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Optimizing Performance of the Statapult® Device Using Lean Six Sigma

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Abstract

This study focuses on optimizing the performance of the Statapult®, a device widely used for teaching statistical concepts and process control, by applying Lean Six Sigma's DMAIC framework. The project was motivated by the critical need to address the device's performance inconsistencies, which disrupted training accuracy and negatively impacted learning outcomes. Over the past six months, the Statapult® exhibited variability in launch distances, averaging 6.45 feet ± 0.88 feet, far from the desired target of 8 feet ± 1 foot. A systematic approach was adopted to identify and address key variables, such as launch angle, ball type, operator technique, and equipment stability. Through structured problem-solving and the implementation of targeted solutions, including optimal angle settings, standardized processes, and stable base enhancements, the study achieved consistent performance improvements. This research highlights the efficacy of Lean Six Sigma in resolving variability, enhancing reliability, and ensuring the long-term sustainability of educational tools.

Keywords
DMAIC, SIPOC, ANOVA, FMEA, Process Capability

1. Introduction
In the era of data-driven decision-making, Lean Six Sigma has emerged as a cornerstone methodology for enhancing process efficiency and reducing variability. This research paper explores the application of the DMAIC framework to address performance inconsistencies in a Statapult® device.The Statapult®, a widely used tool for teaching statistical concepts and process control, has faced growing challenges in maintaining consistent performance, impacting its efficacy in educational and professional training environments. This research focuses on optimizing the Statapult's performance using Lean Six Sigma techniques, a methodology renowned for its structured approach to reducing variability and improving process efficiency. The motivation for this research stems from the critical role the Statapult plays in developing practical, hands-on understanding of statistical methods. However, recent inconsistencies in launch distances, averaging 6.45 feet ± 0.88 feet, have disrupted training reliability, negatively influencing learning outcomes. Addressing these challenges is essential to enhance its utility as a training device and meet client specifications of an average launch distance of 8 feet with a standard deviation of less than 1 foot. This study explores innovative solutions to standardize performance, minimize variability, and ensure sustainable improvements, contributing to broader applications of Lean Six Sigma in educational tools.

1.1 Objectives
The primary objective of this project is to optimize the performance of the Statapult®, a device integral to a California-based professional training institute's curriculum on statistical concepts, process control, and performance measurement. Over the past six months, the Statapult® has faced significant performance issues, characterized by inconsistent launch distances averaging 6.45 feet ± 0.88 feet, adversely affecting training accuracy and reliability.

Using the Six Sigma DMAIC framework, this project aims to systematically reduce variability, enhance process stability, and achieve an average launch distance of 8 feet with a standard deviation of less than 1 foot. By analyzing key factors such as launch angle, ball type, operator technique, and equipment stability, the project seeks to deliver actionable solutions that align the device's performance with the institute's training objectives, ensuring improved learning outcomes for students and professionals. This holistic approach also emphasizes sustainability through standardized processes and training protocols.

2. Literature Review

The Six Sigma DMAIC (Define, Measure, Analyze, Improve, and Control) method has emerged as a transformative approach for improving operational efficiency, reducing defects, and enhancing customer satisfaction across various industries. By focusing on data-driven problem-solving and continuous improvement, Six Sigma enables organisations to optimize processes while achieving measurable results. This review explores the diverse applications of DMAIC, highlighting its methodologies, outcomes, and challenges in sectors ranging from manufacturing to automotive and service industries.Six Sigma, DMAIC in Manufacturing has been a prime area for the implementation of Six Sigma, where reducing defects and improving quality is critical. Smętkowska and Mrugalska (2018) demonstrated how DMAIC improved production quality by systematically addressing inefficiencies in a production process. Their study highlighted the use of statistical tools to identify root causes, leading to significant defect reduction and process optimisation. Correspondingly, Mittal et al. (2023) analysed the impact of DMAIC in an Indian manufacturing firm, focusing on reducing rejection rates for rubber weather strips used in automobiles. By implementing DMAIC, the company achieved a 43% reduction in defects and improved sigma levels from 3.9 to 4.45.

This case underscores the method's ability to deliver tangible cost savings and enhance process stability. In Portugal, Marques and Matthé (2017) illustrated how a small-to-medium enterprise successfully adopted DMAIC to improve the performance of an aluminium die-casting operation. The study emphasized the importance of management support and team collaboration, which were crucial for identifying and addressing the root causes of defects. This example highlights the versatility of DMAIC in addressing quality challenges, even in resource-constrained environments. The integration of Lean principles with Six Sigma has gained traction as organizations seek to combine the benefits of speed and waste reduction with defect minimization. Andersson et al. (2014) explored the joint application of Lean and Six Sigma in a Swedish telecom manufacturing firm. The study found that while Six Sigma enhanced process stability by eliminating variability, Lean principles accelerated workflows and minimized wastage. Together, these approaches resulted in more flexible, robust, and cost-efficient processes. However, the authors noted that achieving agility required additional measures such as staff training and cultural transformation, reflecting the complexity of integrating these methodologies.

DMAIC's adaptability is evident in its successful application across various industries. Sharma et al. (2018) applied the method in the automobile industry to reduce defects in a shock absorber component. Their efforts improved sigma levels from 2.67 to 4.11 and increased process yields by over 10%, showcasing how DMAIC can drive substantial performance improvements in high-precision manufacturing.In the textile industry, Gupta (2013) employed DMAIC to enhance yarn quality by addressing defects in the winding department. This study emphasized the use of source analysis and statistical tools to streamline production processes and reduce defects, demonstrating the method's relevance even in non-engineering sectors. Correspondingly, Setiawan (2020) documented the use of DMAIC to reduce defects in roof panel packaging at an automotive manufacturing firm. Through targeted improvements such as better operator supervision and anti-rust measures, the company achieved a significant reduction in defect rates, increasing its sigma level from 3.33 to 4.37.

