Cluster Analysis of Electric Vehicle Exterior Features:
An Educational Study Using Miro for Online Collaboration and Data Analysis

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The IAFOR International Conference on Education in Hawaii 2025
Official Conference Proceedings

Abstract
This study utilized cluster analysis and the online collaboration whiteboard platform Miro to help students identify and classify the exterior features of electric vehicles, thereby enhancing their online collaboration skills in design classification and complex data analysis, leading to increased efficiency and accuracy. The study was conducted in four main stages: first, students collected 120 representative front-view images of electric vehicles; next, they categorized six key car parts (headlights, front grille, lower grille, windshield, fog lights, and side mirrors) on Miro using an expert-driven method, with each part classified into five design feature styles. Then, hierarchical cluster analysis using SPSS, where the dendrogram generated from the data, identified five optimal clusters; finally, the clusters were divided into five groups using the K-Means clustering method. The ANOVA (Analysis of Variance) results showed significant differences in the selected features between different clusters, validating the effectiveness of the classification method and the clustering results. The results of this study demonstrated that, through expert classification and SPSS hierarchical cluster analysis, five clusters with significant differences were ultimately formed. Therefore, this study successfully conducted online collaborative classification through Miro and applied cluster analysis to perform detailed classification and analysis of the design features of 120 electric vehicle front-view images. This approach not only enhanced students' abilities in identifying and classifying design features but also cultivated their skills in online collaboration and data analysis. Additionally, it provided valuable insights for automotive designers in understanding and applying design feature differences to meet market demands.

Keywords: Cluster Analysis, Electric Vehicle Design, Online Collaboration, Feature Classification, Design Education

Introduction

With the rise of global environmental awareness and technological advancements, the sales of pure electric vehicles (EVs) have steadily increased from 2012 to 2024, and the market continues to expand. Sales have grown exponentially in recent years, doubling yearly (IEA, 2024). According to the Global EV Outlook 2024 report by the International Energy Agency (IEA), global EV sales reached a record-breaking 14 million units in 2023, marking a 35% increase compared to 2022. Nearly one in five cars sold in 2023 was electric, demonstrating the EV market's strong momentum and continuous growth potential. In Taiwan, EVs are also gaining popularity among consumers due to their environmentally friendly characteristics and supportive government policies (Pai et al., 2023).

Motivation

Moreover, with the EV market expanding, consumer demand is growing fast, too. The car's appearance is the most noticeable and the one people care about the most. However, balancing aesthetics with consumer demands has become a significant challenge for automotive designers as the market expands. Many studies have proven that a product's design greatly influences consumer purchasing decisions (Sun & Park, 2024). Therefore, with the continuous expansion of the market and the increasing consumer demand, designers need to invest more effort in understanding consumers' aesthetic preferences. For product designers, understanding consumer preferences in exterior design needs to be faster and more accurate—otherwise, they risk getting left behind in the market. This growing need highlights the importance of finding ways to enable designers to conduct product appearance design research more efficiently, which is the primary motivation for this study.

In traditional design education, studying product appearance features often involves printing many product photos for analysis. Researchers commonly use cluster analysis to classify product morphology and perceptual images, aiming to identify the design features most preferred by consumers (Liu & Zhu, 2023). While this process is tedious and time-consuming, it has long been considered a crucial foundational training for designers, helping them develop a keen eye for aesthetic details and user preferences. However, as technological advancements reshape the way designers work, more efficient and innovative approaches are worth exploring. Digital tools and online collaborative platforms present new opportunities to streamline design research, improve accessibility, and foster teamwork across geographical boundaries. For example, as an intuitive and versatile platform, Miro enables efficient online collaboration, enhancing student engagement and interactive learning experiences (Tucker et al., 2021). This study explores using Miro, an online collaboration platform, to conduct product appearance research in a digital environment.

