

Market Structure Mapping with Interpretable Visual Characteristics

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¹Purdue University

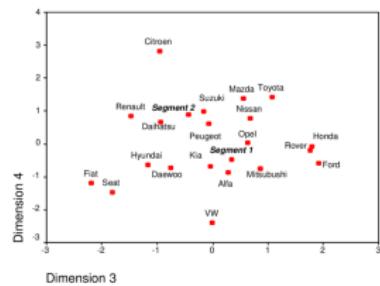
²Yale School of Management

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Marketing Dynamics
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What is a Market Structure Map?

A common element of market structure analysis is the derivation of a **market structure map**, that is, a spatial representation of firms' competitive positions relative to one another based on some measure of their competitive relationships (DeSarbo et al. 1993)

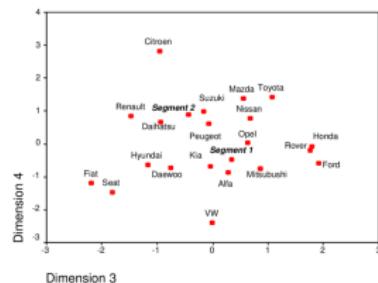
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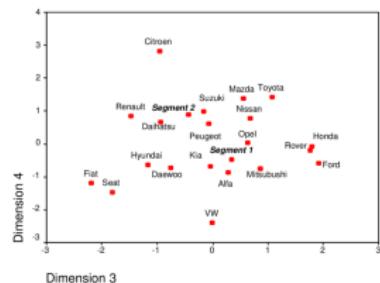
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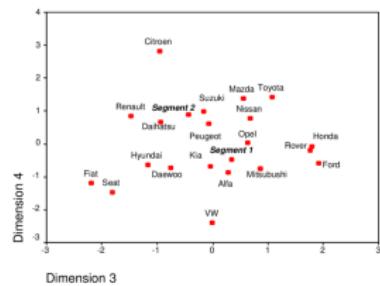
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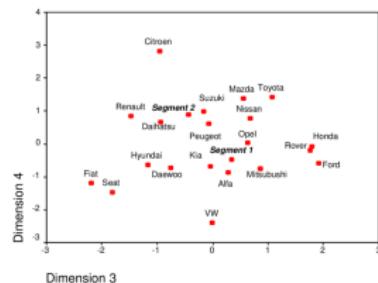
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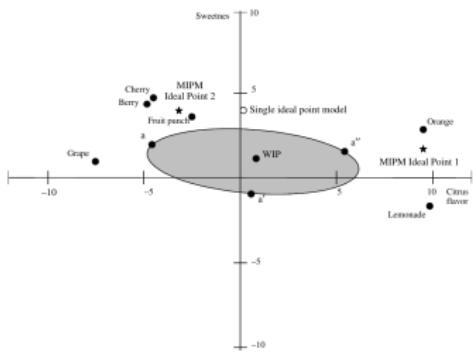
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- Strategic tool for understanding competitive landscape that enable us to:
 - Identify market gaps
 - Spot new opportunities
 - Identify competitors and evaluate positioning

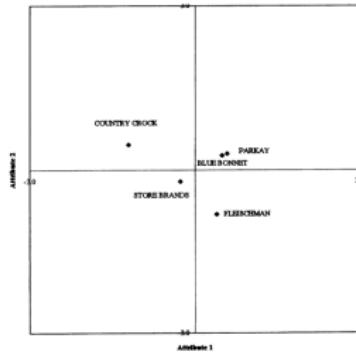


Market Structure Map: Examples

Compositional (Left) & Decompositional (Right)



Lee, Sudhir and Steckel (2002), *Journal of Marketing Research*



Erdem (1996), *Marketing Science*

Market Structure Mapping

Sources of Data

Compositional (Building up)

- Product characteristics – functional, psychological

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices

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What's common?

Neither of these approaches have considered visual characteristics.



Are these cars close substitutes?

First, consider *functional* product characteristics:

(A)

\$179,000-\$243,000, 553 HP,
16-23 MPG

(B)

From \$242,700, 542-650 HP,
14-22 MPG

Are these cars close substitutes?

First, consider *functional* product characteristics:

(A)

\$179,000-\$243,000, 553 HP,
16-23 MPG

Ferrari California



(B)

From \$242,700, 542-650 HP,
14-22 MPG

Bentley Continental GT



Importance of Visual Design

Functional characteristics alone are *not sufficient* to even place the car in an appropriate segment (submarket)

Visual design matters



“Exterior look/design is the top reason shoppers avoid a particular vehicle (30%), followed by cost (17%).”

—JD Power Avoider Study 2015

The Challenge

How to quantify visual design?