While Six Sigma is widely adopted in large enterprises, its implementation in smaller organizations and developing countries presents unique challenges. Marques and Matthé (2017) highlighted the role of leadership and team dynamics in the successful execution of a Six Sigma project in a Portuguese SME. The study revealed that clear communication, goal alignment, and training were critical for overcoming resource constraints. Correspondingly, Setiawan (2020) demonstrated the method's effectiveness in an Indonesian automotive firm, illustrating its global applicability and adaptability to diverse operational contexts.Despite its success, Six Sigma DMAIC is not without challenges. Andersson et al. (2014) noted that smaller firms often struggle with resource limitations, which can hinder the implementation of data-intensive methodologies. Even more than that, Marques and Matthé (2017) emphasized the need for more research into the long-term sustainability of Six Sigma initiatives, particularly in dynamic industries. Future studies could explore the integration of emerging technologies such as artificial intelligence and machine learning to enhance the efficiency and accuracy of DMAIC processes.The reviewed studies affirm Six Sigma DMAIC's transformative potential in driving quality improvement across sectors. By integrating data-driven analysis with structured problem-solving, the method enables organizations to achieve measurable results in cost reduction, defect minimization, and process efficiency. Its adaptability to diverse industries and operational contexts makes it a vital tool for achieving operational excellence. Future research should focus on leveraging technological advancements to address the method's limitations and expand its applicability to emerging industries.

3. DMAIC Methodology

The DMAIC methodology, rooted in Lean Six Sigma, is a structured approach to process improvement aimed at enhancing efficiency, reducing variability, and defects. DMAIC stands for Define, Measure, Analyze, Improve, and Control, outlining the five phases critical to its application.

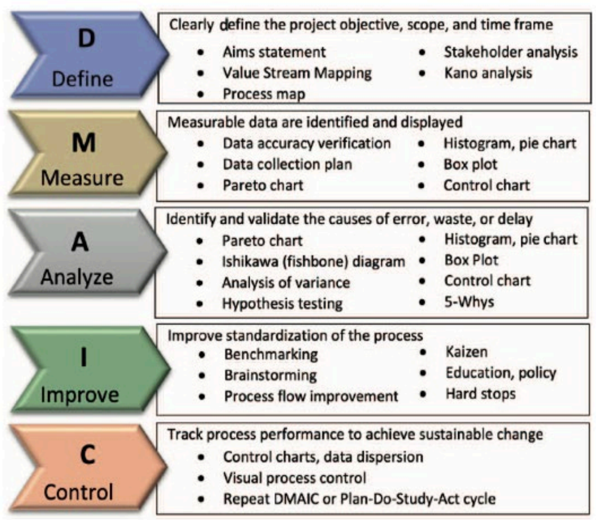


Figure 1. DMAIC Methodology

In the Define phase, project goals, scope, and objectives are clearly identified, aligning stakeholders toward a common aim. The Measure phase involves collecting and validating data to establish a performance baseline using tools like control charts and Pareto diagrams. During Analyze, root causes of inefficiencies, defects, or waste are uncovered through cause-and-effect methods like Ishikawa diagrams and 5-Whys. In the Improve phase, solutions are implemented to address these root causes, emphasizing team collaboration and iterative improvement strategies like Kaizen. Finally, Control ensures sustainability by monitoring performance and preventing regression through process controls and regular reviews. This robust methodology drives lasting improvements across industries, including manufacturing and healthcare.

4. Case Study

A California-based training institute specializing in statistical training encountered significant performance challenges with their Statapult® device, a key tool for teaching statistical concepts. The device exhibited inconsistent launch distances, averaging 6.45 feet ± 0.88 feet, which disrupted training accuracy and negatively impacted learning outcomes. To address this, we employed the DMAIC (Define, Measure, Analyze, Improve, Control) methodology to systematically identify and resolve the root causes of variability.This case study focuses on leveraging DMAIC principles to optimize the performance of the Statapult® device. The project aimed to identify critical factors influencing variability, establish a robust data collection plan, and develop actionable improvements to meet specific performance criteria. Through thorough analysis, the study explored interactions among variables such as launch angle, ball type, and operator handling to formulate process enhancements. This structured approach ensures a replicable methodology for resolving variability in educational tools, ultimately enhancing training effectiveness and reliability.

4.1 Define

The define phase of this case study establishes the foundational understanding and scope of the project, highlighting the significance of optimizing the Statapult® device for a California-based training institute. The client relies heavily on this device to teach statistical concepts; however, performance inconsistencies, particularly in launch distances, have negatively impacted the learning outcomes and training reliability. The device demonstrated an average launch distance of 6.45 feet with a standard deviation of 0.88 feet, necessitating a systematic approach to improve performance.

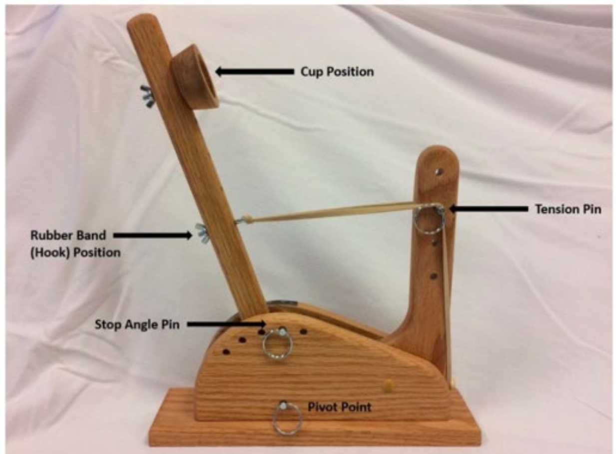


Figure 2. Variables in Statapult® device

This phase identifies the key objective of reducing variability and achieving a target launch distance of 8 feet ±1 foot to meet training specifications. A comprehensive project charter and SIPOC analysis were developed to clarify the inputs, processes, and stakeholders involved. Critical factors such as launch angle, ball type, and operator handling were preliminarily identified for further analysis. The define phase sets the stage for systematic problem-solving using Six Sigma methodologies.

