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A framework for integrating design optimization and manufacturability in electric vehicle production

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Abstract

Electric vehicle design requires integrating diverse specifications with manufacturability constraints to enhance competitiveness. This work presents a framework that combines design optimization and manufacturability analysis to guide strategic decision-making and improve production outcomes. Using data mining, fuzzy logic, and segmentation algorithms, vehicle specifications are categorized into macro-specifications, such as economic accessibility and sustainability. An optimization tool identifies critical design parameters and predicts feasible adjustments within manufacturability limitations. The framework is validated through a case study, with results discussed in terms of design improvements and manufacturability-driven production efficiency, offering insights for product innovation and competitive positioning.

Keywords: Design optimization; Manufacturability; Decision-making; Data-driven manufacturing; Electric vehicle production

1. Introduction

The accelerating shift toward sustainable energy solutions has brought electric vehicles (EVs) to the forefront of the automotive industry as a critical response to the urgent need for cleaner mobility. Despite global efforts for decarbonization, the transition to EVs remains uneven across regions. Countries like Norway and China demonstrate high EV adoption rates, driven by government incentives, strong infrastructure, and rising environmental awareness [1]. In contrast, regions like the USA and parts of Europe [2] show slower adoption due to limited infrastructure, higher costs, and mixed consumer attitudes toward EVs. Beyond emissions reduction, EV adoption improves urban health and environmental preservation [2], with research showing reductions in air pollution, greenhouse gases, and public health benefits, especially in cities. However, widespread adoption depends on various factors, including vehicle attributes, cost-effectiveness, policies, and socio-economic contexts, which shape consumer choice and market penetration. It is important to understand the specific features that resonate with different consumer segments, as well as the policies that could accelerate this transition. In this context, this research work addresses the lack of a strategic framework aligning EV specifications with regional consumer priorities to optimize design support. The framework combines game theory and Maslow hierarchy of needs [3] to evaluate key specifications such as affordability, performance, and sustainability in relation to consumer preferences, segmenting the market into competitive scenarios. This approach provides manufacturers with targeted guidance to refine EV designs that meet market demand, potentially enabling a more competitive and region-specific green transition.

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2. Literature review

Research on EV adoption has explored consumer behavior, machine learning (ML) techniques for optimizing vehicle specifications, and approaches that integrate technical performance with psychological factors. Key studies in these areas highlight the complexities of consumer decision-making and the potential for data-driven methods to improve vehicle design, while also revealing gaps in how these approaches are applied together. Much of the existing research has used consumer surveys to investigate the factors influencing EV purchase intentions. Studies have used modified behavioral models to assess determinants such as attitude, perceived behavioral control, and subjective norms, and have found that concerns about vehicle reliability, cost, and charging infrastructure significantly influence purchase decisions [4]. Other analyses have explored the relationship between consumer attitudes and EV adoption, using statistical techniques such as regression analysis to quantify the impact of perceptions and attitudes [5]. However, these approaches often reflect consumer intentions rather than actual behavior, which introduces potential biases and limitations. There remains a need for objective data that captures actual purchasing patterns and preferences. To address some of these limitations, recent work has incorporated text mining and natural language processing (NLP) techniques to analyze consumer sentiments expressed on social media. In particular, the analysis of consumer opinions related to EV charging infrastructure has highlighted the importance of charging convenience and regional infrastructure disparities [6]. Such method, however, falls short in correlating technical vehicle specifications with actual market performance, leaving room for more integrative data-driven approaches. Emerging methodologies have focused on applying ML to predict consumer preferences based on vehicle specifications. In some cases, artificial neural networks (ANNs) have been used to analyze EV sales data, allowing for the identification of specification combinations that correlate with higher sales [7].

Other approaches, combining K-Means clustering with game theory segment vehicles into competitive categories, enhancing consumer behavior predictions from large-scale data [8] but often ignoring psychological factors in purchasing decisions. To bridge this gap, the use of fuzzy logic and Maslow hierarchy of needs has been proposed to account for the vagueness inherent in consumer decision-making. Fuzzy logic enables partial membership in decision variables, providing a more flexible and accurate categorization of consumer preferences [9]. When combined with Maslow psychological framework, this method allows vehicle specifications to be aligned with consumer needs, ranging from basic functionality to higher-order desires, such as self-esteem or sustainability concerns. This integration provides a more holistic understanding of how both technical and psychological factors drive consumer choices.