Quantifying Visual Design

Sisodia, Burnap and Kumar – JMR (2025)

Research Goals

Obtain **human-interpretable** visual characteristics (not outliers) directly from unstructured product image data:

- *automatically discover and extract characteristics for products*

Quantifying Visual Design

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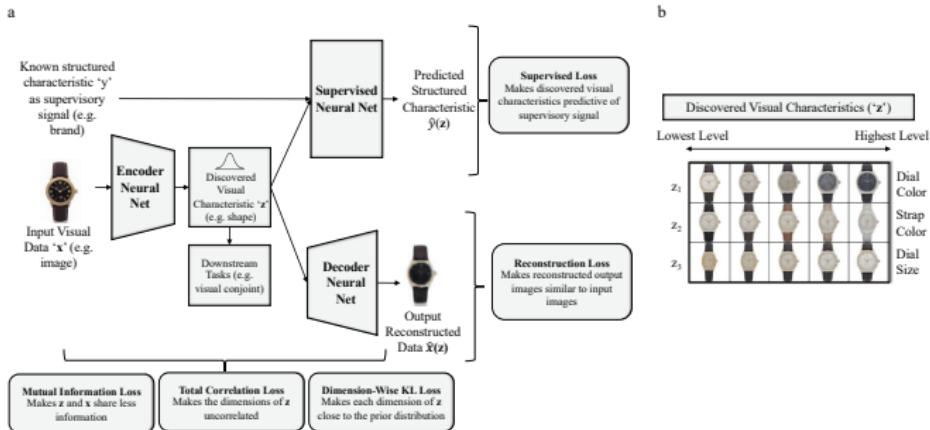
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Hyundai: (3, 8, 5, 9) compared to BMW: (1, 3, 10, 1)

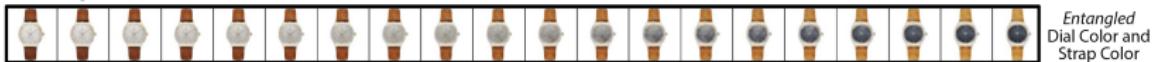
Disentanglement → Visual Characteristics



Sisodia, A., Burnap, A., & Kumar, V. (2024). Generative Interpretable Visual Design: Using Disentanglement for Visual Conjoint Analysis. *Journal of Marketing Research*

Disentangled and Entangled Representations

Example of *Entangled* Visual Characteristics



Entangled
Dial Color and
Strap Color

Example of *Disentangled* Visual Characteristics



Dial Color
Strap Color

Challenges in using visual images for market structure mapping

Three Challenges:

- ① Inputs from Raw Images: Backgrounds, lighting, and camera angles overshadow actual product design, causing mis-clusters.

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 - We need to be able to choose what visual characteristics matter for market structure
 - Does color matter? Does angle matter?

Should Color be included in Visual Characteristics Maps?

- Should a red Ferrari California be close substitute to a red Toyota Corolla?

- **UK Automobile Market**
 - 2,439 make-model-year observations from 2008 to 2017
 - 379 unique models from 49 unique makes
- **Sales and Auto Characteristics:**
 - Characteristics (price, MPG, horsepower, weight, dimensions, etc.) from Parker's
 - Sales from DVM-CAR¹
- **Images:**
 - Front-facing automobile images from DVM-CAR
 - Converted from color to grayscale to *focus on shape* rather than color.
 - (very) Low-resolution: 128×128 pixels

¹Huang, Jingmin, et al. (2022), *IEEE International Conference on Big Data*

Segments in the UK automobile market

Segment	Description	Image	Label
A	Minicars		
B	(Subcompact)		Seg B (Subcompact)
C	Compact		Seg C (Compact)
D	Mid-size		Seg D (Mid-Sized)
E	Mid-size Lux...		Seg E (Mid-Sized Luxury)
J	SUV		Seg J (SUV)
M	MPV		Seg M (MPV)

Summary Statistics of the 2013 UK Auto Market

Variable	Mean	St. Dev.	Min.	Max.
Total Quantity Sold	8,074.834	13,714.100	1	113,390
Price (in £000 units)	26.333	14.668	7.868	108.624
MPG (tens of miles per gallon)	4.999	1.058	2.250	7.200
Weight (in 10 lbs)	327.704	2.444	324.506	332.106
HP/Wt (in HP per 10 lbs.)	0.461	0.169	0.060	1.347
Length (in 1000 inches)	1.724	0.178	1.062	2.054
Width (in 1000 inches)	0.756	0.063	0.580	0.899
Height (in 1000 inches)	0.616	0.054	0.537	0.780
Wheelbase (in 1000 inches)	1.046	0.081	0.735	1.266
Space (length × width)	1.310	0.215	0.697	1.759
Vehicle Segment (Proportion):				
Segment A (Minicars)	0.112	0.316	0	1
Segment B (Subcompact)	0.120	0.326	0	1
Segment C (Compact)	0.162	0.369	0	1
Segment D (Mid-Size)	0.129	0.335	0	1
Segment E (Mid-Size Luxury)	0.071	0.257	0	1
Segment J (SUV)	0.241	0.428	0	1
Segment M (MPV)	0.166	0.373	0	1
Country of Origin (Proportion):				
France	0.108	0.311	0	1
Germany	0.241	0.428	0	1
Japan	0.220	0.415	0	1
South Korea	0.091	0.289	0	1
UK	0.108	0.311	0	1
USA	0.058	0.234	0	1

Match each model with front-facing image

Is this sufficient?

"Market research studies have shown that 70% of consumers identify and judge automobiles by the appearance of headlights and grille located on the face of the automobile."

