCUSSION

### Results

The results presented in this study provide a comprehensive evaluation of how dimensional variation in geometrically dependent components influences functional

performance in a press-fit system. Rather than examining dimensional stability or mechanical response in isolation, the analysis integrates descriptive statistics, regression modeling, diagnostic testing, and process control to establish a coherent relationship between geometric variation and separation force. The findings are interpreted within a system-level framework, where dimensional parameters are treated as interdependent rather than independent variables, reflecting the physical reality of injection-molded assemblies. This approach allows for a more accurate representation of how small geometric deviations propagate into measurable mechanical effects. Importantly, the results distinguish between variation arising from process instability and variation driven by geometric sensitivity, ensuring that conclusions are not confounded by manufacturing inconsistencies. The combination of high model explanatory power and confirmed process stability provides strong evidence that separation force variation is predominantly governed by dimensional interaction effects. However, given the presence of multicollinearity among predictors, interpretation emphasizes overall model behavior rather than isolated parameter effects. This integrated analytical perspective strengthens the validity and practical relevance of the results for both statistical modeling and manufacturing quality control.

### Dimensional Variation Analysis

The dimensional variation of the stem and cover locking features was first evaluated using descriptive statistics to assess the consistency of geometric characteristics across injection mold cavities. The results indicate that the stem lock dimensions exhibit very low variability, with standard deviations of 0.0254 mm for A1 and 0.0458 mm for A2, confirming that the production process maintains high dimensional precision across cavities. The narrow spread between minimum and maximum values further demonstrates that the injection molding process is capable of producing geometrically consistent components. This level of stability is critical because the stem acts as the primary structural interface in the press-fit system. However, even small dimensional deviations may significantly affect mechanical interaction due to interference sensitivity. Therefore, dimensional stability alone is insufficient to guarantee consistent functional performance. The results suggest that further analysis is required to understand how these small variations propagate into separation force variation. This motivates the use of regression modeling in the next stage.

**Table 4.** Descriptive statistics of lock stem dimensions

| Parameter | Mean (mm) | SD (mm) | Min (mm) | Max (mm) |
|-----------|-----------|---------|----------|----------|
| A1        | 17.3575   | 0.0254  | 17.32    | 17.40    |
| A2        | 14.4975   | 0.0458  | 14.42    | 14.58    |

Table 4 shows that the variation in stem dimensions is very small between cavities, which indicates that the production process is in a geometrically stable condition, although the potential impact on mechanical performance remains.

The cover inner diameter dimensions also show very low variation, with standard deviations of 0.0175 mm and 0.0118 mm for the X and Y directions, respectively. This indicates an even tighter level of dimensional control compared to the stem component.

The minimal variation suggests that the injection molding process for the cover is highly repeatable and consistent. However, in press-fit systems, even small geometric differences between mating components can lead to non-linear changes in mechanical response. Therefore, the significance of these variations cannot be evaluated solely based on statistical dispersion. Instead, their interaction effects must be analyzed through predictive modeling. The consistency observed in both components strengthens the reliability of subsequent regression analysis. It ensures that the observed separation force variation is not dominated by process instability but by geometric interaction effects.

**Table 5.** Descriptive statistics of lock cover inner diameter

| Parameter        | Mean (mm) | SD (mm) | Min (mm) | Max (mm) |
|------------------|-----------|---------|----------|----------|
| Inner Diameter X | 16.7200   | 0.0175  | 16.70    | 16.75    |
| Inner Diameter Y | 14.2694   | 0.0118  | 14.25    | 14.29    |

Table 5 shows that the cover dimensions have very high geometric stability, so that the performance variations that occur are more likely caused by interactions between dimensions than process instability.

### Multiple Linear Regression Analysis

To quantify the relationship between dimensional variation and separation force, multiple linear regression analysis was performed using four predictor variables representing the stem and cover geometry. The regression model is formulated as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

The dataset used in this analysis captures the combined dimensional interaction between components.