While significant progress has been made in understanding EV adoption through surveys, text mining, and ML, there remains a clear gap in developing frameworks that integrate these approaches with a strategic decision-making model. The methodology proposed in this study addresses this gap by combining fuzzy logic, K-Means clustering, and Maslow hierarchy of needs, offering a data-driven yet psychologically informed framework for optimizing EV design and positioning in the market. To fill the above-mentioned research gap, the proposed framework moves beyond traditional methods by offering a scalable, adaptable tool for enhancing the competitiveness of EVs in different regions and consumer segments.

3. Framework and methodology

The proposed framework, shown in Fig. 1, is theoretically applicable to any product in a competitive environment. In the preliminary step, the product must be selected, and its technical specifications identified for use in subsequent steps. In this study, passenger cars are chosen as the product, with more than 200 technical specifications defined.

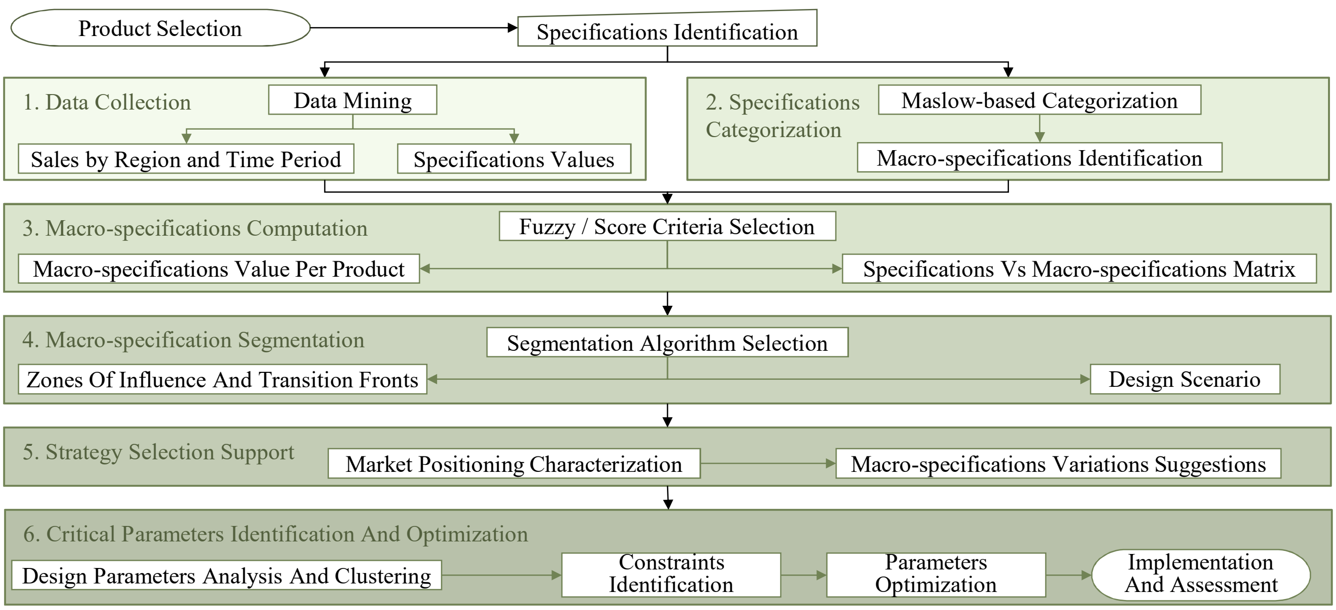

Fig. 1. Overall framework flowchart diagram

3.1. Data collection

This step involves collecting quantitative data on vehicle sales and specifications. Sales data, focused on both EVs and internal combustion engine vehicles (ICEVs), includes regional and temporal figures, trends, and demographic factors such as income levels and government incentives. Product specifications cover engine power, fuel efficiency, dimensions, pricing (retail price and ownership costs), sustainability metrics (e.g., life-cycle emissions), and smart features (e.g., driver assistance and autonomy).

Data mining extracts specifications from public sources, while sales data is sourced from automotive databases and reports. Government policies may add context to regional trends. The result is a structured dataset of regional sales by time and vehicle type, with detailed specifications for each model, ready for further analysis.