Project Charter

Problem Statement

A California-based training institute is facing performance issues with their Statapult used in their employee training program, with an average launch distance of 6.45 feet and variability of upto 0.88 feet. This problem has persisted for 6 months, affecting training effectiveness and overall outcomes.

Business Case & Benefits

Optimizing the Statapult® launch settings will significantly enhance the effectiveness of the training program by improving performance consistency and maximizing launch distance. Achieving a target of 8 feet consistently, by reducing variability will lead to more reliable training results, improved learning experiences, and higher participant satisfaction, driving overall process efficiency.

Goal Statement

The goal is to increase the average launch distance from 6.45 feet to 8 feet, with a standard deviation of less than 1 foot, by 4th December 2024

Timeline

Phase	Planned Completion Date	Actual
Define:	2nd Oct 2024	2nd Oct 2024
Measure:	23rd Oct 2024	6th Nov 2024
Analyze:	6th Nov 2024	6th Nov 2024
Improve:	4th Dec 2024	4th Dec 2024
Control:	4th Dec 2024	4th Dec 2024

Indicator

Average Launch Distance for every 10 observations

Team Members

Position	Name	% of Time
Team Member	Falguni Pande	30%
Team Member	Saurabh Raghuwanshi	30%
Team Member	Gaurav Gujjeti	30%
Stakeholder	Dr.Abolghasem Sepideh	10%

Figure 3. Project Charter

This diagram represents the SIPOC model for the Statapult® experiment. It shows the flow from suppliers, such as the professor providing the Statapult® kit and team members performing the experiment, to inputs like measurement tools and training materials. The process involves setting up the apparatus, conducting the experiment, and recording results. The output includes the distance traveled by the projectile and the statistical reports generated, with the customers being the project stakeholders, team members, and end users like trainees.

The Process flowchart outlines the process of the Statapult® experiment, starting with the assembly of the device and setting variables like launch angle, ball type, and operators. The experiment progresses by loading and launching the ball, measuring the distance, collecting data, and repeating the process. The final step involves documenting the results in a report.

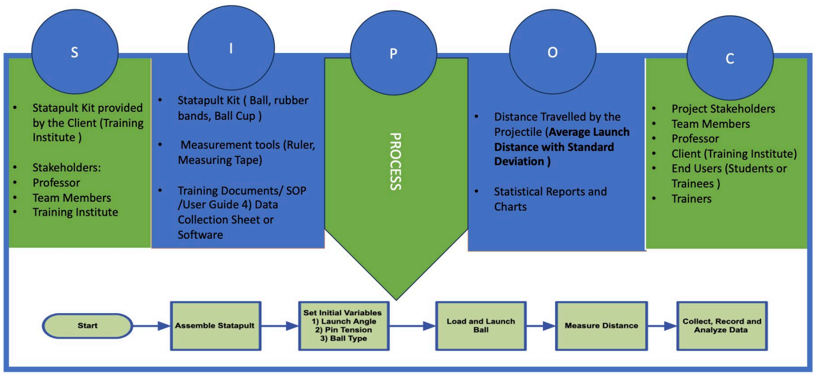


Figure 4. SIPOC Analysis and Process flowchart

4.1 Measure

The Measure phase in the DMAIC process establishes a baseline of current performance, allowing teams to quantify and understand the key metrics influencing outcomes. In this project, the primary focus is on accurately measuring the Statapult® launch distance and identifying sources of variability. By carefully defining metrics like average distance and standard deviation, this phase provides a clear view of existing performance. The data collected here serves as a foundation for evaluating improvements in later stages, offering insights into critical factors affecting consistency. This structured approach ensures the accuracy and reliability of the baseline, guiding effective future interventions.

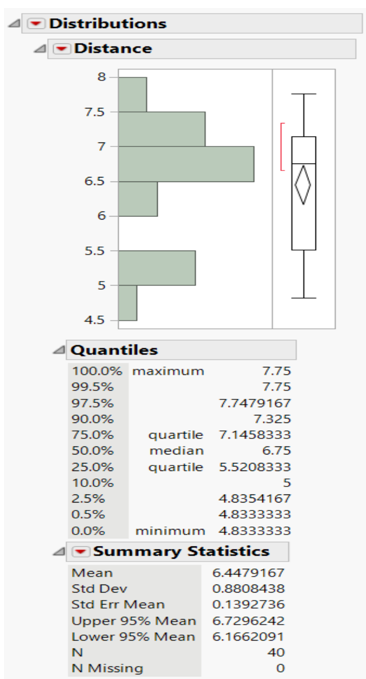
Figure 5. Statapult® Device Assembly

This phase focuses on systematic data collection and precise quantification of inconsistencies in the launch distances. Key activities and findings in the measure phase include:

Key Metrics:
1. Mean: Average Launch distance measured from the Statapult® base to the projectile's landing point.
2. Standard Deviation (Variability) : Standard deviation to assess distance variation for each observation.

Data Collection Plan:
The Data Collection Plan defines how data was systematically gathered to understand the current performance of the Statapult® device. By carefully controlling variables and ensuring consistency in the setup, this plan aims to capture reliable data that reflects true process behavior.Purpose of Data Collection Plan: To systematically capture reliable data on how launch distance is affected by angle, tension, and ball type. This structured approach allows us to establish a performance baseline and identify areas for improvement.