– *The Wall Street Journal*
2006



Loss Function & Supervisory Signals

$$\underbrace{L(\theta, \phi; \mathbf{m}, \mathbf{v})}_{\text{Disentanglement Loss}} = \underbrace{-\mathbb{E}_{q_\phi(\mathbf{v}|\mathbf{m})} [\log p_\theta(\mathbf{m}|\mathbf{v})]}_{\text{Reconstruction Loss}} + \underbrace{I_q(\mathbf{v}, \mathbf{m})}_{\text{Mutual Information Loss}} \\
 + \lambda_1 \underbrace{KL \left[q(\mathbf{v}) || \prod_{j=1}^J q(v_j) \right]}_{\text{Total Correlation Loss}} + \underbrace{\sum_{j=1}^J KL [q(v_j) || p(v_j)]}_{\text{Dimension-Wise KL Divergence Loss}} + \lambda_2 \underbrace{P(\widehat{\mathbf{y}(\mathbf{v})}, \mathbf{y})}_{\text{Supervised Loss}}$$
(1)

Number of Signals	Supervisory Signals	λ_1	λ_2	UDR
3	Wheelbase, Width, Height	50	10	0.739
3	HP/Weight, MPG, Space	50	30	0.710
1	Price	50	30	0.708
1	Weight	50	40	0.708
1	Wheelbase	50	30	0.690
1	Width	50	5	0.689
3	Length, Width, Height	50	40	0.678
1	Length	50	40	0.666
0	Unsupervised β -TCVAE	50	0	0.658
1	Height	30	20	0.378
1	Country of Origin	10	10	0.139
1	Segment	10	10	0.134
1	Unsupervised VAE	1	0	0.073
1	Unsupervised AE	0	0	0.074
1	Make	1	1	0.072

$$\lambda_1 \in [1, 5, 10, 20, 30, 40, 50] \text{ and } \lambda_2 \in [0, 1, 5, 10, 20, 30, 40, 50].$$

Visual Characteristic 1: Body Shape



Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Body Shape	0.30	0.33	0.39	-0.28	0.25	-0.42

- Hatchback-like profiles → smaller wheelbase, lower length, and lighter
- Hatchback-like profiles → taller and narrower

Visual Characteristic 2: Boxiness



Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Boxiness	0.05	-0.07	0.14	-0.59	0.02	-0.49

- Higher degree of boxiness → Taller and upfront from the front
- Lower degree of boxiness → Flatter and sleeker
- Boxiness captures cabin “uprightness” (not related to length or wheelbase)

Visual Characteristic 3: Grille Height



Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Grille Height	0.04	0.02	0.05	-0.04	0.03	-0.05

- Reflects stylistic design choices
- Unrelated to size-related factors

Visual Characteristic 4: Grille Width



Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Grille Width	0.12	0.08	0.12	0.03	0.15	-0.09

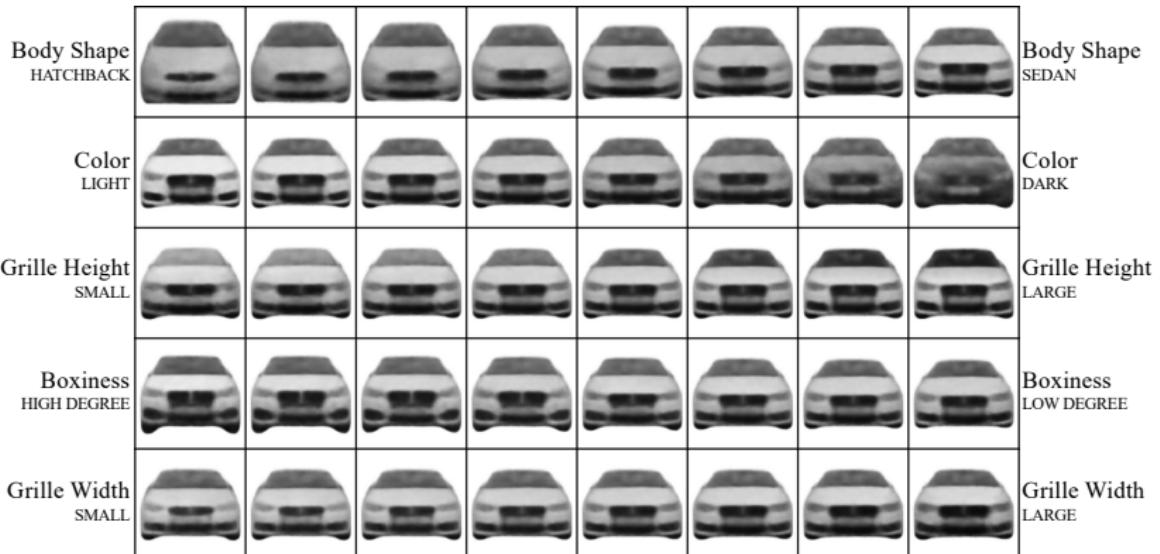
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Visual Characteristic 5: Color



- We find the visual characteristic of *Color*.
- Color should not impact market structure because a car is available in many colors.
- We, therefore, exclude it when we create market structure maps.
- This is only possible because of disentanglement.

Disentanglement obtains four interpretable visual characteristics



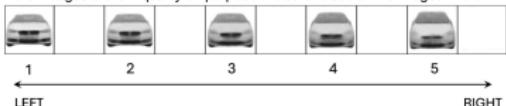
Human Understanding of Visual Characteristics

- Showed respondents sequence of car images

Q1/4: Look at the below image to see the various parts of a car.



