ISRG Journal of Multidisciplinary Studies (ISRGJMS)

ISRG PUBLISHERS

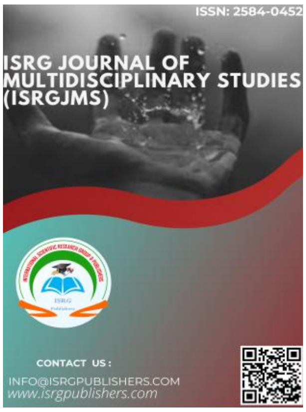
Abbreviated Key Title: isrg j. multidiscip. Stud.

ISSN: 2584-0452 (Online)

Journal homepage: https://isrgpublishers.com/isrgjms/

Volume – III, Issue - III (March) 2025

Frequency: Monthly



Improving Sociological Acceptance of Monitoring Industrial Production Processes Using Median Absolute Deviation

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| **Received:** 08.03.2025 | **Accepted:** 16.03.2025 | **Published:** 18.03.2025

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Abstract

This study investigates the effectiveness and sociological acceptance of Median Absolute Deviation (MAD)-based control charts in monitoring industrial processes. Traditional control charts, such as Shewhart and CUSUM, depend on normality assumptions, making them less effective in detecting variations in non-normal data or environments with outliers. In contrast, MAD-based control charts offer a more robust alternative by enhancing sensitivity to process shifts and minimizing the impact of extreme values. The study explores barriers to adoption, including resistance to change, perceived complexity, and insufficient training. A mixed-methods approach was employed, combining survey responses from 100 stakeholders with a statistical analysis of production data from the Coca-Cola Bottling Company in Ibadan. The analysis utilized descriptive statistics, specifically percentage calculations, and statistical control charts, performed using the R statistical software. Results indicate that MAD-based control charts improve process variability detection and overall quality control compared to traditional methods. However, their adoption is influenced by factors such as training, user familiarity, and managerial support. The study underscores the need for structured training programs, leadership endorsement, and simplified implementation strategies to encourage adoption. It concludes with recommendations for industry-wide acceptance and proposes future research to expand MAD-based monitoring across various manufacturing sectors.

Keywords: *Median Absolute Deviation (MAD), Control Charts, Industrial Monitoring, Technology Adoption, Sociological Acceptance, Statistical Methods.*

DOI: 10.5281/zenodo.15043257

1.0 Introduction

Industrial production processes are critical to modern economies, underpinning the manufacturing, processing, and delivery of goods and services. Maintaining product quality and operational efficiency is essential for achieving business goals and meeting customer expectations. Statistical Process Control (SPC) methods, such as control charts, have traditionally been employed to monitor production processes and detect anomalies. However, these methods often rely on assumptions of normality and are highly sensitive to outliers, rendering them less effective in real-world scenarios characterized by non-normal data distributions or extreme values (Montgomery, 2019).

To address these limitations, robust statistical measures such as the Median Absolute Deviation (MAD) have been introduced. Unlike standard deviation, which is heavily influenced by extreme values, MAD is a non-parametric measure of variability, making it more resilient to outliers (Huber & Ronchetti, 2009). Despite its technical advantages, MAD remains underutilized in industrial quality control, primarily due to sociological barriers such as resistance to change, lack of awareness, and perceived complexity of implementation (Chang et al., 2021).

1.1 Sociological Aspects of Technology Adoption

The adoption of new technologies in industrial settings is influenced by sociological factors such as resistance to change, perceived complexity, and organizational culture. The Technology Acceptance Model (TAM) (Davis, 1989) and Diffusion of Innovations Theory (DOI) (Rogers, 2003) provide frameworks for understanding how perceived usefulness and ease of use affect technology adoption. Social influence, leadership endorsement, and peer support also play critical roles in overcoming resistance to new methods (Venkatesh et al., 2003).