Key Components:
1. Two critical variables were evaluated: launch angle (110° and 140°) and ball type (light and heavy).
2. Two Operators to perform the data collection plan.
3. Consistent factors, such as pull-back tension and cup position, were controlled.
4. A sample size of 40 observations (10 trials for each setup) was collected to ensure data reliability.



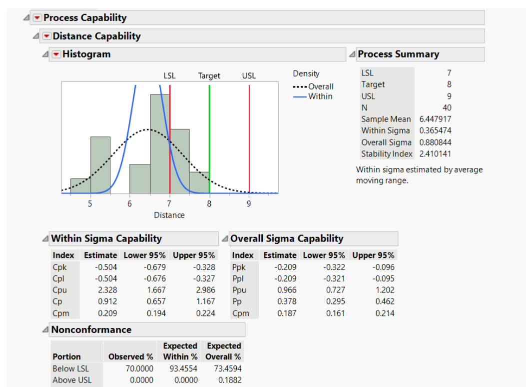


Figure 6. Descriptive Analysis

Figure 7. Process Capability Analysis

- Mean Distance: 6.45 feet, indicating the average launch distance. (Serves as a baseline for performance measurement)
- Median (50%): 6.75 feet (Indicates the central value of the data and skewness if any)
- Standard Deviation: 0.88 feet (Indicates the variability in the launch distances)

Range:
- Maximum: 7.75 feet
- Minimum: 4.83 feet

(Highlights the extent of variation/inconsistency observed in the launches)

Quartiles:
- 25% of the launches are below 5.52 feet, and 75% are below 7.15 feet.

Confidence Interval:
- With 95% confidence interval, the average launch distance is expected to fall between 6.17 and 6.73 feet.

Process Capability Analysis:
Cp and Cpk Values: The process capability indices Cp and Cpk were calculated to evaluate how well the Statapult® can perform within the specified limits.

- Cp (Process Capability Index): This value assesses the potential capability assuming the process is centered. A low Cp indicates that the process variability is too high to consistently meet specifications.
- Cpk (Process Capability Performance Index): This value measures how well the process average aligns with the target. A low Cpk suggests that the mean launch distance is not close to the desired target (8 feet)

Process Capability Insights:

- Cp Value (0.912): Indicates that the process has potential but lacks adequate control to meet specifications consistently.
- Cpk Value (-0.504): Shows the process is off-center, with many values falling below the Lower Specification Limit (LSL).
- Nonconformance Rate: 70% of launches fall below the LSL, reflecting a significant portion of defective outputs.
- Overall Sigma Capability (Pp and Ppk): Pp (0.378) and Ppk (-0.209) highlight poor overall process performance, requiring immediate improvement.
- Target Range Compliance: The process struggles to achieve the desired target of 8 feet $\pm$ 1 foot, emphasizing the need for adjustments in setup and consistency.

Key Insights:

1. Significant Variability in Launch Distances: The data reveals considerable inconsistency in launch distances, making it difficult to consistently meet the target of 8 feet, and highlighting the need for process stabilization.
2. Process Capability Deficiencies: Low Cp and Cpk values demonstrate that the Statapult® device struggles to operate within specification limits high nonconformance rates (70% below specifications), emphasizing the urgency for process optimization and improvement.
3. Impact of Key Variables: Initial analysis identifies critical factors such as launch angle, ball type, and operator handling as major contributors to variability, indicating a need for stricter controls and process standardization (SOP's).

Challenges:

1. Inconsistent Launch Distances:
   Significant variability arises from factors such as operator handling, inconsistent setups, and uncontrolled environmental conditions, leading to unpredictable results.
2. Measurement Errors:
   Potential inaccuracies in measuring distances, caused by manual methods or the absence of standardized measurement procedures, compromise data reliability.
3. Unclear Variable Interactions:
   Limited understanding of the interaction between critical variables (e.g., launch angle, ball type, tension) complicates identifying root causes of variability.
4. Non-Optimized Process Settings:
   Current settings are not sufficiently refined to produce consistent results within the desired specifications, limiting process performance.
5. Insufficient Sample Size:
   A dataset of 40 observations may not adequately capture process behavior, reducing the reliability of statistical conclusions.
6. Operator Dependency:
   Variations in technique and execution between operators (Operator 1 and Operator 2) affect process repeatability and reproducibility, creating inconsistency.

4.2 Analyze

The Analyze phase is crucial in identifying and understanding the root causes of performance issues affecting the Statapult® device. Using tools like process mapping, fishbone diagrams, and ANOVA, this phase examines the variables influencing launch distance and consistency. Key factors, including launch angle, ball type, and operator handling, are analyzed to determine their impact on variability. By systematically breaking down potential causes, the team can focus on high-impact areas that contribute most to inconsistencies. Insights from this phase provide a data-driven foundation for targeted improvements, ensuring that adjustments in subsequent phases directly address underlying performance issues.A detailed process map was created to visualize the operational steps, enabling the identification of inconsistencies and inefficiencies.