3.2. Specifications categorization

In this step, vehicle specifications are grouped into six macro-specifications [10]. Macro-specifications (S_i) are defined as the combination of technical specifications (s_i) that aim to satisfy needs pertaining to the same category according to Maslow hierarchy of needs [3]. The macro-specifications are:

- Economic Accessibility (S_1): focused on price and cost-related attributes;
- Mobility and Transport Capability (S_2): evaluates the vehicle capacity to transport passengers and cargo efficiently;
- Safety (S_3) : covers all features related to occupant protection, from basic safety measures to advanced technologies;
- Performance (S_4): addresses driving dynamics, including power and torque;
- Smart Vehicle Score (S_5) : includes technological advancements related to driver assistance and automation;
- Sustainability (S_6) : incorporates environmental impact measures, including fuel efficiency and estimates of the environmental impact associated to the production and end of life phases.

The categorization is derived by aligning specific vehicle attributes with the corresponding level in Maslow hierarchy [3]. For instance, S_1 and S_3 are mapped to lower-level needs such as security and physiological requirements, while S_4 and S_5 relate to esteem and self-actualization. The result of this step is a vector that represents each vehicle model positioning across six macro-specifications. These vectors are calculated using fuzzy logic and scoring methodologies, enabling effective comparison and segmentation of vehicles in subsequent steps. For instance, the calculation of S_1 incorporates inputs like the manufacturer suggested retail price (MSRP), fuel type, and ownership costs, focusing on affordability [11]. Each macro-specification similarly combines multiple specific attributes to provide a comprehensive assessment of vehicle performance.

3.3. Macro-specifications computation

In this step, the six macro-specifications of each vehicle are computed using fuzzy logic and score-based methods to normalize raw specifications, allowing effective model comparison. Technical specifications (e.g., price, range, horsepower) are mapped to relevant macro-specifications, with the computation tailored to each data type.

Fuzzy logic is applied in categories like S_1 and S_4 to address uncertainty and variability through a fuzzy inference process. This process uses membership functions and fuzzy rules to interpret input data and map it to performance categories [12]. For S_4, for example, inputs such as horsepower, torque, and curb weight are evaluated using membership functions that assign degrees of membership to each value. These values are then processed through fuzzy rules to derive a comprehensive performance score. The final output is a normalized score from 0 to 100, allowing for a detailed comparison of the relative performance of each vehicle.

Score-based methods are used for specifications such as S_2, S_3, S_5 and S_6, relying on weighted sums of normalized values for each attribute. For instance, S_2 is calculated by summing normalized values for attributes like seating capacity, range, and cargo space, with each attribute weighted based on its relative importance.

The score for a the macro-specifications S_2, S_3, S_5 and S_6 can be computed using Eq (1) where $w_i$is the weight assigned to each specification s_i:

$$S = \sum_{i=1}^{n} w_i s_i \quad (1)$$

The tangible output of this step is a matrix of vehicle models represented by their macro-specifications, each with a normalized score (from 0 to 100) for S_1 to S_6. This matrix is then used for segmentation in the next step, enabling comparison and clustering of models based on their overall performance across these macro-specifications.

3.4. Macro-specifications segmentation

In this step, each car model is associated to a vector containing the values of the computed macro-specifications. These vectors are fed into an adapted version of the k-means clustering algorithm which aims at grouping vehicles with similar macro-specification profiles in a defined number (k) of clusters, which will be referred to as segments. Each segment represents a portion of the market where vehicles share common characteristics, such as similar economic accessibility, performance, or sustainability.

Once the vehicles are segmented into k segments, each segment is labelled according to its competitive scenario based on the relative performance of the vehicles in each macro-specification [8]. Therefore, each of the k different identified segments is assigned to one of the following competition scenarios:

- *Dominant*: at least an EV in the segment outperforms all traditional vehicles in every macro-specification;

- *Dominated*: at least a traditional vehicle outperforms all EVs in the segment;
- *Equivalent*: EVs and traditional vehicles have equivalent scores in all macro-specifications;
- *Mixed*: Some specifications favor EVs, while others favor traditional vehicles.