1.2 Traditional Control Charts vs. MAD-Based Charts

Traditional control charts, such as Shewhart and CUSUM charts, assume normality in data distributions and are highly sensitive to outliers (Montgomery, 2005). In contrast, MAD-based charts are more robust and effective in detecting process shifts in non-normal data environments. Empirical studies have demonstrated the superiority of MAD charts in industries such as steel manufacturing and food processing, where data often exhibits skewness or outliers (Runger et al., 2019).

1.3 Sociological Acceptance of MAD-Based Tools

The adoption of MAD-based control charts is influenced by factors such as training, perceived usefulness, and organizational support. Effective training programs, simplification of tools, and leadership endorsement are essential for overcoming resistance and ensuring successful adoption (Zhang & Lee, 2022).

The accurate estimation of standard deviation in production processes is crucial for ensuring quality control and making informed decisions. However, traditional estimation methods may not be suitable when data is contaminated with outliers or has non-normal distributions. The adoption of innovative statistical methods in industrial settings is often hindered not by their technical shortcomings but by sociological resistance from stakeholders. This resistance may stem from inadequate training, fear of disrupting established workflows, or skepticism toward new methodologies. This study seeks to implement robust estimators, such as MAD, for estimating the standard deviation of production processes and to improve the sociological acceptance of MAD as a viable tool for monitoring industrial production processes.

2.0 Aim and Objectives

The aim of this study is to enhance the sociological acceptance of Median Absolute Deviation (MAD) in industrial settings by demonstrating its effectiveness and addressing the factors that influence stakeholder attitudes toward its adoption. The specific objectives are:

1. To develop control charts based on Median Absolute Deviation (MAD).
2. To evaluate the performance of MAD-based charts in comparison with traditional control charts using production process data.
3. To assess the sociological acceptance of MAD-based control charts.

2.1 Hypotheses

H_{01}: MAD-based control charts perform better than traditional SPC methods in detecting process variability and handling outliers.

H_{02}: Sociological factors, such as training, familiarity, and perceived complexity, significantly influence the acceptance of MAD in industrial production monitoring.

H_{03}: Awareness and targeted interventions positively impact the sociological acceptance of MAD-based methodologies in quality control.

3.0 Methodology

The study employs a mixed-methods approach to assess the effectiveness and sociological acceptance of Median Absolute Deviation (MAD)-based control charts in industrial process monitoring. Data collection involved surveys, interviews, and statistical analysis of industrial production data. The survey, targeting production workers, quality control specialists, and managers, focused on resistance to change, perceived complexity, and lack of understanding of MAD charts. Additionally, semi-structured interviews were conducted with key stakeholders to explore adoption barriers and perceptions of effectiveness. A stratified random sampling technique ensured diverse representation, while purposive sampling was used for interviews. Industrial data from Coca-Cola Bottling Company and other manufacturing firms in Nigeria provided real-world insights into MAD-based control chart performance compared to traditional methods.

The statistical analysis cantered on MAD as a robust estimator for process variation. The MAD for a random sample of size n observations $x_{1,}\ x_{2\ ,...,}\ x_n$ is defined as follows:

$$MAD = 1.482median\{|x_i - median(x_i)|\} \qquad (1)$$

Where MAD is the sample median. The statistic $x_1, x_2, \ldots, x_n$ is an unbiased estimator of σ if the random sample $x_1,\ x_2, \ldots, x_n$ are normally distributed. The correction factor b_n is given for different values of n. The main properties of the MAD, is that, it has a maximal 50% breakdown point which is twice as much as the interquartile range, IQR.

Let $x_1, x_2, \ldots, x_n$ be a random sample of size n of independent observations taken at period where i = 1,2, ... the samples are

DOI: 10.5281/zenodo.15043257

assumed to be equal, independent and taken from continuous identical distribution functions. The control limits is defined as

$$UCL = \bar{\bar{X}} + 3\frac{b_{nMAD}}{\sqrt{n}} \quad (2)$$

$$CL = \bar{\bar{X}} \quad (3)$$

$$LCL = \bar{\bar{X}} - 3\frac{b_{nMAD}}{\sqrt{n}} \quad (4)$$

The robust control chart based on the MAD estimator is a chart of subgroup standard deviations in which the control limits for the sake of robustness are set using the median absolute deviation from the sample median (MAD).