Purpose

This study focuses on electric vehicles (EVs)—a rapidly evolving and highly relevant product category to provide a practical application of this approach. By integrating Miro into the research process, this study aims to experiment with different research methodologies and generate valuable insights for product designers. This study seeks to contribute to the growing discourse on digital transformation in design education, offering a new perspective on how online tools can be leveraged to enhance efficiency, accuracy, and collaboration in product appearance analysis. Here are the three main objectives of this study:

1. Explore using online collaboration tools (Miro) for categorizing product features.

2. Determine the best method for classifying electric vehicle exterior designs while ensuring the reliability of the results.
3. Provide reference data for the electric vehicle design field, enabling designers to understand market trends better.

Literature Review

Miro was selected for this study due to its robust online collaboration capabilities, which make it particularly suitable for data analysis and research. It allows users to tag and categorize images, manipulate their arrangement freely, and export data directly to Excel, enhancing efficiency and usability (Miro, n.d.).

Table 1 summarizes Miro's key functionalities and advantages based on information from its official website. The platform supports real-time multi-user collaboration, facilitating effective team-based classification and discussion. Its visualization capabilities enable intuitive manipulation of images and classification tags through a drag-and-drop interface, improving readability. Miro's seamless data integration also allows for direct Excel exports, streamlining subsequent analysis. These features collectively enhance classification efficiency by optimizing the organization and reorganization of data.

Table 1: Miro's Functions and Advantages

Functions	**Advantages**
Online Collaboration	Supports real-time multi-user editing, suitable for team classification and discussions.
Visualization	Allows direct drag-and-drop of images and classification tags, improving readability.
Data Integration	The data can be exported to Excel for convenient subsequent data analysis.
Improved Classification Efficiency	Speeds up the classification process through drag-and-drop operations and tagging.

Previous research has recognized Miro as an effective tool for online collaboration, particularly in educational settings where teamwork and ideation play a critical role. Tucker et al. (2021) found that Miro's real-time interaction capabilities help simulate face-to-face brainstorming sessions, making it a valuable resource for design-focused courses. The study also highlighted that Miro supports structured design processes, such as empathy mapping and journey mapping, enabling teams to analyze user needs and behaviors systematically. Additionally, Miro accommodates step-by-step and continuous brainstorming approaches, allowing for more significant idea generation and refinement flexibility. These findings underscore Miro's potential as a practical and interactive tool for collaborative design research and education (Tucker et al., 2021).

Cluster analysis is widely utilized in product design research as a systematic approach to classifying product attributes and identifying key design elements. Sutono (2016) applied cluster analysis in automotive design research to categorize descriptive adjectives, demonstrating its effectiveness in identifying meaningful patterns within large datasets. This method has proven particularly valuable for large-scale product design data analysis due to its efficiency in detecting trends and organizing complex information (Sutono, 2016).

Building on this foundation, this study employs cluster analysis to classify the exterior design features of electric vehicles systematically. By creating structured and meaningful groupings, this approach provides valuable insights into emerging design trends, making it an effective tool for analyzing large-scale product design data and supporting informed decision-making in design research.

Methodology

This study employed a structured cluster analysis approach to categorize the exterior design features of electric vehicles (EVs). The research process was conducted in four key phases: (1) data collection, (2) feature classification using Miro, (3) hierarchical cluster analysis using SPSS, and (4) validation of clusters through K-Means clustering and ANOVA (Analysis of Variance). Integrating Miro as an online collaboration tool was crucial in efficiently organizing and analyzing design features.

Data Collection

According to the Global Electric Vehicle Outlook 2024 report, China dominates the electric vehicle (EV) market (IEA, 2024). Given this significant influence, ensuring a representative dataset was a key priority for this study. To achieve this, data was sourced from China's XCAR website, a well-regarded platform for automotive information. One hundred twenty front-view images of electric vehicles were selected from the platform's internal rankings, as shown in Figure 1, ensuring that the study was based on valuable and relevant comparisons. The selection criteria prioritized diversity in design while maintaining consistency in image angles and resolution to facilitate accurate feature analysis.