The segmentation process divides the multi-dimensional space defined by the six macro-specifications into zones of influence. Each point in this space represents a potential vehicle configuration, and proximity to a particular segment's centroid determines which points belong to that zone of influence. The boundary between any two zones of influence defines a transition front, described by the hyperplane that is equidistant from the centroids of the two segments. Mathematically, this transition front between two generic segments C_k and C_j is defined by Eq. (2):

$$T_{k,j} = \{S \in \mathbb{R}^6 \,|\, \|S - \mu_k\| = \|S - \mu_j\|\} \quad (2)$$

where: μ_k and μ_j are the centroids of segments C_k and C_j, respectively and S represents a vehicle configuration in the space of the six macro-specifications.

By examining these zones of influence and the transition fronts between segments, manufacturers can identify which vehicle specifications make a product competitive within a given market segment. The transition fronts help highlight the boundaries where EVs begin to outperform traditional vehicles or vice versa, providing strategic insights into how manufacturers can position their vehicles or adjust their specifications to optimize competitiveness.

3.5. Strategy Selection Support

Here, the outputs from the previous steps are used to develop actionable strategies for enhancing vehicle competitiveness.

The analysis of the segments and of the competitive scenario within each segment helps identifying which macro-specifications need enhancement to boost market performance. For instance, if a vehicle is categorized as dominated due to low scores in S_1 or S_3, strategies might include lowering production costs or adding safety features.

Such adjustments could help shift the vehicle into a more competitive position [13]. The segmentation reveals the zones of influence, which give a more aware understanding of the market positioning of the vehicles in the 6-dimensional space. These zones can be used to refine market positioning, as manufacturers can target regions where consumer preferences align more closely with the vehicle strengths. Furthermore, transition fronts, i.e., the boundaries between confining zones of influence, could offer clear strategic targets for improving vehicle adoption by refining specifications or pricing.

The transition fronts could aid EV adoption since they could help clearly identify the set of specifications needed by an EV to outperform its competing ICEVs. The output of this step is a set of detailed, data-driven recommendations for optimizing vehicle specifications or repositioning them in the market.

3.6. Critical Parameters Identification and Optimization

In this stage, the framework systematically identifies and adjusts critical parameters influencing vehicle specifications to enhance manufacturability and performance. Data on product specifications and design parameters are organized into two vectors: $s = [s_1, s_2, \cdots, s_n]$, representing the n specifications for each vehicle, and $p = [p_1, p_2, \cdots, p_m]$, representing the m design parameters. This dataset is structured into a matrix where each row corresponds to a distinct car model, with columns comprising both s and p values. A dependency matrix D, constructed via stepwise regression, indicates whether a specification s_j depends on parameter p_i (1 for dependency, 0 for no influence). This matrix highlights parameters likely to impact specific vehicle attributes. The Spearman correlation coefficient is used to measure the strength of these relationships, resulting in a correlation matrix C with values from -1 (strong negative correlation) to +1 (strong positive correlation). Hierarchical clustering then groups parameters and specifications based on interdependencies, isolating critical parameters for targeted adjustments [14].

An optimization function is defined to maximize the impact of these critical parameters on relevant macro specifications. This function is designed to maximize the variation Δp_j of each parameter and is represented as per Eq. (3):

$$\max_p Z = \sum_j [\omega_j \Delta p_j - \lambda P(p_j)] \quad (3)$$

where Z represents the overall objective function, ω_j denotes the weight of each parameter p_j based on its correlation with relevant specifications, $\Delta p_j = p_{jf} - p_{ji}$ represent the difference between final optimized and initial values of each parameter, λ is a penalization coefficient, and $P(p_j) = |\Delta p_j|$ is a penalty function preventing excessive deviations from the initial parameter values, particularly for parameters with lower weights. The Z function maximizes the weighted variation Δp_j of critical parameters, with the sign of each weight ω_j directing positive or negative changes. Each Δp_j translates into an improvement in s_j, as every specification depends on one or more parameters. The weighted sum in Z drives each Δp_j to move correlated specifications toward their optimal values, indirectly optimizing macro-specifications.

Manufacturability constraints establish the feasible boundaries for parameter adjustments in EV design. Each type of constraint limits parameters analytically, ensuring adjustments remain viable within production, cost, and compliance limits:

- *Technological*: defined ranges based on material properties and processing capabilities, e.g., $p_{\min} \leq p \leq p_{\max}$;
- *Economic*: costs limit adjustments when they exceed budget constraints;
- *Supply chain*: upper bounds on material availability, influenced by logistical limits, $p \leq p_{\text{supply max}}$;
- *Production*: process limits, such as cycle times and equipment tolerances, constrain parameter values;
- *Regulatory*: compliance requirements enforce fixed values, e.g., $p \leq p_{\text{required}}$;
- *Environmental*: sustainability targets cap emissions and resource use, $E(p) \leq E_{\max}$.