The traditional X-bar chart (mean-based control chart) for the given dataset has control limits as follows;

$$UCL = \bar{\bar{X}} + 3\sigma \quad (5)$$

$$CL = \bar{\bar{X}} \quad (6)$$

$$UCL = \bar{\bar{X}} - 3\sigma \quad (7)$$

The study developed MAD-based charts by calculating the median, absolute deviations, and control limits. Performance evaluation focused on process monitoring accuracy, efficiency, and impact on product quality. The findings aimed to demonstrate MAD charts' superiority in detecting process shifts and reducing defects while addressing sociological adoption barriers through training and management endorsement. Ethical considerations ensured participant anonymity and voluntary engagement in the study.

4.0 Analysis, Results and Discussion

This section analyses the study's findings, interpreting the data in relation to the research objectives. The results are presented using tables and figures to highlight key trends.

4.1 Data presentation

A survey of 100 respondents was conducted to evaluate perceptions and experiences with control charts, particularly MAD-based charts compared to traditional methods like Shewhart and CUSUM. Key findings are summarized in *Table 4.1*.

Table 4.1: Tabulated Responses

Question	**Response Options**	**% of Respondents**	**Number of Respondents**
1. Role in the Company	Production Worker	20%	20
	Quality Control Specialist	30%	30
	Production Manager	25%	25
	Data Analyst	15%	15
	Technical Expert	10%	10
2. Years of Experience in the Industry	0-2 years	40%	40
	3-5 years	35%	35
	6-10 years	20%	20
	11+ years	5%	5
3. Educational Background	High School	10%	10
	Associate's Degree	20%	20
	Bachelor's Degree	40%	40
	Master's Degree	20%	20
	PhD	10%	10
4. Familiarity with Control Charts	Very familiar	10%	10
	Somewhat familiar	50%	50
	Not familiar at all	40%	40
5. Perceived Ease of Understanding MAD-based Control Charts	Much easier	20%	20
	Slightly easier	30%	30
	About the same	40%	40
	Slightly harder	10%	10
6. Received Training on MAD-based Control Charts	Yes	15%	15
	No	80%	80
	Don't know what MAD charts are	5%	5
7. Perceived Complexity of MAD-based Control Charts (1=Simple, 5=Complex)	1 (Very Simple)	5%	5
	2	10%	10

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	3	40%	40
	4	30%	30
	5 (Very Complex)	15%	15
8. Openness to Adopting MAD-based Control Charts	Yes, very open	15%	15
	Somewhat open	40%	40
	Not very open	35%	35
	Not open at all	10%	10
9. Reasons for Resistance to Adoption of MAD-based Control Charts	Lack of understanding or knowledge	55%	55
	Fear of job displacement	25%	25
	Perceived complexity	40%	40
	Preference for existing methods (Shewhart, CUSUM)	30%	30
	Lack of leadership support	10%	10
10. Belief in Improved Process Monitoring with MAD-based Control Charts	Yes, significantly	50%	50
	Yes, slightly	40%	40
	No change	10%	10
11. Main Factor Encouraging Adoption of MAD-based Control Charts	Clear benefits to quality and efficiency	40%	40
	Proper training programs	35%	35
	Management or leadership endorsement	20%	20
	Peer influence or recommendations	5%	5
12. Familiarity with Control Charts	Shewhart Chart	50%	50
	CUSUM Chart	45%	45
	MAD-Based Control Chart	5%	5
13. Perception of Effectiveness of MAD-based Control Charts vs. Traditional Methods	MAD charts are much more effective	10%	10
	MAD charts are slightly more effective	20%	20
	MAD charts are about the same as traditional methods	40%	40
	MAD charts are slightly less effective	20%	20
	MAD charts are much less effective	10%	10
14. Comparison of MAD-based Charts and Traditional Methods in Detecting Process Shifts	MAD-based charts detect shifts more accurately	35%	35
	MAD-based charts detect shifts with similar accuracy	40%	40
	Shewhart or CUSUM charts detect shifts more accurately	10%	10
	I don't know	15%	15
15. Effectiveness of MAD-based Charts for Non-Normal Data or Outliers	Yes, much more effective	50%	50
	Yes, slightly more effective	30%	30
	No, they are about the same	10%	10