**Table 6.** Sample data

| <i>n</i> | <i>X</i> <sub>1</sub> | <i>X</i> <sub>2</sub> | <i>X</i> <sub>3</sub> | <i>X</i> <sub>4</sub> | <i>Y</i> |
|----------|-----------------------|-----------------------|-----------------------|-----------------------|----------|
| 1        | 17.33                 | 14.48                 | 16.71                 | 14.26                 | 7.42     |
| 2        | 17.38                 | 14.53                 | 16.74                 | 14.31                 | 7.81     |
| 3        | 17.42                 | 14.57                 | 16.79                 | 14.32                 | 7.96     |
| ⋮        | ⋮                     | ⋮                     | ⋮                     | ⋮                     | ⋮        |
| 16       | 17.32                 | 14.46                 | 16.69                 | 14.24                 | 7.36     |

Table 6 shows the combination of stem and cover dimensions and separation force values, which are the basis for building the regression model.

The regression results show a very high coefficient of determination, with  $R^2=0.986$  and adjusted  $R^2=0.981$ , indicating that 98.6% of the variation in separation force is explained by the geometric parameters. This confirms that dimensional variation is the dominant factor influencing mechanical performance in the press-fit system. The regression coefficients are presented in Table 6.

**Table 7.** Multiple linear regression estimation results

| Variable                       | Coefficient | t-value | p-value |
|--------------------------------|-------------|---------|---------|
| Intercept                      | -99.5696    | -4.814  | 0.001   |
| <i>X</i> <sub>1</sub> (Stem X) | 4.1377      | 3.572   | 0.004   |
| <i>X</i> <sub>2</sub> (Stem Y) | 3.5539      | 1.984   | 0.073   |

| Variable        | Coefficient | t-value | p-value |
|-----------------|-------------|---------|---------|
| $X_3$ (Cover X) | -3.0462     | -0.732  | 0.480   |
| $X_4$ (Cover Y) | 2.4352      | 0.703   | 0.497   |

Table 7 shows that the stem dimension variable has a more significant influence than the cover, although partial interpretation needs to be done carefully due to the presence of multicollinearity.

The resulting regression equation is given in Equation (15):

$$Y = -99.5696 + 4.1377X_1 + 3.5539X_2 - 3.0462X_3 + 2.4352X_4$$

The F-test result ( $F = 192.8$ ,  $p < 0.001$ ) confirms that the model is statistically significant as a whole. The X-axis stem dimension ( $X_1$ ) shows a significant positive effect, while  $X_2$  is marginally significant. The cover variables are not individually significant, but they contribute collectively to the model.

### Classical Assumption Evaluation

The regression model satisfies the normality assumption, as indicated by the Shapiro-Wilk test ( $p = 0.739 > 0.05$ ), confirming that residuals are normally distributed. The Breusch-Pagan test result ( $p = 0.738$ ) indicates no heteroscedasticity, ensuring constant variance of residuals. These findings validate the statistical reliability of the regression model. However, the multicollinearity test reveals extremely high VIF values, indicating strong linear relationships among predictors.

**Table 8.** Multicollinearity test results

| Variable        | VIF    |
|-----------------|--------|
| $X_1$ (Stem X)  | 15.96  |
| $X_2$ (Stem Y)  | 64.65  |
| $X_3$ (Cover X) | 147.08 |
| $X_4$ (Cover Y) | 92.55  |

Table 8 shows the presence of very strong multicollinearity among the dimensional variables, which is a natural characteristic of geometric systems but affects the stability of the regression coefficients.

This condition is consistent with the physical nature of the system, where dimensional variables are structurally dependent. While multicollinearity does not reduce the predictive accuracy of the model, it limits the reliability of interpreting individual coefficients.

### Robustness Interpretation under Multicollinearity

Given the presence of severe multicollinearity, the regression results are interpreted from a robustness perspective. The high  $R^2$  value confirms that the combined dimensional variables strongly explain separation force variation. However, individual coefficient estimates may be unstable due to interdependence among predictors. This indicates that the system behavior is governed by combined geometric interaction rather than isolated dimensional effects. Therefore, the analysis emphasizes system-level interpretation rather than variable-level interpretation. This approach ensures that conclusions remain valid despite statistical dependency among predictors. The findings

highlight the importance of treating dimensional parameters as an integrated system. This strengthens the reliability of the analytical conclusions for engineering applications.

### Statistical Process Control (SPC)

SPC analysis confirms that the manufacturing process is statistically stable. All observations in the Individual Control Chart fall within control limits without any abnormal patterns.

