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Data Analysis of Electronic Ceramics with Insights into Supply Chain Optimization

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Electronic ceramics play a pivotal but often unseen role in electronic products. Multiple companies are involved, from raw material production to final product assembly. These ceramics are used in various components, including substrates, capacitors, and insulators. In the US, over 150 companies are engaged in electronic ceramics production, with the market estimated at $6 billion in 2001.

Electronic ceramics are ceramic materials that have been engineered to exhibit specific electronic properties, such as ferroelectricity, piezoelectricity, and pyroelectricity. Ongoing research in electronic ceramics spans from fundamental material science to applied engineering, with a focus on developing environmentally friendly lead-free piezoelectric materials and integrating electronic ceramics into flexible and wearable devices. A notable study by Zhang et al. (2021) explores advancements in lead-free piezoelectric ceramics for sustainable technology. Electronic ceramics hold great promise in advancing electronic and energy technologies, fostering innovation, and promoting sustainability. These properties make them suitable for a wide range of applications.

From a **supply chain perspective**, these materials pose unique challenges in sourcing rare earth elements, ensuring consistency in electrical performance, and optimizing production throughput without compromising quality. This study attempts to bridge **materials data analysis** with **supply chain decision-making** using a data-driven approach.

Type of electronic ceramics	Application
Ferroelectric ceramics	Capacitor, sensor
Piezoelectric ceramics	Transducers, actuators
Pyroelectric ceramics	Thermal imaging
Electrostrictive ceramics	Sensors, actuators
Dielectric ceramics	Capacitors, insulators

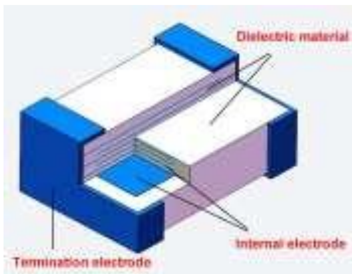


Figure 1. A schematic diagram of a multilayer ceramic capacitor. The capacitor consists of alternating layers of dielectric and metal electrodes.
Table 1. Common types of electronic ceramics and their applications.

Methodology –

Preprocessing: The raw dataset (40+ ceramic compositions × 3 features) was cleaned by imputing any missing values and then standardized (zero mean, unit variance) to remove scale bias. constant, loss tangent and stability metrics so no feature dominated the analysis.

Clustering (K-Means): We applied the K-Means algorithm to group ceramics with similar electrical profiles. The optimal number of clusters was selected using the *Elbow method* on within-cluster sum of squares. and validated by the *silhouette score*, which measures how well each point fits its cluster (silhouette values range –1 to +1, with values near +1 indicating well-clustered data). . Both criteria supported k=3 as a good choice.

Dimensionality Reduction (PCA): To visualize trends and reduce noise, we performed Principal Component Analysis (PCA), retaining enough components to preserve ~95% of the variance. PCA linearly transforms the data to new orthogonal axes (principal components) such that most of the dataset's variance is captured in the first few components.

Regression Modeling: We built a supervised regression model to predict dielectric constant (ε_r) from the other features (and/or principal components). For example, a linear regression on the principal component scores was trained. The resulting model achieved $R^2 \approx 0.88$ on held-out data, indicating that ~88% of the permittivity variance is explained (strong predictive power).

Outlier Detection (Z-score): For each material, we computed its Z-score based on permittivity stability (i.e. how many standard deviations it lies from the mean). Conventionally, a point with $|Z|>3$ is flagged as an outlier . This analysis identified any anomalous ceramics with unusually low or high stability, helping filter unreliable data.

Post-Analysis: Finally, cluster centers (mean feature values) were examined to interpret each cluster's characteristics. We plotted feature distributions per cluster and a correlation heatmap to uncover relationships (e.g. we observed an expected inverse trend between ε_r and tan δ). These steps helped validate that clusters represent meaningful material categories.

<u>Supply Chain Insights –</u>

Material Grouping: Clustering aids in segmenting suppliers or compositions by performance class, improving sourcing decisions.