Figure 1: 120 Front-View Images of Electric Vehicles

__Feature Classification Using Miro__

After selecting the images, we applied the Quasi-Expert Method to categorize them. According to relevant studies, even if participants are not highly specialized experts, experienced scholars can still employ the Expert Method—an approach referred to as the Quasi-Expert Method. This method allows for a structured and informed classification process without direct industry expertise. This study's classification was conducted by graduate students specializing in industrial design. The quasi-expert classification approach is widely utilized in design research, particularly when access to industry professionals is limited. This ensures that categorization is based on informed judgment rather than general perception. Tsai (2016) demonstrated that design students could reliably assess creative products using structured evaluation criteria, further supporting the validity of this approach.

To enhance classification accuracy, we invited three graduate students with extensive design experience to participate in the Quasi-Expert Method. Their role was to systematically classify the exterior design features of electric vehicles using Miro's interactive tagging and categorization tools. This method facilitated real-time collaboration, ensuring structured classification and consistency in feature categorization across all selected vehicle images. In the second phase, six key exterior components of EVs were selected for classification, as shown in Figure 2.

Figure 2: Key Exterior Components of Electric Vehicles for Classification

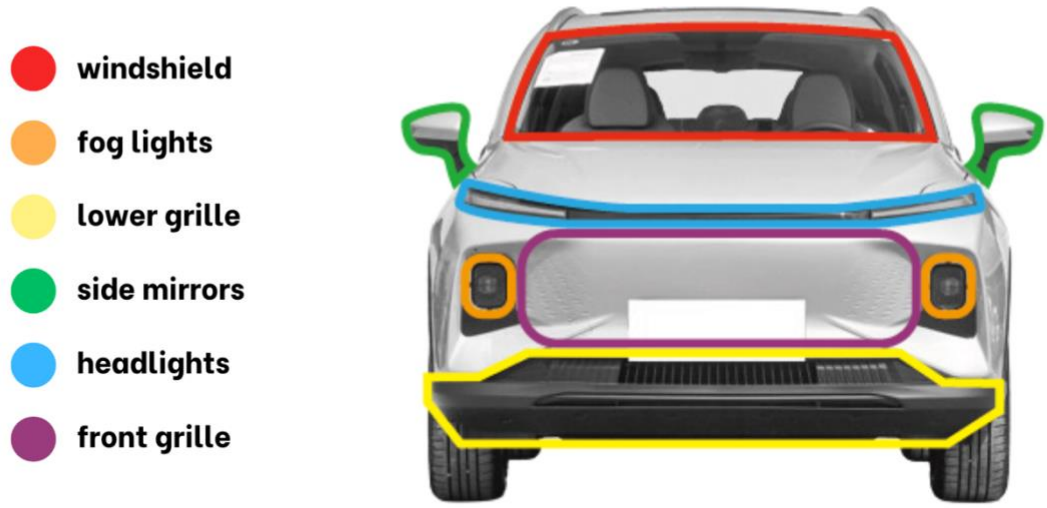

Figure 2 illustrates the six key exterior components of electric vehicles (EVs) that were selected for classification in this study. Each component is highlighted in a distinct color for clarity: Windshield (Red), Fog Lights (Orange), Lower Grille (Yellow), Side Mirrors (Green), Headlights (Blue) and Front Grille (Purple). Each feature was categorized into five distinct design styles using an expert-driven classification method. Miro's interactive features enabled real-time tagging, sorting, and collaborative refinement of these classifications, ensuring a systematic and organized approach.

Each feature was classified into five distinct design styles through an expert-driven methodology. Miro's interactive functionalities facilitated real-time tagging, sorting, and collaborative refinement, ensuring a systematic and well-structured classification process.

Table 2 presents the classification of six key exterior features of electric vehicles: headlights, front grille, lower grille, windshield, fog lights, and side mirrors. Each feature has been systematically categorized into five distinct design styles, labeled using an expert-driven classification method. These classifications reflect the most common design variations observed in the dataset of 120 electric vehicle images.