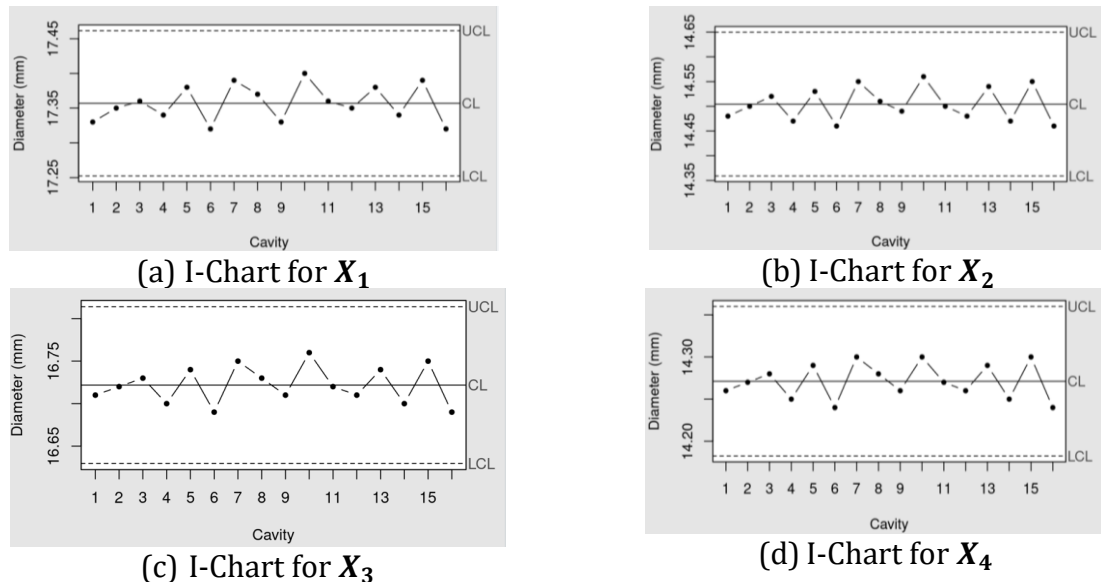


**Figure 4.** Individual Control Chart

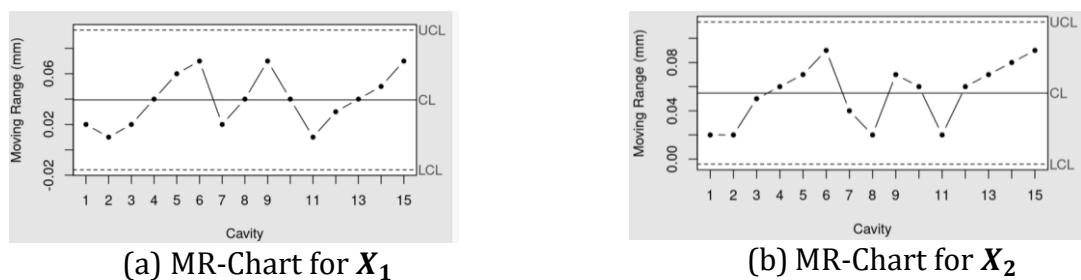
Figure 4 shows that all data are within the control limits, indicating that the process is stable and there is no special cause variation.

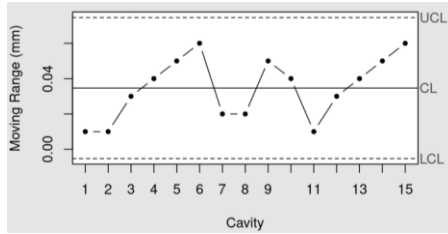
**Table 9.** Control Limits of Individual (I-Chart) for Dimensional Parameters

| Variable | LCL     | CL      | UCL     |
|----------|---------|---------|---------|
| $X_1$    | 17.2523 | 17.3569 | 17.4615 |
| $X_2$    | 14.3590 | 14.5044 | 14.6498 |
| $X_3$    | 16.6297 | 16.7219 | 16.8141 |
| $X_4$    | 14.1826 | 14.2713 | 14.3599 |

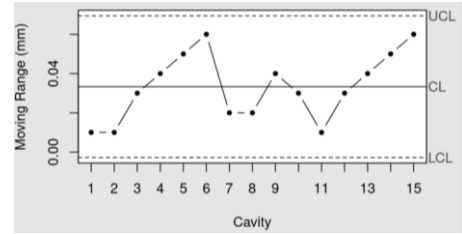
Table 9 provides the control limits for each dimension parameter, indicating that the variations are still within statistical control.