Now, carefully examine each car image below from 1 to 5, going from left to right.
Note: Images are low-quality on purpose. Be sure to see all the images 1 to 5.



How does the car change the most as you go from image 1 to 5? Go through each part of the car one by one before deciding your response. Write it in a few words.

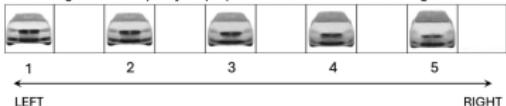
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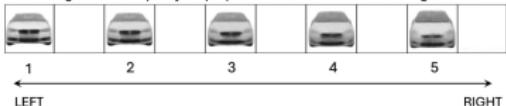
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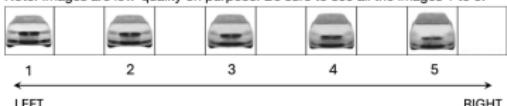
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- Example: LLM summarizes that respondents are saying that cars becoming lower, flatter, and wider can be thought of as boxiness

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Quantification Validation Survey Question

Which pair of cars in your judgment are visually more similar? Carefully check both large and small visual aspects. Do not consider any non-visual features like brand or price.



Left Pair

Right Pair

Correlation Between Different Characteristics

	Price	Functional Characteristics			Boxiness	Visual Characteristics		Grille Width
		MPG	HP/Weight	Space		Body Shape	Grille Height	
Price	1.00							
MPG	-0.60	1.00						
HP/Weight	0.74	-0.48	1.00					
Space	0.67	-0.47	0.36	1.00				
Boxiness	0.06	0.04	0.29	0.09	1.00			
Body Shape	0.50	-0.25	0.54	0.36	0.13	1.00		
Grille Height	0.11	0.03	0.12	0.05	0.04	-0.02	1.00	
Grille Width	0.07	-0.05	0.04	0.15	0.01	-0.12	-0.05	1.00

Does Form Follow Function? Insight 1: Products close in functional space are differentiated visually

- *Operationalization:* Calculate correlation between distances in functional product characteristics and visual product characteristics for each pair of make-models within each segment

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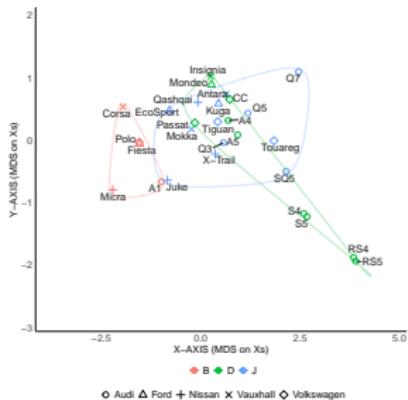
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Segment	Correlation	Std. Error
A (Minicars)	-0.08	0.05
B (Subcompact)	-0.05	0.05
C (Compact)	-0.05	0.04
D (Mid-size)	0.02	0.04
E (Mid-size Luxury)	0.13	0.10
J (SUV)	0.09	0.03
M (MPV)	0.11	0.04

Market Structure Maps

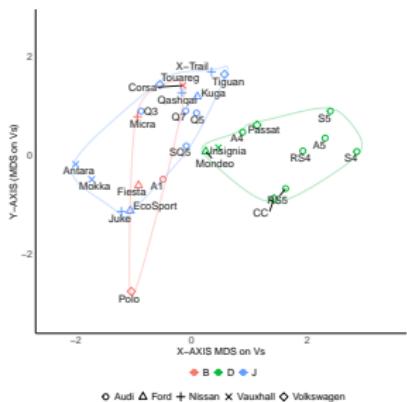
Market Structure Map using only functional characteristics

Segment	Description
B	Subcompact
D	Mid-size
J	SUV



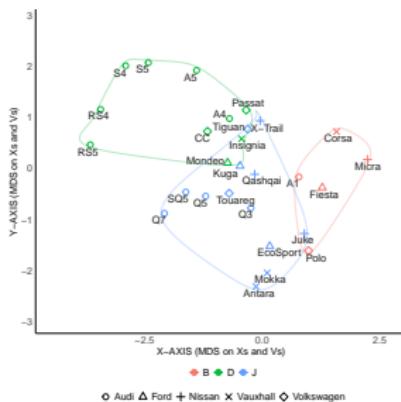
Market Structure Map using only visual characteristics

Segment	Description
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D	Mid-size
J	SUV



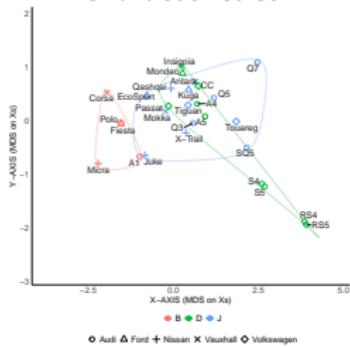
Market Structure Map using both type of characteristics