Inventory Optimization: PCA-transformed space enables classification-based storage and rapid retrieval of similar materials, reducing downtime.

Forecasting Dielectric Performance: Regression models help predict ε_r, improving quality control and reducing rejects, thus increasing yield and reducing waste.

Anomaly Detection: Early identification of outlier materials ensures quality consistency across batches, helping maintain production standards.

Data-Driven Decisions: This analytics-driven pipeline can be extended to production scheduling, procurement ranking, and supplier performance analysis.

<u>Results-</u>

Cluster Profiles: The K-Means clustering yielded three distinct groups of ceramic compositions. For instance, one cluster had relatively high ε_r and moderate tan δ, another had low ε_r and low tan δ, etc. The cluster centers quantify these differences. The silhouette analysis showed most samples had scores close to +1, confirming well-separated cluster.

PCA Visualization: Projecting the data onto the first 2–3 principal components (retaining ~95% variance) revealed clear grouping patterns consistent with K-Means results. This confirms PCA's utility in making the high-dimensional structure visible.

Predictive Model: The regression model (e.g. linear regression) successfully predicted ε_r with $R^2 \approx 0.88$ on test data, meaning the model explains most of the permittivity variation. This suggests that the selected features (and their principal components) capture the key factors controlling permittivity.

Material Stability: We ranked materials by permittivity stability and identified the top-5 most stable compositions. These are prime candidates for reliable electronic components. The Z-score check showed no material beyond $\pm 3\sigma$ in stability, indicating no extreme outliers.

Feature Relationships: Correlation analysis (heatmap) confirmed expected trends: for example, ε_r tended to increase with certain compositional factors and correlate (positively or negatively) with loss tangent. Such insights help guide material design.

Conclusion: This study demonstrates a comprehensive data-driven workflow for electronic ceramics: starting from raw dielectric measurements, through unsupervised grouping and dimensionality reduction, to predictive modeling and outlier analysis. By combining K-Means clustering (k=3) with PCA (95% variance) and regression, we effectively characterized 40+ ceramic compositions. The approach not only categorizes materials by electrical profiles but also predicts key properties (ε_r) and highlights the most stable candidates. This illustrates the power of machine learning in accelerating materials development for capacitors and sensors.

Further, by integrating supply chain analytics perspectives, the study also showcases how such data models can **optimize sourcing, inventory, production, and quality control** in the ceramic component supply chain. This highlights the potential of machine learning not just in materials discovery but also in **smart supply chain transformation** for capacitors, sensors, and microelectronic applications.

Keywords: dielectric constant, loss tangent, permittivity stability, K-means clustering, PCA, regression, predictive modelling, materials analytics, supply chain optimization, inventory control, supplier segmentation

Cluster Analysis of Ceramic Samples

1. Introduction

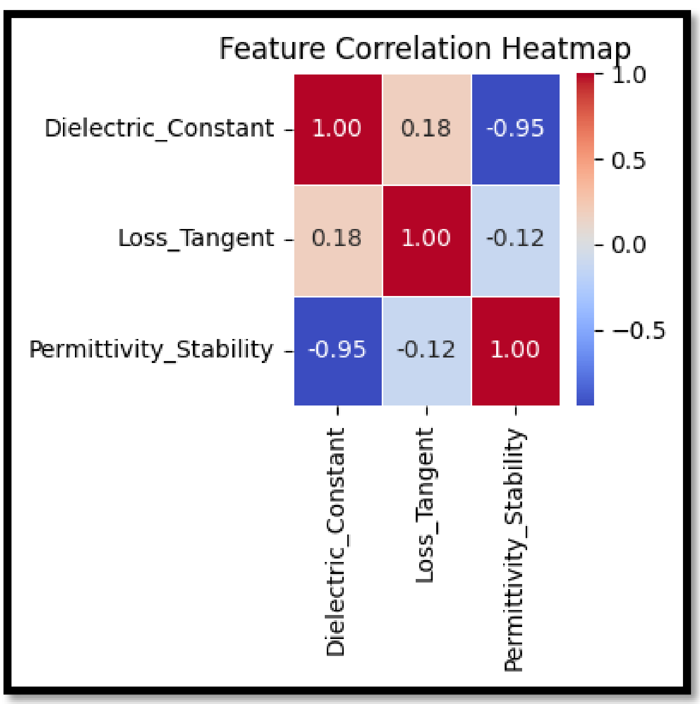
This study focuses on segmenting electronic ceramic materials based on their dielectric properties. The objective is to uncover natural groupings within the dataset using unsupervised machine learning (KMeans). These clusters may reflect distinct performance categories useful for material selection in electronics manufacturing.