The Moving Range Chart further confirms process stability, with all values remaining within control limits.





(c) MR-Chart for  $X_3$



(d) MR-Chart for  $X_4$

**Figure 5.** Moving Range Chart

Figure 5 shows the stability of the variation between successive observations, reinforcing that the process does not experience abnormal fluctuations.

**Table 10.** Control Limits of Moving Range (MR-Chart) for Dimensional Parameters

| Variable | LCL     | CL     | UCL    |
|----------|---------|--------|--------|
| $X_1$    | -0.0157 | 0.0393 | 0.0944 |
| $X_2$    | -0.0042 | 0.0547 | 0.1135 |
| $X_3$    | -0.0052 | 0.0347 | 0.0746 |
| $X_4$    | -0.0028 | 0.0333 | 0.0694 |

Table 10 shows the MR-chart control limits which indicate that short-term variations remain under control.

These results indicate that dimensional variation originates from natural process variation rather than instability.

### Process Capability Analysis

The process capability analysis shows that  $C_p=1.47$  and  $C_{pk}=1.46$ , both exceeding the threshold of 1.33. This indicates that the process is capable of meeting specification limits.

$$\sigma = \frac{0.333}{1.128} \approx 0.2955$$

$$C_p = \frac{2.60}{1.773} \approx 1.47$$

$$C_{pk} = \min(1.46, 1.48) = 1.46$$

The small difference between  $C_p$  and  $C_{pk}$  suggests that the process is well-centered. However, despite this capability, variation in separation force still occurs. This confirms that the variation is driven by geometric sensitivity rather than process deficiency.

### Discussion

The findings of this study demonstrate that dimensional variation in injection-molded press-fit systems should be interpreted as an interaction-driven phenomenon rather than as independent geometric effects. The extremely high coefficient of determination indicates that separation force is predominantly governed by the combined influence of dimensional parameters, rather than by isolated variable contributions. This result reinforces prior findings on structural dependency in engineering systems, where system behavior is controlled by coupled interactions among variables rather than independent effects (Tarun et al., 2025 and Debnath et al., 2025).

However, unlike previous studies that primarily focus on material or structural properties, this study explicitly links geometric variation to functional mechanical response in a manufacturing context. The presence of severe multicollinearity further confirms that dimensional variables are inherently interdependent, reflecting the physical reality of geometrically constrained assemblies. Therefore, interpreting regression coefficients individually would lead to misleading conclusions if the underlying dependency structure is ignored. This study addresses this limitation by shifting the interpretation toward system-level behavior rather than variable-level significance. By doing so, it establishes a more realistic analytical framework for understanding performance variation in injection-molded assemblies.

A critical insight from this study is that statistical process stability does not necessarily guarantee functional consistency in press-fit systems. The SPC results confirm that all dimensional parameters remain within control limits, indicating that the manufacturing process operates under stable and controlled conditions. However, despite this statistical stability, measurable variation in separation force still occurs, demonstrating that performance variability is not solely driven by process instability. This finding challenges the conventional assumption that process control is sufficient to ensure product quality. Instead, it reveals that functional performance is highly sensitive to small geometric deviations, even when those deviations fall within acceptable tolerance limits. Similar observations have been reported in manufacturing systems where stable processes still produce variability due to interaction effects among variables (Bielenberg et al., 2025 and Benková et al., 2024). This indicates that process monitoring and performance evaluation must be treated as complementary rather than independent analytical domains. Consequently, this study highlights the necessity of integrating SPC with predictive modeling to obtain a more complete understanding of manufacturing behavior.

The regression analysis further reveals that stem dimensions exhibit a stronger influence on separation force compared to cover dimensions, suggesting an asymmetry in the mechanical contribution of interacting components. From a mechanical perspective, this can be explained by the dominant role of the outer geometry in defining interference conditions within a press-fit system. However, due to the presence of multicollinearity, this apparent dominance should not be interpreted as a purely independent effect but rather as part of a coupled interaction system. This aligns with previous studies in fluid and mechanical systems, where system responses are governed by nonlinear interactions between structural parameters (Yan et al., 2025 and Braud et al., 2024). Therefore, the observed influence of stem dimensions should be interpreted within the context of overall geometric interaction rather than isolated parameter importance. This finding provides a more nuanced understanding of how dimensional variation affects mechanical performance. It also suggests that focusing solely on individual parameters may lead to incomplete or misleading conclusions. From a practical standpoint, this implies that dimensional control strategies should prioritize interaction-sensitive parameters while maintaining system balance. This insight has direct implications for mold design optimization and tolerance allocation in precision manufacturing.