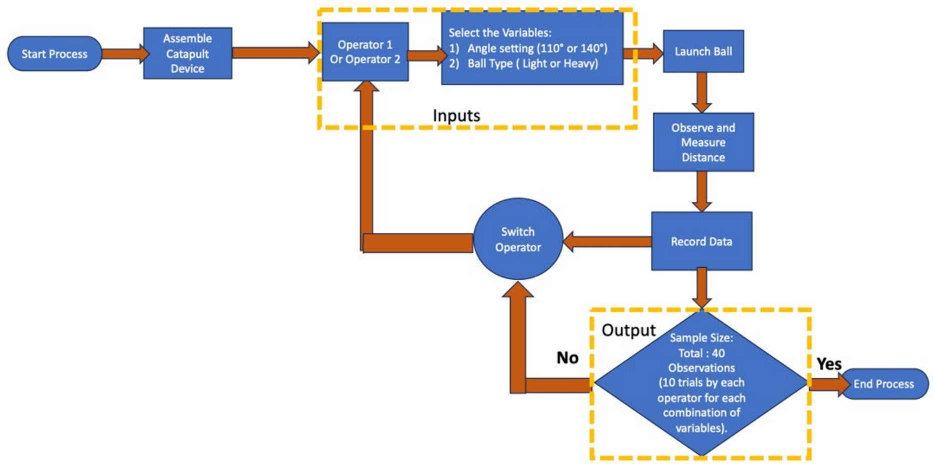


Figure 8. Detailed Process Map

A fishbone diagram (Ishikawa) was employed to systematically categorize potential sources of variability, including operator handling, equipment setup, environmental factors, and inconsistencies in materials. Through this root cause analysis, critical factors such as launch angle, ball type, and operator handling were identified as key contributors to performance variability. These insights provided the foundation for targeted improvements in subsequent phases.

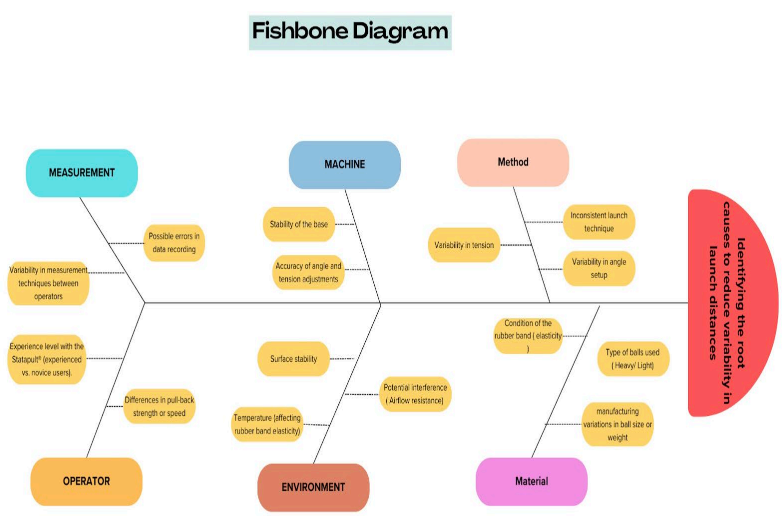


Figure 9. Fishbone Diagram (Ishikawa)

ANOVA, or Analysis of Variance, was utilized in the Analyze phase to identify the critical factors affecting the performance of the Statapult® device. By comparing variability within groups (e.g., specific angle and ball type settings) and between groups, ANOVA uncovered statistically significant contributors to launch distance variability. The analysis revealed that the launch angle and ball type were the most impactful variables, with their interaction showing a significant combined effect on performance. These insights enabled the team to reject the null hypothesis that factors had no effect on launch distance and guided targeted process improvements to achieve the desired consistency and accuracy in the device's operation.

This statistical analysis revealed significant main effects and interaction effects between variables, particularly the interplay between launch angle and ball type.

Statistical Analysis (ANOVA):

- Main Effects: Impact of individual factors such as angle and ball type on the launch distance.
- Interaction Effects: Combined impact of variables, such as how angle and ball type together affect the outcome.

Summary of Fit

RSquare	0.862417
RSquare Adj	0.850952
Root Mean Square Error	0.340065
Mean of Response	6.447917
Observations (or Sum Wgts)	40

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	26.096354	8.69878	75.2202
Error	36	4.163194	0.11564	Prob > F
C. Total	39	30.259549		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.4479167	0.053769	119.92	<.0001*
Angle[110]	0.4895833	0.053769	9.11	<.0001*
Ball Type[Heavy Ball]	0.3354167	0.053769	6.24	<.0001*
Angle[110]*Ball Type[Heavy Ball]	-0.547917	0.053769	-10.19	<.0001*

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Angle	1	1	9.587674	82.9066	<.0001*
Ball Type	1	1	4.500174	38.9139	<.0001*
Angle*Ball Type	1	1	12.008507	103.8400	<.0001*

Figure 10. ANOVA Analysis

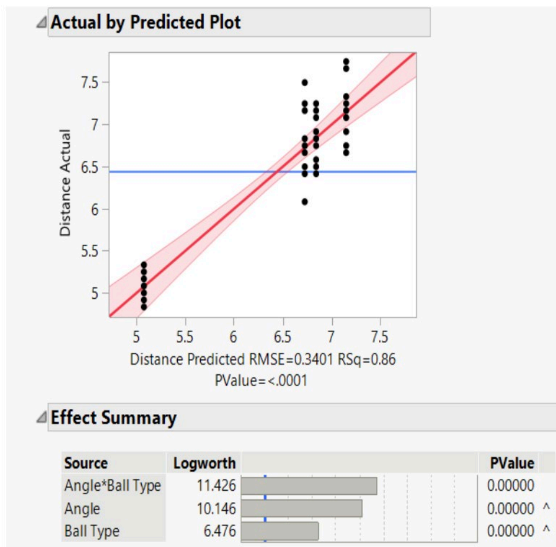


Figure 11. ANOVA Analysis

Parameter Estimates:

- Intercept (6.4479): Baseline mean launch distance when other factors are at their reference levels.
- Angle [110°] (0.4896): A significant positive impact on launch distance, indicating that increasing the angle improves performance.
- Ball Type [Heavy Ball] (0.3354): Heavy ball tend to increase the launch distance compared to lighter ones.
- Interaction (Angle [110°] * Ball Type [Heavy Ball]) (-0.5479): Negative interaction suggests that using a heavy ball at a 110° angle reduces the launch distance, highlighting the complexity of variable interactions.