Additional considerations include actor-dependency (how constraints impact stakeholders differently), interdependencies (where adjusting one parameter affects others, like cell size impacting module configuration), and constraint dominance (where one constraint, such as a regulatory limit, overrides others). These constraints define the feasible design space, allowing optimization within analytically set boundaries and ensuring that all design adjustments meet real-world production requirements.

Once implemented, the methodology can be assessed by the manufacturer through iterative testing and validation stages, to ensure that the recommendations gathered with the tool provide a balanced design for the product.

4. Case study

The case study exemplifies the methodology using 2023 automotive market data from Germany. Sales data were sourced from the goodcarbadcar.net database [15], and specifications were obtained from edmunds.com. An excerpt of this dataset is shown in Table 1. Subsequently, the specifications have been categorized into six macro specifications as per section 4.2.

The values of macro specifications have then been computed using fuzzy logic for S_1 and S_4 and score-based criteria for the others, as per Section 4.3. An example of macro specifications and their component specifications is shown in Eq. 4, while their full modelling is reported in the supplementary material.

$$\begin{cases} S_1 = S_1\,(s_1, s_8, s_9) \\ \vdots \\ S_6 = S_6\,(s_2, s_8, s_{25}, s_{26}, s_{27}, s_{128}) \end{cases} \quad (4)$$

Once the macro specifications values have been computed for all the car models in the database, each car model is associated to a 7-dimension vector, in which the first six positions are occupied by the numeric values of the six macro specifications which range from 0 to 100, and the last position contains a string giving information about the vehicle type (e.g., ICEV, EV, hybrid). An excerpt of the dataset containing the above-mentioned vectors is shown in Table 2 while the full dataset is reported in the supplementary material.

The vectors in the dataset were subsequently fed into a k-means clustering algorithm to identify segments based on the competitive scenario, as described in section 3.4. Fig. 2 presents the resulting segments in a 3D scatter plot, illustrating a selected projection of the 6-dimensional space along the S_1, S_4 and S_6 axes. Each point in the plot corresponds to an individual car model. The 2023 Volkswagen ID.4 Standard (ID 173 in the supplementary material) was selected as a test model to assess the effectiveness of the proposed framework, and its initial positioning is shown in Fig. 2.

Competition within each represented segment is classified as mixed. Fig. 3 shows the zones of influence along the S_1, S_4 and S_6 axes, depicting transition fronts, i.e., hyperplanes that define boundaries between each segment and its neighbors. The analysis focusses on battery-related design parameters due to their complexity and critical role in EV cost and performance.

Table 1. Car model database excerpt. Germany 2023, from [15].

Car model	s_1 (MSRP)	s_2 (Drive Type)	…	s_{225} (Overall width with mirrors)
VW ID.4	$38,995	RWD	…	83.0 inches
…	…	…	…	…

Table 2. Example of Macro Specification values

Car model	S1	S2	S3	S4	S5	S6	Type
VW ID.4	81.8	22.8	57.4	27.9	81.5	96.7	EV
…	…	…	…	…	…	…	…
BMW M3	72.0	37.0	82.0	63.0	44.4	46.4	ICEV