DOI: 10.5281/zenodo.15043257

	No, traditional charts are more effective	5%	5
	I don't know	5%	5
16. Likelihood of Adopting MAD-based Control Charts if Implemented	Very likely	15%	15
	Somewhat likely	40%	40
	Neutral	30%	30
	Somewhat unlikely	10%	10
	Very unlikely	5%	5
17. Perceived Impact of MAD-based Charts on Work Efficiency	Significantly improve efficiency	25%	25
	Slightly improve efficiency	40%	40
	No impact	25%	25
	Reduce efficiency	10%	10
18. Confidence in MAD-based Charts Improving Process Monitoring and Reducing Defects	Very confident	30%	30
	Somewhat confident	40%	40
	Neutral	20%	20
	Not very confident	5%	5
	Not confident at all	5%	5
19. Challenges in Implementing MAD-based Control Charts	Resistance from employees	50%	50
	Lack of adequate training	45%	45
	Technical challenges in using the tool	30%	30
	Lack of leadership support	25%	25
20. Additional Comments	-	N/A	See comments below

Additional Comments.

i. "We need more hands-on training for MAD charts to understand their true potential."
ii. "I think leadership needs to endorse MAD-based charts for them to be taken seriously."
iii. "MAD charts are promising, but I still have concerns about their implementation in large-scale operations."

The survey reveals key trends and insights regarding MAD-based control charts (Table 4.1): only 5% of respondents are familiar with MAD charts compared to 50% for Shewhart charts, and 80% lack training, highlighting a significant knowledge gap. While 70% perceive MAD charts as complex, 50% find them easier or slightly easier to understand than traditional methods. Adoption barriers include lack of understanding (55%), perceived complexity (40%), and resistance to change (30%). However, 50% believe MAD charts are significantly more effective for non-normal data and outliers, and 35% think they detect process shifts more accurately, indicating their potential benefits despite adoption challenges.

4.2 Evaluation of Responses in line with Objectives and Hypotheses

4.2.1 Realization of Set Objectives

Objective 1: Development of control charts based on Median Absolute Deviation (MAD).

Table 4.2: Data of actual content level of a create of 50cl CocaCola

DAY	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
1	50.11	48.15	50.01	50.01	50.01	48.92	50.21	50.01	50.01	49.89
2	50.01	49.11	50.01	49.11	49.11	48.92	50.21	50.01	49.11	49.89
3	49.11	50.13	49.11	48.11	48.11	48.92	50.21	50.01	50.00	49.89
4	48.11	49.11	48.11	48.15	49.91	48.92	50.21	50.01	50.00	49.89
5	48.15	49.06	48.15	49.11	50.01	50.01	50.01	50.01	50.01	49.89
6	49.11	50.11	49.11	50.13	49.11	49.11	49.11	50.01	49.11	50.01