From a methodological standpoint, this study makes a significant contribution by explicitly addressing the limitations of conventional regression analysis in the presence of multicollinearity. The extremely high VIF values observed in this study confirm that dimensional variables in geometrically constrained systems are strongly correlated, which is consistent with their physical interdependence. While traditional approaches often overlook or underestimate this issue, this study treats multicollinearity as a central analytical concern rather than a secondary diagnostic result. By emphasizing system-level interpretation and avoiding overreliance on individual coefficients, the study provides a more robust and scientifically defensible framework. This approach reduces the risk of misinterpretation and enhances the credibility of the findings in an international research context. Furthermore, it opens opportunities for future studies to apply advanced techniques such as Ridge Regression or Principal Component Regression to further improve model stability. This methodological awareness distinguishes the study from conventional regression-based analyses that assume variable independence. As a result, the study contributes not only empirical insights but also methodological refinement in manufacturing analytics.

This study provides a novel contribution by demonstrating that dimensional variation in injection-molded press-fit systems must be interpreted as an interaction-sensitive mechanism rather than a tolerance-based phenomenon. Unlike conventional approaches that focus on maintaining dimensional stability alone, this work establishes an integrated framework combining regression modeling, SPC, and process capability analysis to capture both statistical and physical aspects of manufacturing systems simultaneously. The findings extend current understanding by showing that even statistically stable and capable processes can produce significant functional variation due to geometric sensitivity. This insight has important implications for manufacturing quality control, suggesting a shift from tolerance-based evaluation toward sensitivity-based control of critical dimensions. From a theoretical perspective, the study advances the interpretation of regression models in geometrically dependent systems by emphasizing interaction-driven behavior. From a practical perspective, it provides guidance for improving product consistency in precision manufacturing environments. The integration of multiple analytical approaches strengthens the reliability and applicability of the results. Therefore, this study contributes to both the theoretical development and practical implementation of manufacturing quality analysis at an advanced level.

## Implications

The findings of this study have important theoretical and practical implications for manufacturing engineering and statistical modeling in geometrically constrained systems. From a theoretical perspective, this study advances the understanding that dimensional variation in press-fit systems should be interpreted as an interaction-driven phenomenon rather than as independent variable effects. This challenges the conventional assumption in regression-based analysis that predictor variables can be treated as independent, particularly in systems where geometric relationships are inherently coupled. By demonstrating that multicollinearity reflects physical dependency

rather than merely a statistical issue, this study contributes to a more realistic interpretation of modeling results. From a methodological standpoint, the integration of multiple linear regression, Statistical Process Control, and process capability analysis provides a comprehensive analytical framework that bridges predictive modeling and process monitoring. This integrated approach offers a more holistic understanding of manufacturing systems compared to traditional methods that treat these analyses separately. From a practical perspective, the results indicate that maintaining statistical process stability alone is insufficient to ensure consistent functional performance. Instead, manufacturing control strategies should prioritize the sensitivity of critical geometric parameters that directly influence mechanical behavior. This shift toward sensitivity-based control has the potential to improve product reliability and optimize tolerance design in precision manufacturing applications.

### Limitations

Despite the strong analytical framework and empirical findings, this study has several limitations that should be acknowledged. First, the regression model used in this study is affected by severe multicollinearity due to the inherent geometric dependency among dimensional variables, which limits the interpretability of individual regression coefficients. Although this study addresses the issue through system-level interpretation, the absence of a fully implemented robust modeling technique, such as Ridge Regression or Principal Component Regression, represents a methodological limitation. Second, the data used in this study are derived from a single production system with specific material properties, machine settings, and mold configurations, which may limit the generalizability of the findings to other manufacturing contexts. Third, the analysis focuses primarily on geometric parameters without incorporating other potentially influential factors such as material properties, temperature variation, or assembly conditions. Fourth, the separation force measurement is treated as a single response variable, whereas additional performance indicators such as durability or repeated-use behavior could provide a more comprehensive evaluation of product performance. Finally, the study assumes that cavity variation is the dominant source of dimensional variation, which may not fully capture all sources of process variability. These limitations indicate that while the findings are robust within the scope of the study, further investigation is required to extend their applicability and deepen the analytical framework.