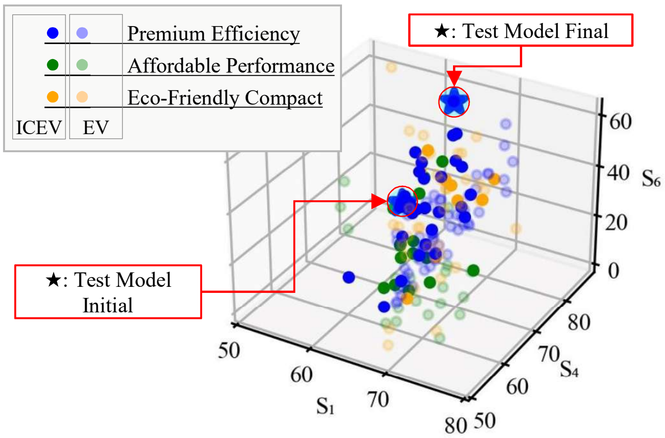

Fig. 2. Identified segments under Mixed Scenario

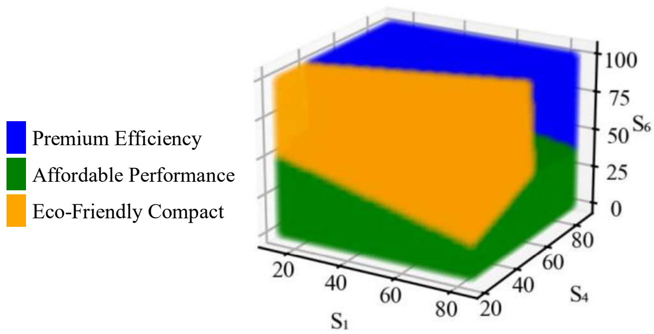

Fig. 3. Transition fronts between zones of influence

Vehicle specifications and battery parameters were sourced from edmunds.com and batterydesign.net, respectively. A set of 20 parameters was selected for analysis according to their impact on physical quantities influencing the technical specifications concurring to S_1, S_4 and S_6. The full list of parameters is reported in the supplementary material. This dataset was used to construct a dependency and correlation matrix between specifications and parameters.

Hierarchical clustering (using the Spearman distance metric and Ward linkage) identified 3 critical clusters with 10 key parameters related to the 16 specifications in S_1, S_4 and S_6, which showed the strongest correlation with battery design parameters. As a result, S_1, S_4 and S_6 require to be improved for the car to reach a more competitive standing.

A Genetic Algorithm (GA) was used for the optimization of the parameters values based on the specific change requested and the s-p correlation information. A penalization coefficient $\lambda = 0.4$ was used. As concerns the manufacturability constraints, the optimization function incorporates limits related to the dimensional, material, and configuration properties of the battery system, the complete list of constraints is available in the supplementary material. The application of the GA optimization to the selected EV model yielded results partially presented in Table 3 and reported in the supplementary material. Categorical parameters are converted to numerical values by ranking each category according to its performance, assigning higher values to better-performing categories. The identified changes are used to estimate the variations to the related specifications through machine learning-based regression model [16] trained on the complete dataset provided in the supplementary material. Specifically, a support vector regression model was trained, with parameters as input and specifications as the target. Subsequently, the optimized parameter values were used to estimate the technical specifications, and the S_1 , S_4 and S_6 macro-specification values were recalculated accordingly. The results, presented in Fig. 2 to facilitate comparison, show how the optimized parameters bring the vehicle design closer to the segment competitive optimum, enhancing both performance and product sustainability though the estimated cost increase suggests a potential shift toward a higher market category.

5. Concluding discussion

This research work presented a methodology that integrates design optimization with manufacturability constraints to support strategic decision-making in EV production. The proposed framework maps market dynamics via macro-specification values, enabling vehicle benchmarking and assessing competitive conditions. Furthermore, its capability to identify design modifications, such as battery configuration and material selection, highlights its potential to support manufacturers in making strategic design decisions that balance cost, performance, and manufacturability.

As a limitation of the proposed approach, the precise quantification of changes in macro-specification values depends on the quality of the regression paradigm, which in this work relies on a limited dataset. Additionally, the analysis yielded only a mixed competitive scenario, primarily due to the specific conditions of the automotive market in the examined year and region. This outcome reflects a competitive landscape where electric and traditional vehicles demonstrate varying strengths across distinct specifications.

Table 3. Parameters optimization results

Critical Parameter	Initial Value p_{ji}	Weight ω_j	Final Value p_{jf}
P9- Length of Battery Box (cm)	145	0.99	169
...			
P20- Enclosure Material	Aluminium	0.86	Aluminium-SMC

Despite the lack of alternative competitive scenarios, the analytical tool remains valuable for strategic planning, supporting the positioning of new models and providing a detailed, data-driven overview of the current market context.

Future work should focus on refining the estimation of changes resulting from design parameter adjustments, aiming for a more precise assessment of their impact on targeted macro-specifications. This may also include a sensitivity analysis to explore the relationship between macro-specifications and sales data, estimating how changes in macro-specifications influence sales variations.

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