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7	50.13	50.04	50.13	49.90	48.11	48.11	48.11	50.01	48.11	49.11
8	49.11	48.15	49.11	49.90	48.15	48.15	48.15	49.11	48.15	48.11
9	49.06	49.11	50.01	50.01	49.11	49.11	49.11	48.11	49.11	48.15
10	50.11	50.13	50.01	49.11	50.13	50.13	50.13	48.15	50.01	49.11
11	50.04	50.22	49.11	48.11	49.11	49.11	49.11	49.11	49.11	50.13
12	50.51	49.22	48.11	49.70	49.06	48.92	49.06	50.13	48.11	49.11
13	49.11	49.22	48.15	51.80	50.91	48.92	50.11	49.11	48.15	49.06
14	50.06	50.22	49.11	50.90	48.91	48.92	50.31	49.06	49.11	50.11
15	50.05	49.22	50.13	49.90	49.91	51.92	51.21	48.01	50.13	50.01
16	50.09	50.10	49.11	50.90	49.91	48.92	50.01	49.01	50.00	49.11
17	50.08	50.02	49.06	50.01	50.01	48.92	49.11	48.01	49.30	48.11
18	48.72	50.20	50.11	49.11	49.11	48.92	50.00	50.11	49.00	48.15
19	49.11	50.12	50.01	48.11	48.11	48.92	48.15	49.01	46.00	49.89
20	50.10	50.00	49.11	48.15	48.15	48.92	49.11	48.91	49.00	49.89
21	50.01	49.22	50.01	49.90	49.11	48.92	50.13	50.01	49.40	49.89
22	50.11	48.22	50.01	49.90	49.91	48.92	50.21	48.01	49.00	49.89

Source: Authors' observations for 22 consecutive days, January, 2025.

Table 4.3: Control limits for x-bar chart

Statistic	Value
Mean $\bar{X}$ (Center Line)	49.41
Upper Control Limit (UCL)	49.91
Lower Control Limit (LCL)	48.91