Model Fit: The Actual vs. Predicted plot shows a strong alignment of data points along the diagonal line, indicating that the model predicts launch distances accurately with an R^2 value of 0.86 and a low RMSE of 0.3401. This confirms the model's robustness in explaining the variability.

Effect Significance: Highlights the most influential factors on launch distance.

- Angle * Ball Type Interaction (Log worth: 11.426): This is the most significant effect, indicating a strong dependency between the angle and ball type in determining the outcome.

- Angle (Log worth: 10.146): A critical factor individually impacting launch distance.
- Ball Type (Log worth: 6.476): Significant but less impactful than the angle and its interaction with the ball type.

P-Value:

Ho = Everything is occurring By Chance (no factor influencing)
Ha = Factors (angle, ball type and their interaction) are responsible for affecting launch distance

ANOVA Results:
- Ball Type: $p < 0.0001$
- Angle: $p < 0.0001$
- Interaction Ball Type * Angle: $p < 0.0001$

Conclusion: P value < Alpha (0.05) : Reject Null hypothesis

The model fit, with an R^2 value of 0.86 and a low Root Mean Square Error (RMSE) of 0.34, confirmed the robustness of the findings. P-values for all variables and their interactions were less than 0.0001, leading to the rejection of the null hypothesis, which posited no significant factor influence. These results validated the need for process standardization and provided a scientific basis for selecting the most impactful improvements in the subsequent phases of the project.

Overall Insights gained from ANOVA Analysis:

Critical Variables Identified:
- Launch angle and ball type are the most influential factors impacting launch distance.
- The interaction between angle and ball type significantly affects launch distance.
- The model has the capability to achieve the target launch distance but demands for optimization of the process and controlling the variables effectively.

Statistical Evidence of Influence:
ANOVA results (p-values < 0.0001 for angle, ball type, and their interaction) confirm that these factors significantly impact launch distances. The null hypothesis Ho (factors have no effect) is confidently rejected.

Observation: "Using Heavy Ball and increasing the angle more than 110 can help achieve better results"

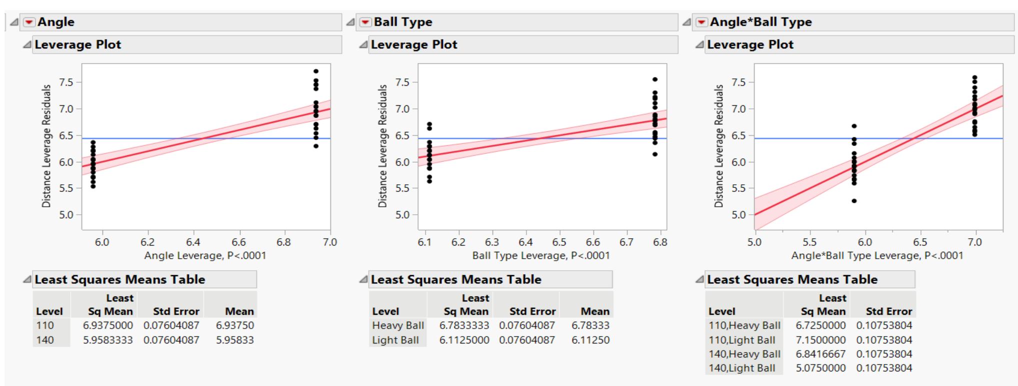


Figure 12. ANOVA Analysis

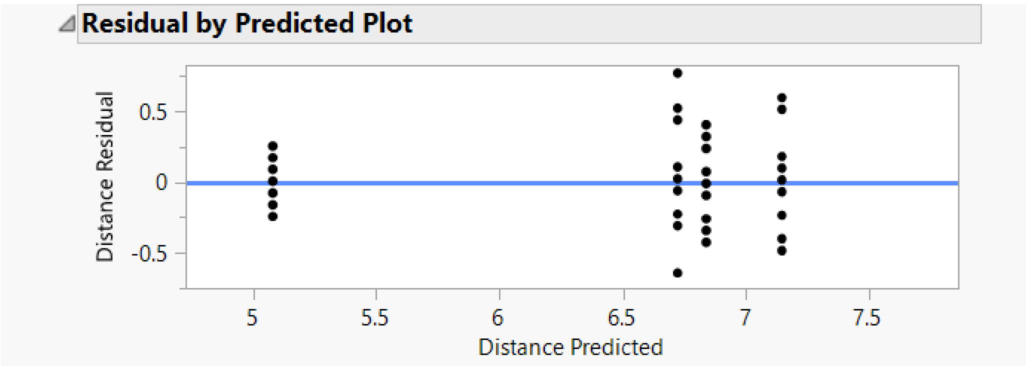


Figure 13. ANOVA Analysis

4.3 Improve

The Improve phase of this case study shows that implementing targeted interventions significantly enhances the performance and consistency of the Statapult® device. Based on insights from the Analyze phase, key process parameters were adjusted to reduce variability and achieve the desired outcomes. The first step involved Brainstorming all the possibilities to reduce the variability in the launch distances recorded in the Measure Phase. Next step is to evaluate all the solutions based on their feasibility, cost, time constraints, sustainability, risks, effectiveness, and impact using Impact-Effort Matrix or Pugh Decision Matrix. In this case study, we have used Impact-Effort Matrix. After evaluating all the solutions, select the baseline solution and develop a Design of Experiment followed by FMEA.

Brainstorming: Objective: Generate potential solutions to reduce variability in the Statapult® launch distance and improve process consistency.