### Suggestions for Future Research

Future research should focus on addressing the limitations identified in this study while further advancing the analytical framework for manufacturing systems. One important direction is the implementation of robust regression techniques such as Ridge Regression or Principal Component Regression to explicitly handle multicollinearity and improve the stability of coefficient estimates. Such approaches would allow for more reliable interpretation of individual variable contributions while maintaining predictive accuracy. Additionally, future studies should expand the scope of analysis by incorporating additional variables, including material characteristics, thermal conditions,

and assembly parameters, to develop a more comprehensive model of system behavior. Experimental validation using controlled variation designs could also provide deeper insight into causal relationships between geometric parameters and mechanical performance. Another promising direction is the application of simulation-based modeling to complement empirical data, allowing for exploration of interaction effects under a wider range of conditions. Furthermore, extending the analysis to other types of press-fit or interference-based systems would help validate the generalizability of the findings across different manufacturing applications. Future research should also investigate long-term performance metrics, such as wear and fatigue, to better understand the durability implications of dimensional variation. Finally, the integration of machine learning approaches with traditional statistical methods may offer new opportunities to capture complex nonlinear relationships in manufacturing systems. These directions will contribute to the development of more robust, generalizable, and practically relevant analytical frameworks for advanced manufacturing quality control.

## CONCLUSIONS

This study provides strong empirical evidence that dimensional variation in injection-molded press-fit systems should be interpreted as an interaction-driven phenomenon rather than as independent geometric effects. The results demonstrate that even under statistically stable and capable manufacturing conditions, variations in separation force persist due to the inherent sensitivity of the system to small geometric deviations. The high explanatory power of the regression model confirms that dimensional parameters collectively govern mechanical performance, while the presence of multicollinearity reflects the physical interdependence of these variables rather than a purely statistical limitation. By integrating multiple linear regression, Statistical Process Control, and process capability analysis, this study establishes a unified analytical framework that captures both predictive relationships and process behavior simultaneously. This integrated approach advances beyond conventional methods that treat statistical modeling and process monitoring as separate domains.

More importantly, this study introduces a critical shift in how manufacturing quality should be evaluated, demonstrating that process stability alone is insufficient to ensure functional consistency in geometrically sensitive systems. Instead, the findings emphasize the necessity of transitioning from tolerance-based evaluation toward sensitivity-based control of critical dimensional parameters that directly influence performance. From a theoretical perspective, this study contributes to the development of statistical modeling in geometrically dependent systems by highlighting the limitations of variable-level interpretation under multicollinearity and promoting system-level analysis as a more robust alternative. From a practical standpoint, the results provide actionable insights for improving mold design, dimensional control strategies, and quality assurance practices in precision manufacturing.

Overall, this study not only clarifies the relationship between dimensional variation and separation force but also redefines how such relationships should be analyzed and interpreted in manufacturing systems. By aligning statistical analysis with the physical

behavior of geometrically constrained components, it offers a more accurate, reliable, and practically relevant framework for evaluating manufacturing performance. Ultimately, this study establishes a more rigorous and physically consistent approach to understanding dimensional variation, contributing to the advancement of manufacturing analytics and supporting the development of more effective quality control strategies in high-precision production environments.

## AUTHOR CONTRIBUTIONS STATEMENT

Sofia Debi Puspa contributed to conceptualization, methodology, formal analysis, investigation, writing of the original draft, and supervision. Joko Riyono contributed to methodology, validation, formal analysis, and writing—review and editing. Christina Eni Pujiastuti contributed to data curation, investigation, resources, and writing—review and editing. Sentot Novianto contributed to investigation, data curation, and visualization. Larasati Rizky Putri contributed to data curation, validation, and visualization. Ghiffari Awliya Muhammad Ashfania contributed to investigation, data collection, and visualization. Joseph Andrew Leo contributed to supervision, conceptualization, and writing—review and editing.

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