Segment	Description
B	Subcompact
D	Mid-size
J	SUV

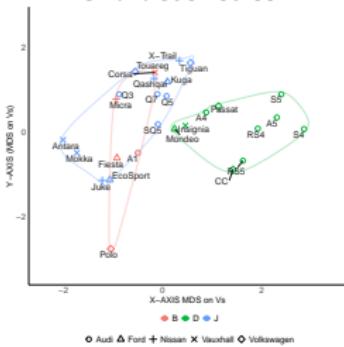


Insight 2: Visual increases differentiation and helps separate segments

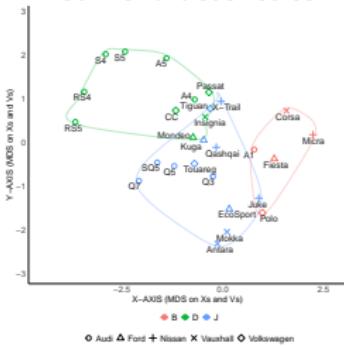
Only Functional Characteristics



Only Visual Characteristics



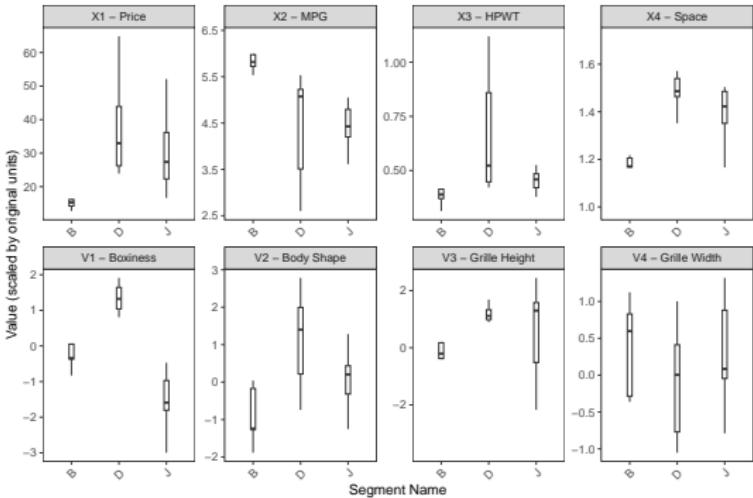
Both Characteristics



Does Disentanglement Provide Further Insights?

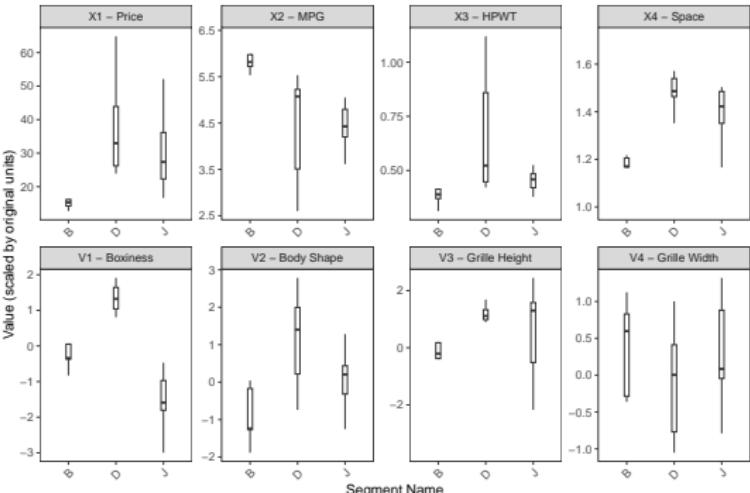
Insight 2D: Which visual characteristics increase differentiation?

- Disentanglement identifies interpretable characteristics contributing to differentiation



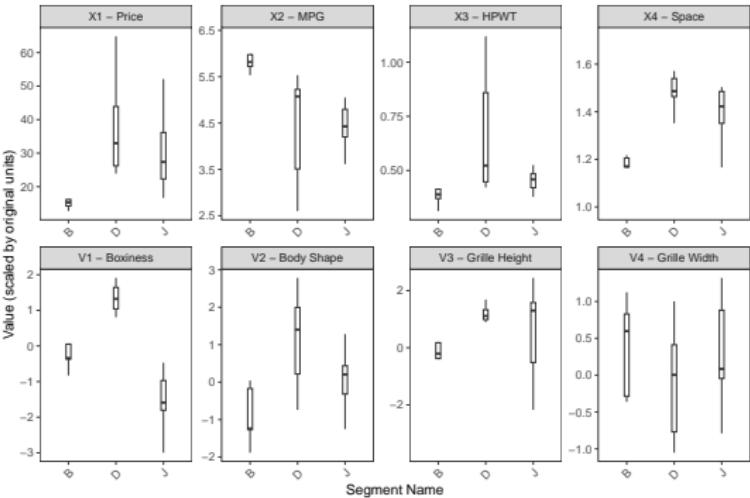
Insight 2D: Which visual characteristics increase differentiation?

- Disentanglement identifies interpretable characteristics contributing to differentiation
- Seg D & J overlap on most of the functional characteristics but Seg B is different



Insight 2D: Which visual characteristics increase differentiation?