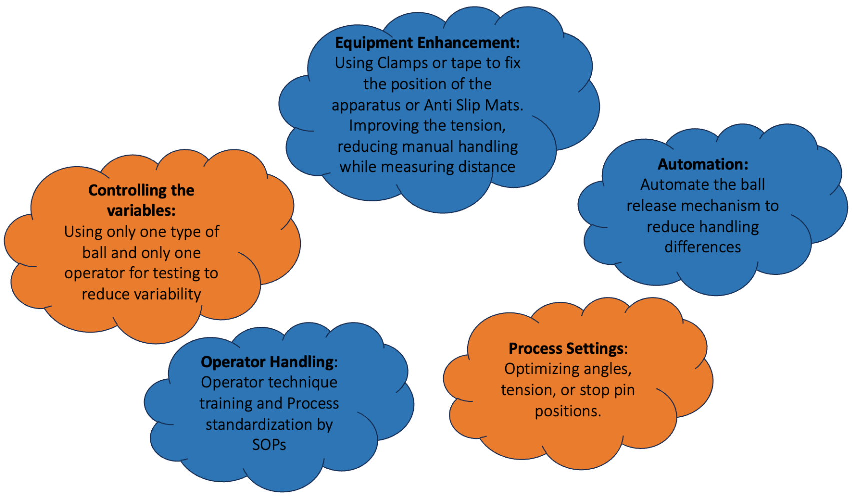
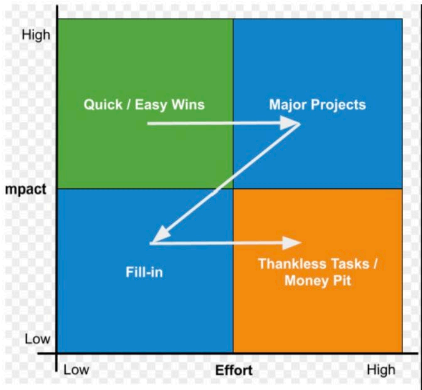


Figure 14. Brainstorming

Impact-Effort Matrix:



1. Using one ball type and fixing one operator to reduce variability, experimenting on an angle range from 110 to 140 deg 2. Clamping Catapult to Floor using tape for Base Stability	1. Hold Lever for 10 Seconds Before Release: Requires training but provides consistent results. 2. Operator Training and Standardization: Moderate effort with sustained impact.
1. Automate Ball Release Mechanism: High effort with limited incremental benefit at this stage. 2. Using Fixing metal Clamps to fix the base	Introduce Digital Measurement for Accuracy: Useful for long-term process improvement but not critical for immediate results.

Figure 15. Impact-Effort Matrix

FMEA: (Failure Modes and Effects Analysis): FMEA is a structured approach used to identify and prioritize potential failure modes within a system, process, or design. It assesses the severity, occurrence, and detection of failures to prioritize risks and implement corrective actions.

Key Steps in FMEA:

1. **Identify Failure Modes:** Understand how a process or component could fail.
2. **Assess Effects:** Determine the impact of these failures on performance or outcomes.
3. **Evaluate Causes:** Pinpoint the root causes of failure.
4. **Assign Scores:**

- **Severity (S):** The impact of the failure (1 = minimal, 10 = catastrophic).
- **Occurrence (O):** The likelihood of the failure happening (1 = rare, 10 = frequent).
- **Detection (D):** The ability to detect the failure before it occurs (1 = easy, 10 = hard).

5. **Calculate Risk Priority Number (RPN):**

- RPN=S×O×DRPN=S×O×D

6. **Develop Action Plans:** Address failure modes with the highest RPNs to reduce risks.

Process Setup	Failure Mode	Effect	Cause	S	O	D	RPN	Action Proposed
Angle Setup	Incorrect Angle Setting	Inconsistent Launch Distances	Operator Error	8	5	7	280	Introduce label markings for the angle setup
Fixing the base	Base Movement	Reduced Stability	Inadequate clamping	7	6	5	210	Use clamps or anti-slip mats
Pull-Back Technique	Variability in strength	Inconsistent Launch Distance	Lack of operator training	6	4	6	144	Train operators for consistent technique
Ball Type Selection	Use of Wrong Ball	Variability in Launch Performance	Lack of standardization	5	3	7	105	Use only heavy balls

Figure 16. FMEA

Key Insights from FMEA:

Angle Setup and Base Stability are Critical:

- These factors have the highest RPN scores, indicating they are the most significant contributors to inconsistencies.
- Addressing these issues can significantly improve launch distance consistency.

Operator Training and Standardization are Essential:

- Proper training and consistent pull-back techniques are necessary to reduce operator-induced variability.

Ball Type Standardization:

- Using the heavy ball consistently minimizes variability and ensures repeatability.

Risk Mitigation Prioritization:

- Focusing on implementing fixes for high RPN items (angle setup and base stability) before addressing lower-priority issues.

Design of Experiment (DoE):

The Design of Experiment (DoE) is a systematic approach used to determine the relationship between factors affecting a process and the output of that process. In this research, DoE was employed to optimize the Statapult®'s performance by analyzing the effects of key variables such as launch angle, ball type, and operator technique. This method allows for precise identification of optimal settings to achieve consistent results. By controlling and testing specific variables while keeping others constant, the DoE approach ensures data-driven decision-making. The insights from this experiment provide a robust foundation for implementing sustainable improvements in process performance.

Step 1) Fixing the Catapult Base using tape.

Step 2) Fixing/ Controlling other variables:

a) Ball Type: Heavy Ball
b) Operator (only one)

Step 3) Variable: Angle (Range)

a) 110 Deg
b) 125 Deg
c) 140 Deg

Step 4) Operating Method:

Holding the Lever (Launch Arm) for 10 seconds, then release

Figure 17. Design of Experiment

5. Results of Experiment:

A Design of Experiments (DoE) approach was utilized to identify optimal settings for launch angle. Three angles: 110°, 125°, and 140° were tested systematically, holding all other variables constant. The results demonstrated that a launch angle of 125° consistently achieved distances closest to the target of 8 feet with minimal variability. This phase also explored improvements in tension control and ball release methods, such as holding the lever for 10 seconds before release to ensure consistency. The findings underscore the effectiveness of targeted process adjustments in achieving the desired specifications and reducing nonconformance rates, setting the stage for sustained improvements in the control phase.