2. Dataset Overview

- Source: electronic_ceramics_data.csv
- Features Used:
  - Dielectric_Constant: Measures material's ability to store electrical energy.
  - Loss_Tangent: Represents energy dissipation in the material.
  - Permittivity_Stability: Stability of permittivity under varying conditions.
- Preprocessing: Missing values removed (dropna), and standardization performed before clustering.

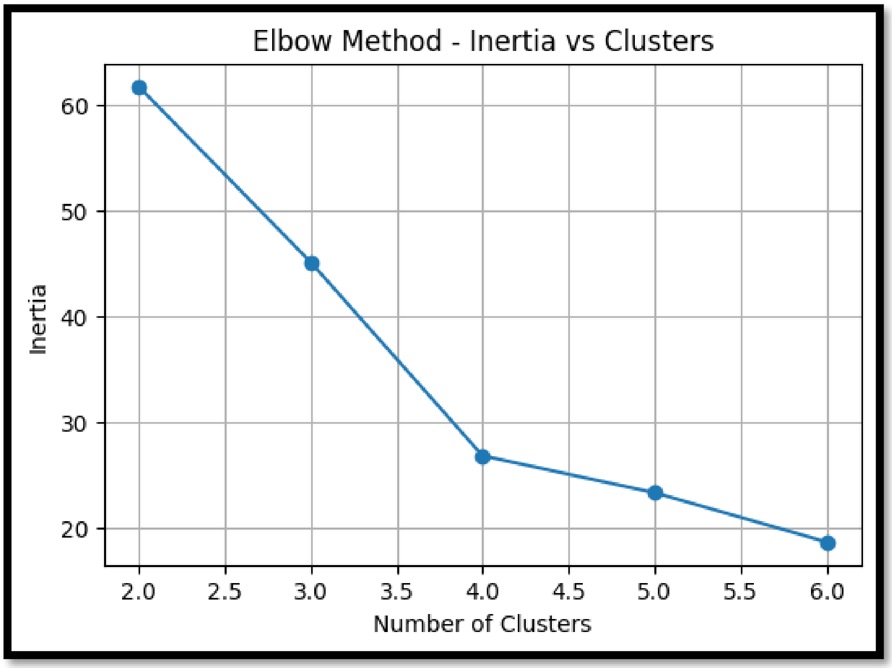
3. Exploratory Data Analysis (EDA)