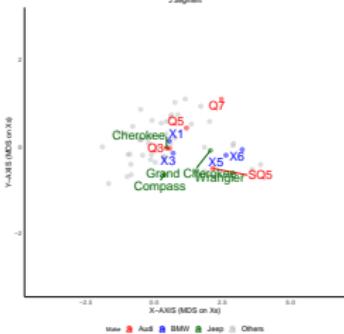
- Disentanglement identifies interpretable characteristics contributing to differentiation
- Seg D & J overlap on most of the functional characteristics but Seg B is different
- Seg D & J are different in boxiness and grille



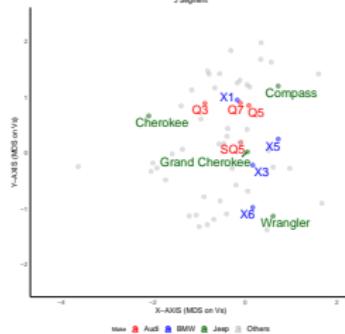
Insight 3: Different Visual Strategy Across Brands

Segment J – SUVs

**Only Functional
Characteristics**

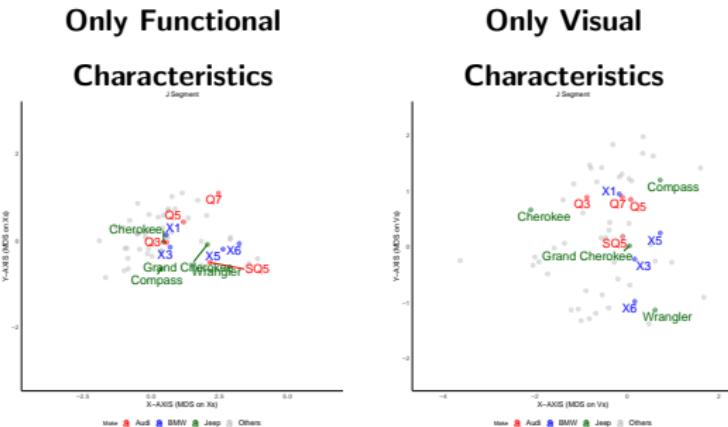


**Only Visual
Characteristics**



Insight 3: Different Visual Strategy Across Brands

Segment J – SUVs



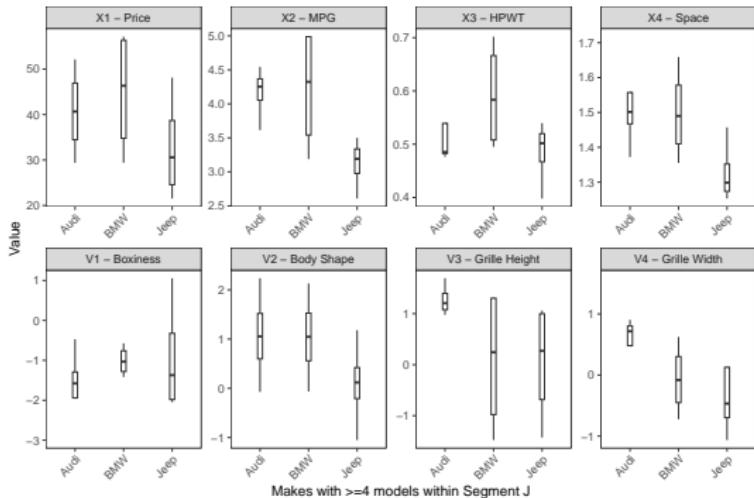
Area Share of a Make in Functional Space & Visual Space (Segment J: SUVs)

Make	Models	Area Share (Functional)	Area Share (Visual)	Ratio
Audi	4	17.90%	2.96%	6.05
BMW	4	6.35%	6.48%	0.98
Jeep	4	9.38%	28.42%	0.33

Insight 3D: Different Visual Strategy Across Brands

Disentanglement identifies interpretable characteristics

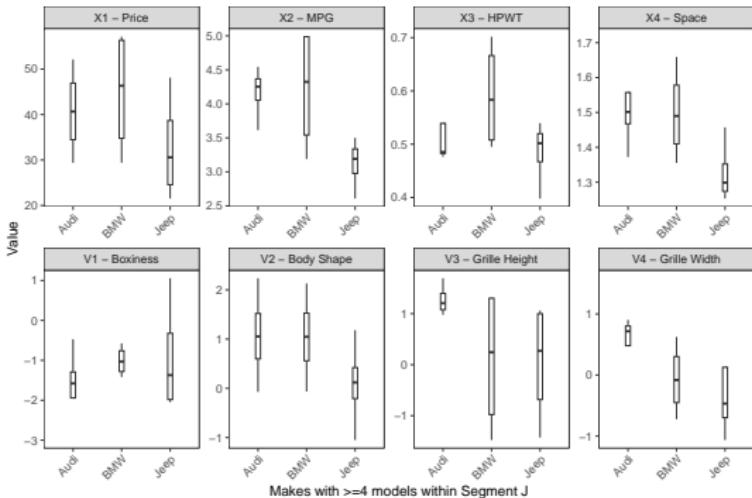
- Audi is very tight on some visual characteristics, notably, grille height and grille width \Rightarrow distinctive look