Table 2: Classification of Electric Vehicle Exterior Design Features

Headlights X1	**Front grille X2**	**Lower grille X3**	**Windshield X4**	**Fog lights X5**	**Side mirrors X6**
Rectangle X11	Panel X21	Connected to the Bottom of the Car X31	Flat Trapezoid X41	Slender Type X51	Triangle X61
Arc Shape X12	Grille X22	Framed Structure X32	Tall Trapezoid X42	Block Type X52	P-Shape X62
Polygon X13	Pattern X23	Connected to Fog Lights X33	Arc Shape X43	Connected Type X53	D-Shape X63
Slender Shape X14	Curved Line X24	Frame Connected to the Bottom X34	Rectangle X44	Extended Type X54	Rectangle X64
Irregular Shape X15	Horizontal Line X25	None X35	Curved Shape X45	None X55	Circle X65

For example, headlights (X1) are classified into five primary shapes, including Rectangle (X11), Arc Shape (X12), Polygon (X13), Slender Shape (X14), and Irregular Shape (X15). Similarly, the front grille (X2) includes design variations such as Panel (X21), Grille (X22), Pattern (X23), Curved Line (X24), and Horizontal Line (X25). Each category represents a fundamental stylistic choice in automotive design, helping to identify distinct trends and aesthetic preferences across different electric vehicle models.

Hierarchical Cluster Analysis (HCA) Using SPSS

The classified data were analyzed using hierarchical cluster analysis (HCA) in SPSS software. A dendrogram was generated to identify the optimal number of clusters by examining similarity patterns among the classified features. This process facilitated the formation of five primary clusters, ensuring a data-driven categorization of electric vehicle (EV) design elements. To prepare the data for statistical analysis in SPSS, One-Hot Encoding was applied to categorize different feature groups (X11–X15). The data were then converted into binary (0/1) markers to ensure that each image classification remained mutually exclusive, meaning each image could belong to only one category within a given feature set.

K-Means Clustering for Refinement and ANOVA for Statistical Validation

Following HCA, the K-Means clustering algorithm was applied to refine the clusters, ensuring consistency and reducing intra-cluster variability. The algorithm reassigned feature categories iteratively to optimize classification accuracy. An Analysis of Variance (ANOVA) test was conducted to validate the clustering results' effectiveness. The statistical comparison of feature variations across different clusters confirmed significant differences ($p<0.05$), ensuring that the classifications were meaningful and reliable.

Results

The cluster analysis and K-Means clustering successfully categorized the 120 electric vehicle (EV) front-view images into five clusters based on their exterior design features. The clustering process focused on six key components: headlights, front grille, lower grille, windshield, fog lights, and side mirrors. The classification allowed for a systematic evaluation of common design trends in EV aesthetics.

The initial cluster centers were established through cluster analysis, followed by iterative refinements using the K-Means clustering algorithm to achieve optimal intra-cluster similarity and differentiation. The clustering process converged after nine iterations, with minimal variation between the final cluster centers, ensuring stability in the results.

Cluster Centers Analysis

As shown in Table 3, the final cluster centers reveal how different exterior features correspond to each cluster.

Table 3: Cluster Center Interpretation

	Cluster				
	1	2	3	4	5
Headlights	4	1	3	4	3
Front grille	4	2	4	4	2
Lower grille	3	3	2	2	3
Windshield	2	3	2	4	1
Fog lights	2	3	2	2	4
Side mirrors	2	3	4	4	3

From Table 3, this study hypothesizes and observes the following:

- Cluster 1 features traditional designs, with rectangular headlights, panel-based grilles, and a standard windshield shape.
- Cluster 2 leans toward modern, sporty aesthetics, with arc-shaped headlights and structured grilles.
- Cluster 3 incorporates more dynamic, angular elements, likely in performance or futuristic models.
- Cluster 4 emphasizes streamlined, elongated shapes, indicating a trend towards sleek, aerodynamic designs.
- Cluster 5 showcases unconventional, concept-like features, making it the most unique and futuristic design category.

Cluster Distance and Differentiation

The distance between cluster centers determines how distinct each group is. As shown in Table 4, the larger the distance, the more significant the design differentiation.