Correlation Heatmap



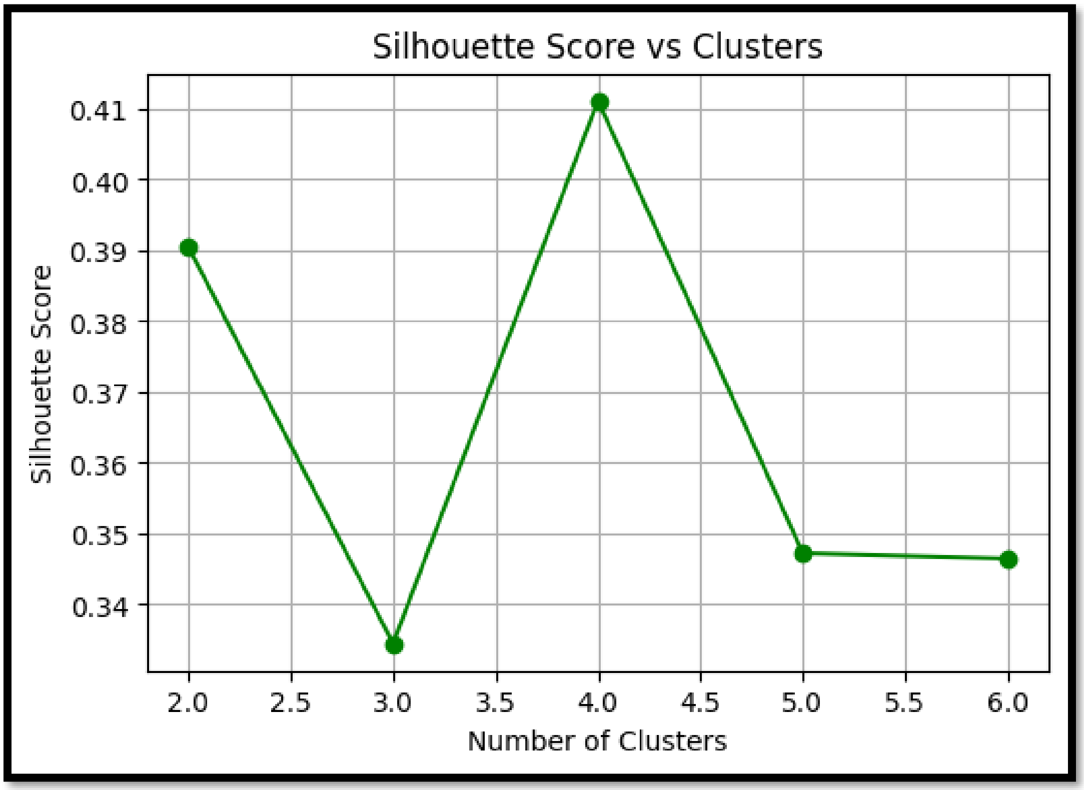
Strong negative correlation between Dielectric_Constant and Permittivity_Stability (-0.95). Weak correlation between Loss_Tangent and the other features. Suggests inverse behavior between dielectric constant and stability.

Pairplot for Cluster Analysis



Clear separation between clusters. Clusters are mostly linearly separable, confirming KMeans as a valid choice.