Insight 3D: Different Visual Strategy Across Brands

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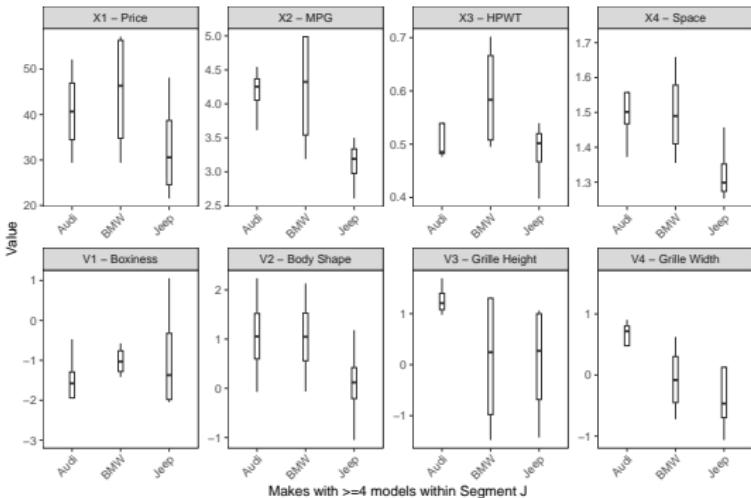
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Insight 3D: Different Visual Strategy Across Brands

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- Audi is very tight on some visual characteristics, notably, grille height and grille width \implies *distinctive look*
- BMW is typically a more “boxy” look
- Jeep varies on most visual characteristics



Insight 3: Different Visual Strategy Across Brands

Audi Q3



Audi Q5



Audi Q7



Audi SQ5



BMW X1



BMW X3



BMW X5



BMW X6



Jeep Cherokee



Jeep Compass



Jeep Grand
Cherokee

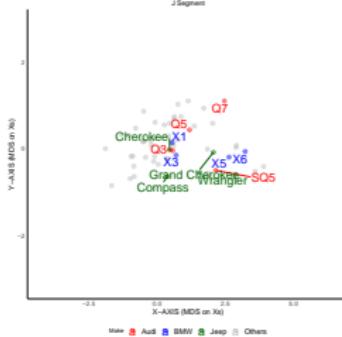


Jeep Wrangler

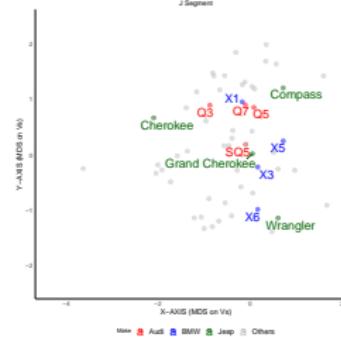


Insight 4: Product-Level

Only Functional
Characteristics



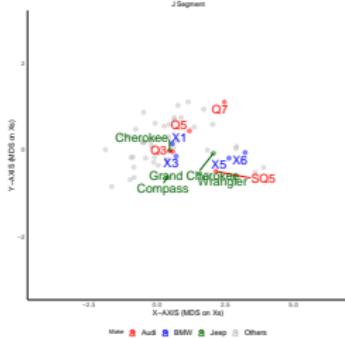
Only Visual
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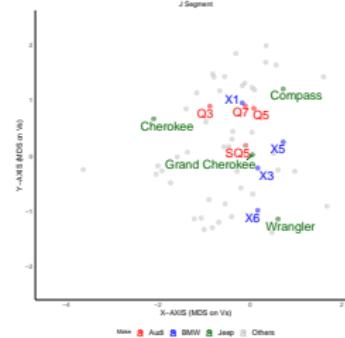
- Looking only at functional characteristics, BMW seems to be positioning X5 and X6 too close (cannibalization risk)

Insight 4: Product-Level

Only Functional Characteristics



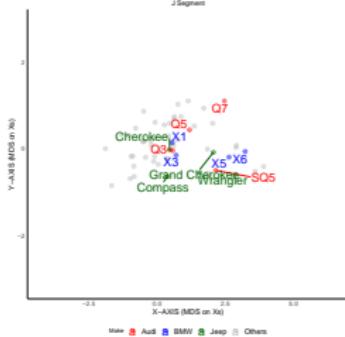
Only Visual Characteristics



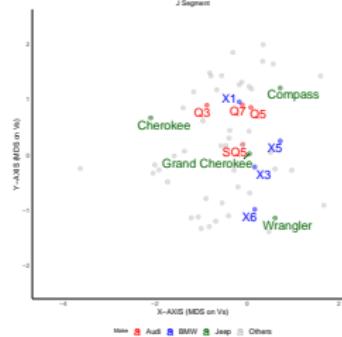
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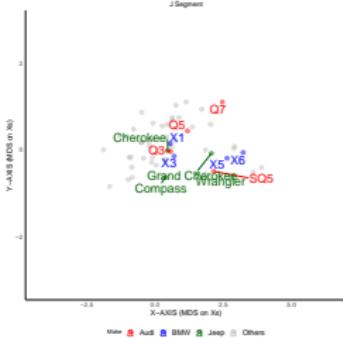
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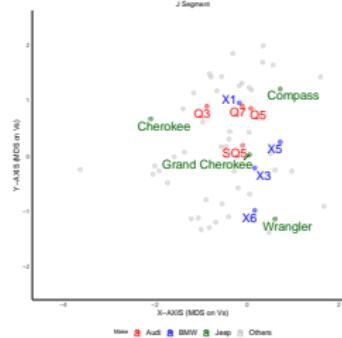
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- Positioning BMW X3: Should I focus on Cherokee (which is what functional map suggests)?