Source: Computation by authors using R codes, 2024

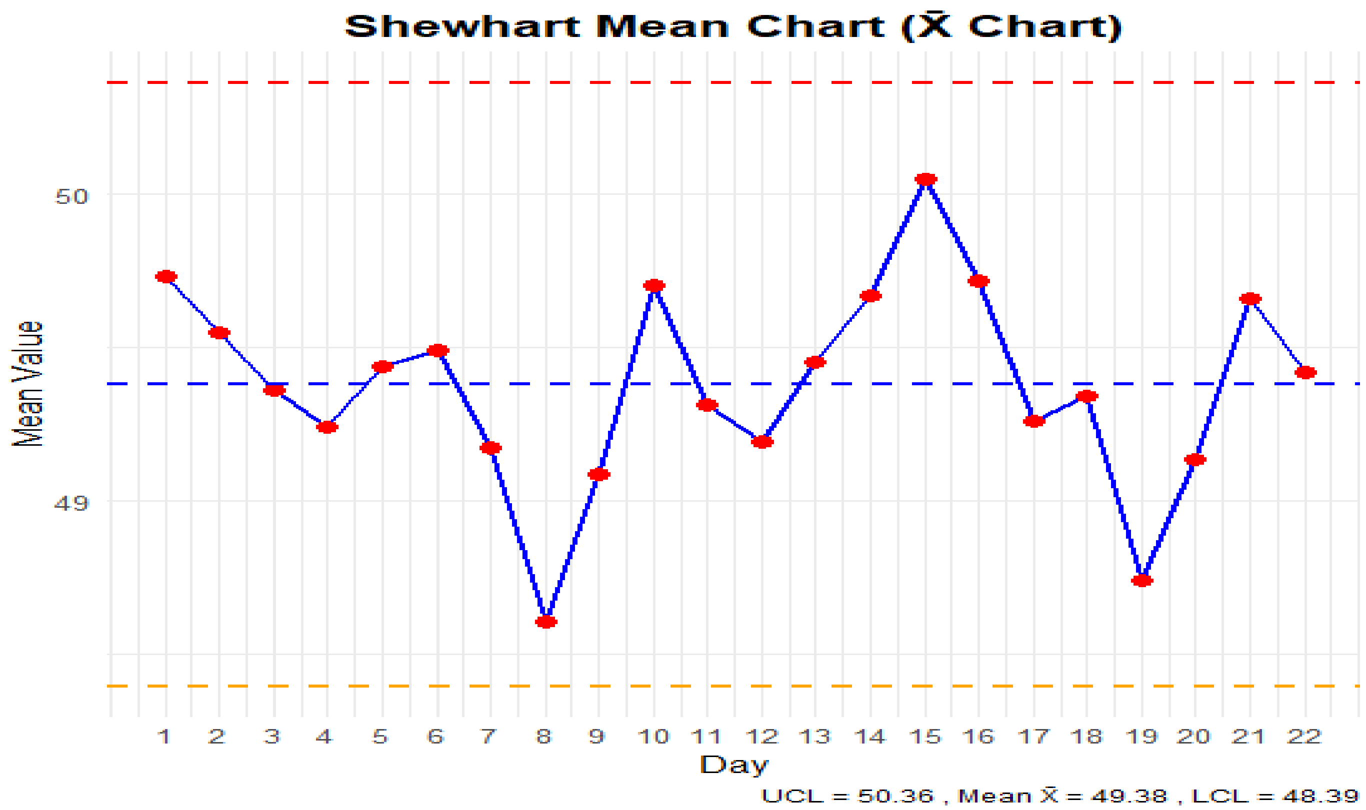

Fig. 4.1: Mean chart: Source: Computation by authors using R codes, 2024

DOI: 10.5281/zenodo.15043257

Table 4.4: Control Limits for MAD control chart:

Statistic	Value
Mean MAD (Center Line)	0.6673
Upper Control Limit (UCL)	1.1529
Lower Control Limit (LCL)	0.1817

Source: Computation by authors using R codes, 2024

Table 4.5: Individual MAD Values Per Day:

Day	MAD Value	Day	MAD Value	Day	MAD Value	Day	MAD Value
1	0.5450	7	1.0000	13	0.9550	19	1.0000
2	0.4500	8	0.4500	14	0.5450	20	0.5450
3	0.4500	9	0.4500	15	1.4050	21	0.5450
4	0.5450	10	0.5450	16	0.5450	22	0.9550
5	0.4500	11	0.5450	17	0.6675		
6	0.5450	12	0.9550	18	0.5450		