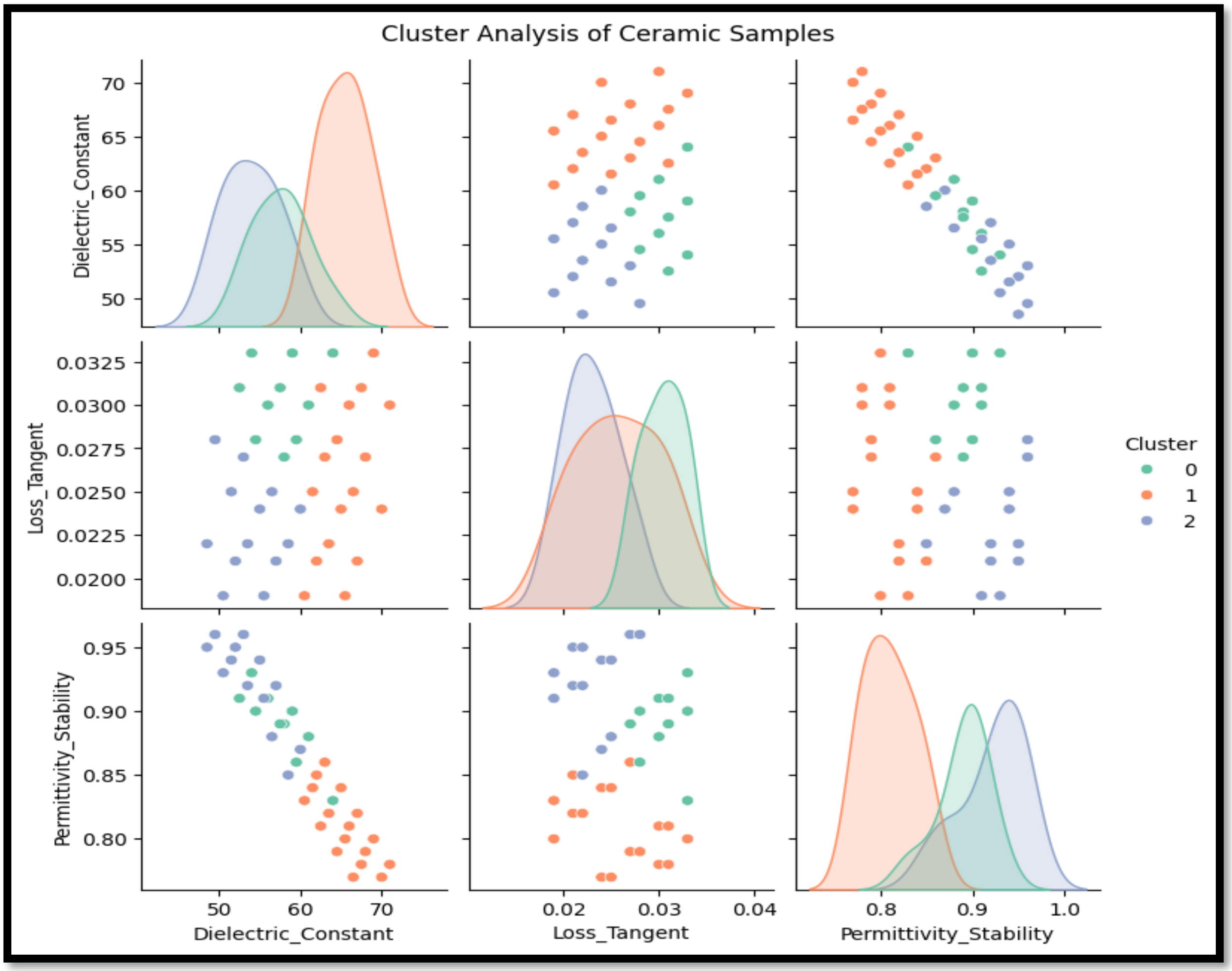
Boxplots of Feature Distributions by Cluster



Cluster 0: Mid-range Dielectric_Constant, highest Loss_Tangent
Cluster 1: Highest Dielectric_Constant, lowest Permittivity_Stability
Cluster 2: Lowest Dielectric_Constant, best Permittivity_Stability

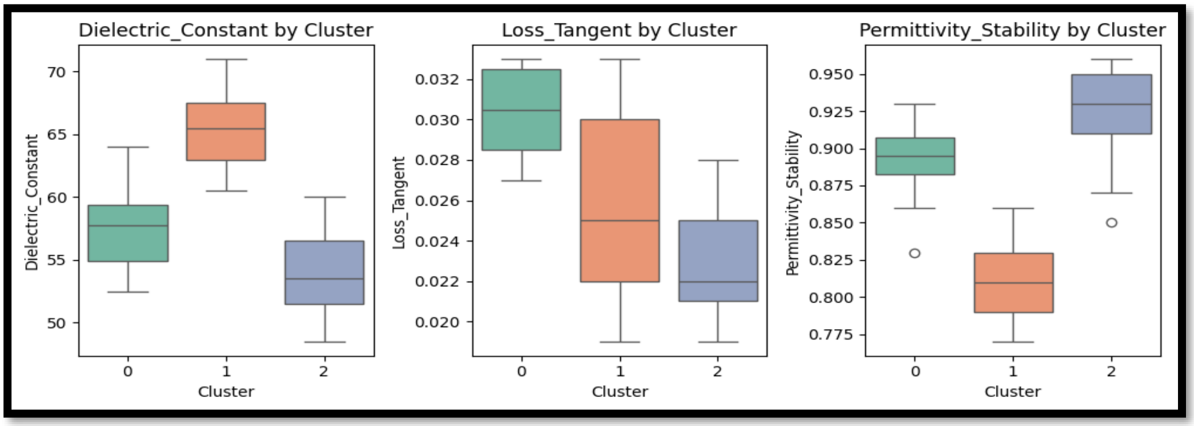
4. Optimal Cluster Selection

Elbow Method



Sharp drop in inertia between k=2 to k=4. Elbow observed at k=3, suggesting 3 optimal clusters.