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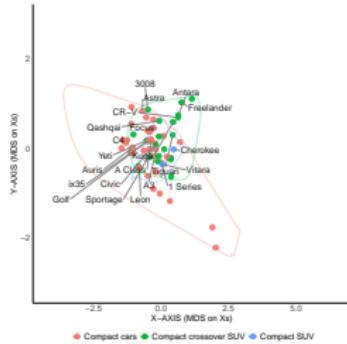
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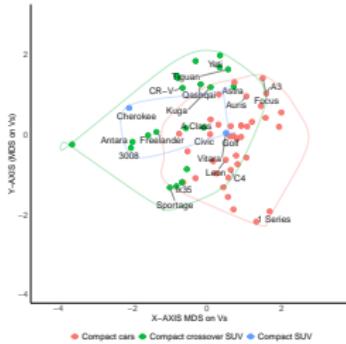
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- Positioning BMW X3: Should I focus on Cherokee (which is what functional map suggests)?
 - Visual map suggests the Grand Cherokee is closer instead

Insight 5: Leaping to Another Category

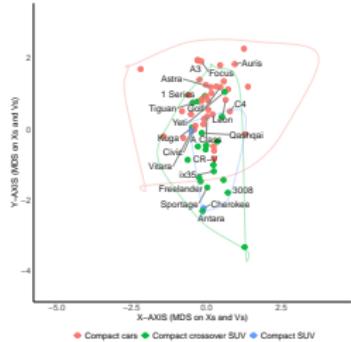
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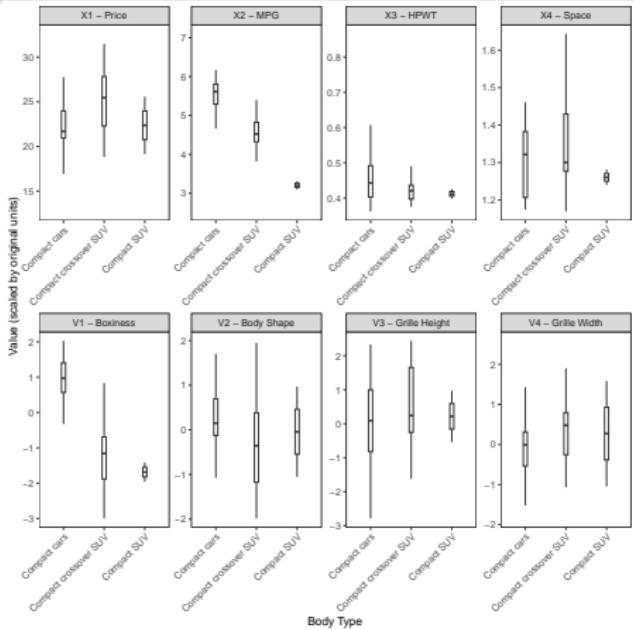


Both Characteristics



Insight 5D: Leaping to Another Category

- Compact cars and compact crossover SUVs differ in boxiness
- Compact cars and compact crossover SUVs overlap across most functional characteristics
- Compact crossover SUVs and compact SUVs are similar in visual characteristics
- Compact crossover SUVs and compact SUVs differ in some



Connecting Consumer Search to Market Structure Maps

Consumer Search \iff Market structure maps?

We use Google Trends to look for consumers searching pairs of models

- Consumer searching for “Honda Civic” and “Toyota Corolla” more likely to be comparing

$$\log_{10}(Y_{AB} + 1) = \beta_0 + \beta_1(|X_A - X_B|) + \beta_2(|V_A - V_B|) + \epsilon_{AB}$$

²Raw Google Trend values are scaled by each pair's segment sales share

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Consumer Search \iff Market structure maps?

	(1)	(2)	(3)	(4)
Constant	2.778*** (0.205)	9.509*** (1.425)	2.974*** (0.291)	8.871*** (1.479)
Δ HP/Weight	-2.395 (1.691)	-3.761** (1.460)	-2.886* (1.638)	-4.021*** (1.453)
Δ Space	-1.685 (1.068)	1.200 (0.851)	-1.444 (1.031)	1.431* (0.853)
Δ MPG	-0.601*** (0.199)	-0.407** (0.163)	-0.599*** (0.196)	-0.432*** (0.165)
Δ Price	-0.214*** (0.037)	-0.188*** (0.031)	-0.203*** (0.036)	-0.194*** (0.032)
Δ Boxiness			-0.263 (0.161)	0.249 (0.154)
Δ Bodyshape			0.149 (0.108)	-0.361** (0.144)
Δ Grille Height			-0.284*** (0.072)	-0.007 (0.065)
Δ Grille Width			0.324** (0.138)	-0.001 (0.145)
Make Fixed Effects	No	Yes	No	Yes
Observations	306	306	306	306
R ²	0.168	0.590	0.247	0.602
Adjusted R ²	0.157	0.559	0.227	0.566

Note: * p<0.1; ** p<0.05; *** p<0.01

Consumers search for visually similar cars even after accounting for functional similarity

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