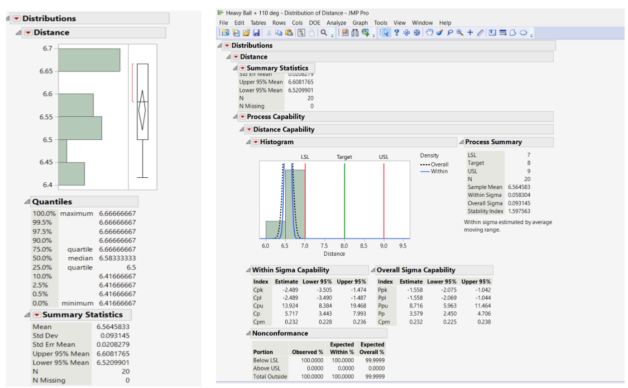
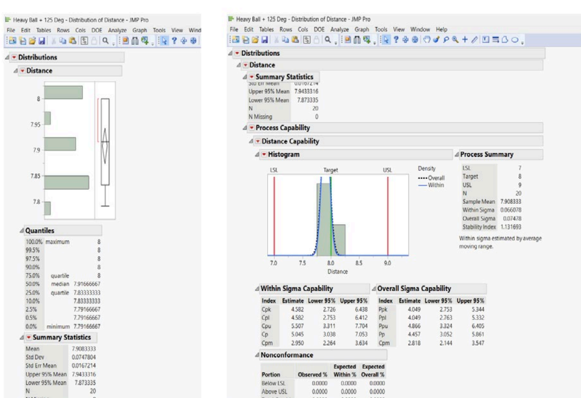


Figure 18. Heavy Ball + 110 Deg Launch Angle



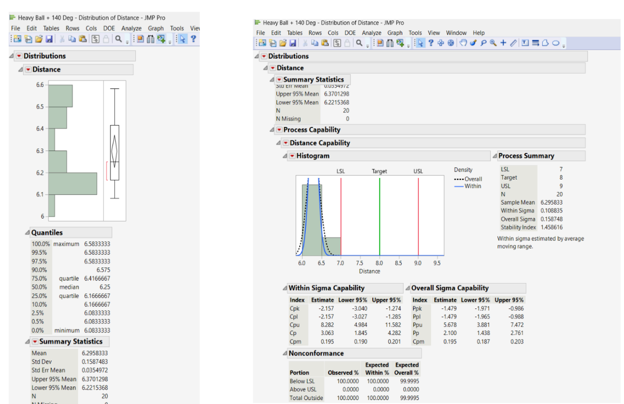


Figure 19. Heavy Ball + 125 Deg Launch Angle Figure 20. Heavy Ball + 140 Deg Launch Angle

Optimal Angle Identified:

- At 125°, the Catapult consistently achieved a distance close to 8 feet with minimal variation.

Compared to other angles:
- 110° resulted in shorter distances (~6.5 feet on average).
- 140° also underperformed (~6.2 feet on average).

Ball Type:
- The heavy ball provided the most consistent results, as lighter balls likely introduced variability due to differences in elasticity and resistance.

Operator Standardization:
- Assigning one operator minimized variability caused by differences in technique, ensuring repeatability of the process.

Stable Base Criticality:
- Fixing the Statapult to the floor using tape significantly reduced movement during launches, enhancing the consistency of results.

Process Optimization:
- A controlled pull-back tension and holding the lever for 10 seconds before release allowed the apparatus to build sufficient momentum, contributing to consistent performance at the 125° angle.

5. Conclusion and Future Work

Conclusion: This case study successfully demonstrates the application of Lean Six Sigma principles through the DMAIC framework to optimize the performance of the Statapult® device. By addressing critical variables such as launch angle, ball type, operator technique, and base stability, the project achieved significant improvements in performance. The optimized settings of a 125° angle with a heavy ball, combined with a stabilized base and standardized operator technique, consistently delivered the target launch distance of 8 feet with minimal variability. These outcomes underline the effectiveness of structured problem-solving methodologies in resolving performance inconsistencies and enhancing reliability in educational tools.

Future Scope: The study opens pathways for further exploration and refinement, including:

- Automation Opportunities: Implementing automated ball release mechanisms for enhanced precision and reduced operator dependency.
- Advanced Data Analysis: Leveraging predictive analytics and machine learning to model and predict performance under varying conditions.
- Broader Applications: Applying similar optimization methodologies to other training tools and educational devices for consistent performance.
- Scalability: Extending the findings to large-scale training programs to evaluate long-term sustainability and impact.

This research provides a replicable model for combining Lean Six Sigma techniques with data-driven insights to address variability and enhance process efficiency.

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Biographies

Falguni Pande is pursuing her Master's in Engineering Management and Manufacturing Systems from California State University, Northridge. She has over seven years of experience in automotive manufacturing, specializing in quality engineering and process improvement. Her work focuses on driving operational efficiency, defect reduction, and process optimization in complex manufacturing environments.With expertise in Lean Six Sigma methodology, she has led multiple projects aimed at achieving measurable improvements in production processes. Her recent work includes exploring innovative applications of DMAIC methodology for optimizing device performance. Falguni combines technical proficiency with strategic problem-solving, ensuring impactful and sustainable solutions in her research and professional endeavors.

Gaurav Gujjeti is currently pursuing a Master's in Engineering Management at California State University, Northridge. He has a strong foundation in engineering principles and specializes in implementing Lean Six Sigma methodologies for process improvement. His academic and professional pursuits focus on applying data-driven approaches to optimize operational performance and enhance decision-making processes.

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