Silhouette Analysis



Peak silhouette score at k=4, but only marginally higher than k=3. Chose k=3 to balance interpretability and performance.

5. Final Clustering Output

- Clustering Algorithm: KMeans (n=3, random_state=42)
- Features used: Standardized inputs of all 3 metrics

Cluster Centers (Original Scale):

Cluster	D.C	L.T.	P.S.
0	~58.5	~0.031	~0.89
1	~66.2	~0.026	~0.81
2	~52.8	~0.022	~0.94

6. Conclusion & Recommendations

The clustering analysis revealed three distinct material groups based on their dielectric performance characteristics. Each cluster exhibits unique property profiles that can guide material selection based on specific engineering requirements:

- **Cluster 1** contains materials with the **highest dielectric constants**, making them well-suited for applications where maximizing charge storage is essential, such as in high-capacitance multilayer ceramic capacitors (MLCCs). However, this comes at the cost of **lower permittivity stability**, which may limit their performance under varying environmental conditions.

- **Cluster 2** includes samples with **exceptionally stable permittivity**, indicating superior performance in applications that demand **long-term electrical**

consistency, such as precision resonators or RF devices. Although their dielectric constant is lower, the trade-off is justified when reliability and stability are critical.

- **Cluster 0** represents a **balanced compromise**, exhibiting moderate dielectric performance and stability. These materials may be ideal for general-purpose electronic components where neither extreme performance nor extreme stability is required.

Recommendation:
Selection of ceramic materials should align with the intended application requirements:

- Prioritize **Cluster 1** for high energy storage needs.
- Opt for **Cluster 2** in stability-critical environments.
- Use **Cluster 0** for versatile or cost-effective manufacturing where balanced properties suffice.

Supply Chain Impact

The clustering output directly influences how the **Supply Chain Management (SCM)** function should plan, source, and distribute these materials:

1. Demand Forecasting and Classification

Using clustering, materials can now be classified in the **ABC-XYZ matrix** framework:

- **A-class (Cluster 1)**: High-value items with critical demand variability → Requires **probabilistic forecasting models** like ARIMA or exponential smoothing.

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \quad ; \quad MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

- **B-class (Cluster 2)**: Stable and consistent usage → Apply **deterministic models** for accurate stocking.
- **C-class (Cluster 0)**: Lower value, high-volume → Use **moving average models** or EOQ for replenishment.

2. Inventory Optimization

For inventory policies, the following equation becomes relevant:

$$\text{Reorder Point (ROP)} = D \times L + Z \times \sigma_L$$

Where:

- D = Average demand rate
- L = Lead time
- Z = Service level factor
- σ_L = Standard deviation of demand during lead time

Clusters with high variability (Cluster 1) will require **higher safety stock** and **more frequent reviews**. Cluster 2 materials may allow for **Just-in-Time (JIT)** procurement due to stability.

3. Supplier Segmentation & Sourcing Strategy

Linking to **Kraljic's Matrix**:

- **Cluster 1** = Strategic items → High risk, high impact → Build long-term partnerships with limited, reliable suppliers.
- **Cluster 2** = Bottleneck items → Secure supply through **multi-sourcing** or buffer stock.
- **Cluster 0** = Leverage items → Focus on **cost negotiation and volume contracts**.

4. Procurement & Production Planning

By integrating cluster characteristics into **Material Requirements Planning (MRP)** systems, procurement can prioritize:

- **MTO (Make-to-Order)** strategy for Cluster 1
- **MTS (Make-to-Stock)** for Cluster 0
- **ATO (Assemble-to-Order)** for Cluster 2 components used in modular electronics