Source: Computation by authors using R codes, 2024

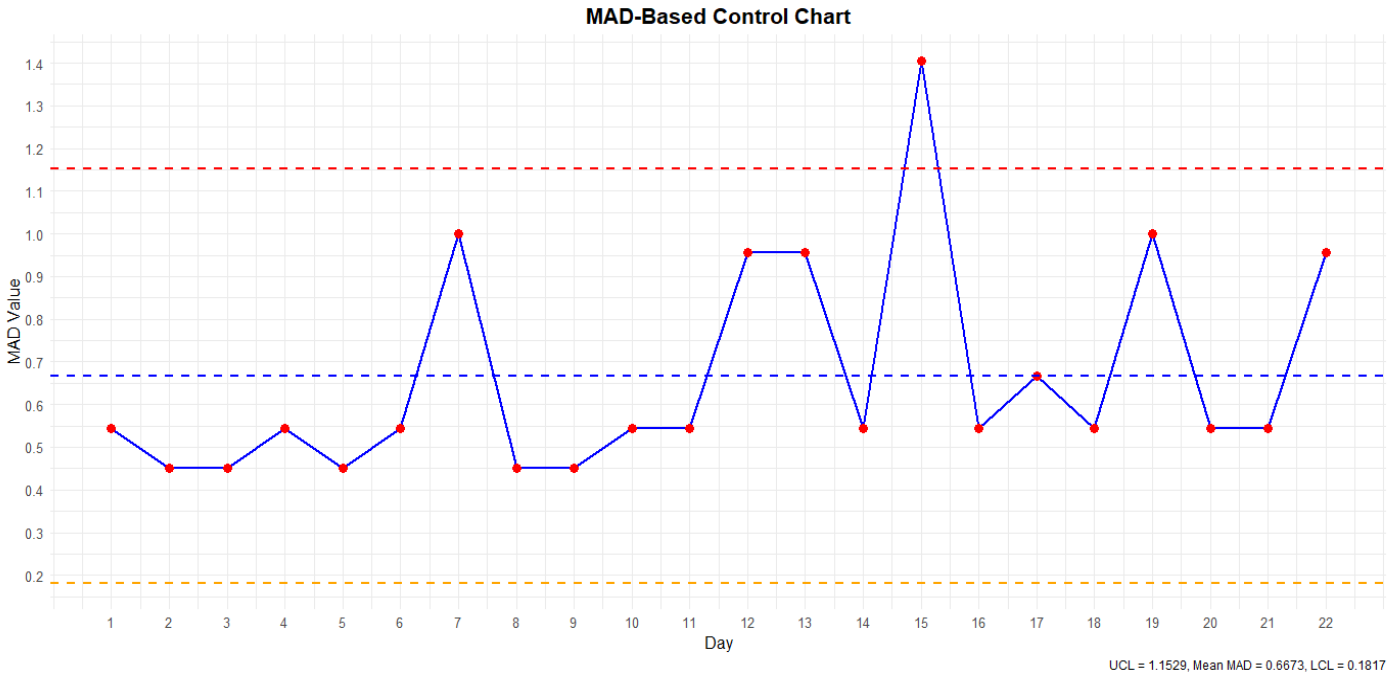

Fig.4.2: MAD control chart: Source: Computation by authors using R codes, 2024

Objective 2: Evaluation of the performance of the proposed charts in comparison with traditional control chart (Mean Chart) using production process data.

Table 4.6: Comparison of Mean Chart and MAD Chart

Aspect	Mean Chart	MAD Chart
Process Stability	Indicates stable process mean with no significant shifts or trends.	Indicates stable process variability with no significant changes in dispersion.
Sensitivity	Less sensitive to minor fluctuations; focuses on central tendency.	More sensitive to small changes in variability; detects subtle shifts.
Out-of-Control	No out-of-control points; all mean values within control limits.	No out-of-control points; all MAD values within control limits.

DOI: 10.5281/zenodo.15043257

Aspect	Mean Chart	MAD Chart
Control Limits	Narrower limits, focusing on detecting shifts in the process mean.	Wider limits, emphasizing sensitivity to variability.
Use Cases	Best for monitoring process mean and detecting shifts in central tendency.	Best for monitoring process variability, especially with non-normal data.
Combined Insights	Confirms stability in process mean.	Ensures stability in process variability.

Conclusion: The Mean Chart and MAD Chart provide complementary insights into process performance. The Mean Chart confirms that the process mean remains stable over time, with no significant shifts or trends, while the MAD Chart ensures that process variability is also under control, with no significant changes in dispersion. The Mean Chart is less sensitive to minor fluctuations and is ideal for monitoring central tendency, whereas the MAD Chart is more responsive to small changes in variability, making it particularly useful for detecting subtle shifts in dispersion, especially in the presence of non-normal data or outliers. Together, these charts offer a comprehensive view of process stability, highlighting both the central tendency and variability. For robust process monitoring, it is recommended to use both charts in tandem to ensure that both the mean and variability are effectively controlled. This combined approach enhances the ability to detect potential issues early and maintain overall process efficiency.

Objective 3: Assessment of the sociological acceptance of the proposed (MAD) scheme

A significant proportion of respondents (55%) identify a lack of understanding or knowledge as a primary barrier to adopting MAD-based control charts, while 70% perceive them as somewhat to very complex (rated 3-5), highlighting perceived complexity as a critical obstacle. Additionally, 60% of respondents emphasize the lack of adequate training as a major challenge. These findings clearly indicate that sociological barriers, including resistance to change, perceived complexity, and insufficient training, significantly hinder the adoption of MAD-based control charts.

4.2.2 Testing of Hypotheses

Inference based on Table 4.1:

Hypothesis 1: Performance of MAD-based Control Charts.

H_{01}: There is no significant difference in the performance of MAD-based control charts compared to traditional control charts in detecting process shifts.