Table 4: Cluster Distance Matrix

Group	1	2	3	4	5
1		4.306	3.132	3.199	3.851
2	4.036		3.374	3.341	3.343
3	3.132	3.374		2.872	3.305
4	3.199	3.341	2.872		4.125
5	3.851	3.343	3.305	4.125	

From Table 4, this study hypothesizes and observes the following:

- Clusters 1 and 2 are the most distinct, with a distance of 4.036, suggesting they represent entirely different design trends.
- Clusters 3 and 4 are closely related (distance=2.872), indicating similarities in lower grille and windshield features.
- Cluster 5 has moderate distances from all other clusters, implying a blend of different features.

ANOVA Significance of Feature Differences

To validate whether these cluster differences are statistically significant, ANOVA (Analysis of Variance) was conducted. The F-values and significance levels are shown in Table 5:

Table 5: ANOVA Results

	Group		Error			
	Mean Square	Degrees of Freedom	Mean Square	Degrees of Freedom	F-test	Significance
Headlights	34.787	4	1.133	115	30.698	.000
Front grille	30.167	4	.959	115	31.466	.000
Lower grille	9.418	4	1.529	115	6.161	.000
Windshield	29.919	4	1.151	115	26.003	.000
Fog lights	11.905	4	1.284	115	9.269	.000
Side mirrors	24.781	4	1.216	115	20.385	.000

Components with the highest F-values, which contribute most to classification, include:

- Headlights ($F=30.698$, $p<0.001$) → Headlamp design is a major distinguishing factor.
- Side Mirrors ($F=31.466$, $p<0.001$) → Side mirror styling significantly affects overall vehicle aesthetics.
- Headlights, windshields, and side mirrors have the highest F-values, indicating that these elements contribute the most to distinguishing the clusters.
- Lower grille and fog lights have lower F-values, meaning their role in defining vehicle clusters is less pronounced.
- All features have p-values<0.001, confirming a statistically significant difference among clusters for each feature.

These results validate the reliability of the K-Means clustering, ensuring that the identified groups accurately reflect real-world design variations.

Conclusion

This study utilized Miro to classify electric vehicle exterior features and evaluated its feasibility in online collaboration and design education.

- Advantages: Miro provides real-time collaboration, drag-and-drop functionality, and structured data labeling, making the classification process more intuitive and efficient.
- Challenges: Some participants reported that handling many images simultaneously could lead to system crashes, disrupting discussions. Additionally, screen size limitations affected image clarity, making classification more challenging.

Despite these limitations, Miro proved an effective platform for collaborative classification, demonstrating its potential for digital design education and remote teamwork. These findings highlight the role of digital tools in design research, with future studies exploring ways to enhance user experience and system performance.

For the data analysis component, this study utilized a one-way analysis of variance (ANOVA) to examine the statistical significance of design differences across the five clusters. The results indicate that headlights ($F=30.698$, $p<.001$), front grille ($F=20.385$, $p<.001$), lower grille ($F=9.269$, $p<.001$), windshield ($F=26.003$, $p<.001$), fog lights ($F=6.161$, $p<.001$), and side mirrors ($F=31.466$, $p<.001$) all exhibited significant differences among clusters.

The findings confirm that K-Means clustering effectively differentiates distinct design categories, offering a structured electric vehicle design classification framework. The following conclusions have been drawn based on the analyzed data:

1. Cluster analysis successfully categorized electric vehicle designs into five groups based on key exterior features.
2. High ANOVA F-values indicate that Headlights, windshields, and side mirrors are the most influential design elements.
3. Clusters 1 and 2 exhibit the most differentiation, while Clusters 3 and 4 share overlapping characteristics.
4. Cluster 5 represents a hybrid or emerging design trend, potentially blending futuristic elements with mainstream styles.

These findings provide valuable insights for automotive designers, allowing them to align their future designs with distinct market trends and consumer preferences. However, since K-

Means clustering is inherently designed to maximize inter-group variance, the ANOVA results should be interpreted primarily for descriptive analysis rather than hypothesis testing. Future research could integrate market demand analysis to further validate the applicability of this classification system in understanding consumer design preferences.

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