H_{11}: There is significant difference in the performance of MAD-based control charts compared to traditional control charts in detecting process shifts.

Analysis

- 35% of respondents perceive MAD-based charts as more accurate in detecting process shifts compared to traditional methods, while 40% believe their performance is similar.
- 50% consider MAD-based charts significantly more effective for handling non-normal data, with 30% viewing them as slightly superior.
- However, only 10% of respondents regard MAD-based charts as substantially more effective than conventional control charts overall.

Inference: H_{01} is rejected; MAD charts excel in specific scenarios but are not universally superior.

Hypothesis 2: Factors Influencing Adoption

H_{02}: The adoption of MAD-based control charts is not significantly influenced by familiarity, training, or perceived complexity.

H_{12}: The adoption of MAD-based control charts is significantly influenced by familiarity, training, and perceived complexity.

Analysis

- A significant 80% of respondents have not undergone training on MAD-based control charts.
- The primary barriers to adoption include a lack of understanding (55%) and perceived complexity (40%).
- Despite this, half of the respondents (50%) express at least some openness to adopting MAD-based charts.
- However, familiarity remains low, with only 5% aware of MAD-based charts, compared to 50% for Shewhart charts and 45% for CUSUM charts.

Inference: H_{02} is rejected; training and perception significantly impact adoption.

Hypothesis 3: Sociological Acceptance and Implementation

H_{03}: The sociological acceptance of MAD-based control charts does not significantly impact their implementation and usage in industrial settings.

H_{13}: The sociological acceptance of MAD-based control charts significantly impacts their implementation and usage in industrial settings.

Analysis

- Only 15% of respondents are "very open" to adopting MAD-based charts, while 35% are "not very open."
- 40% believe MAD-based charts offer clear benefits to quality and efficiency, and 35% state proper training programs would encourage adoption.
- 50% cite employee resistance as a major challenge, while 45% highlight lack of adequate training.
- Management endorsement is seen as a critical factor for adoption by 20% of respondents.

Inference: Resistance to change and lack of awareness are major hurdles in sociological acceptance. Since nearly half of the respondents are hesitant or opposed to adoption, and many see leadership support and training as essential for implementation, H_{03}

DOI: 10.5281/zenodo.15043257

is rejected in favour of H_{13}. This means sociological acceptance plays a crucial role in the success of MAD-based control charts.

4.2.3 General comment

The sociological acceptance of MAD-based control charts in industrial environments is influenced by several factors, including resistance to change, training needs, and the perceived utility of the tool. By addressing these barriers through effective communication, training programs, and simplifying the tools, industries can promote wider adoption. MAD-based charts provide significant advantages in terms of statistical reliability and ease of use, making them a viable alternative to traditional control charts. Policy recommendations that focus on clear adoption guidelines, incentivizing early adoption, and fostering continuous support can help industries embrace these advanced monitoring tools and ultimately improve their overall operational efficiency.

5.0 Conclusion

The sociological acceptance of MAD-based control charts in industrial environments is influenced by several factors, including resistance to change, training needs, and the perceived utility of the tool. By addressing these barriers through effective communication, training programs, and simplifying the tools, industries can promote wider adoption. MAD-based charts provide significant advantages in terms of statistical reliability and ease of use, making them a viable alternative to traditional control charts. Policy recommendations that focus on clear adoption guidelines, incentivizing early adoption, and fostering continuous support can help industries embrace these advanced monitoring tools and ultimately improve their overall operational efficiency.

To promote the adoption of MAD-based control charts, the study recommends the establishment of clear adoption guidelines by developing standardized procedures for training, technical support, and system integration. Comprehensive hands-on training programs should be provided to enhance user competence and confidence, while simplifying tools and ensuring seamless workflow integration to make MAD-based charts more user-friendly and compatible with existing systems. Additionally, fostering leadership support through management endorsement and resource allocation for training and implementation will be critical to overcoming adoption barriers and ensuring successful integration.

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DOI: 10.5281/zenodo.15043257