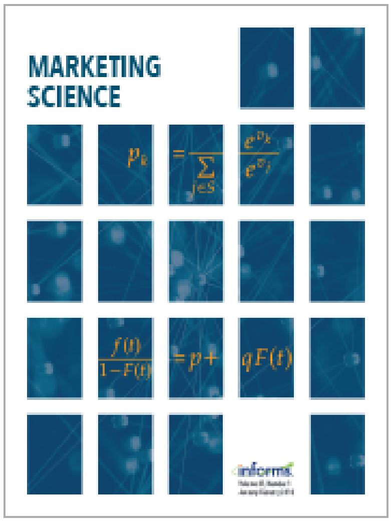

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Gut Liking for the Ordinary: Incorporating Design Fluency Improves Automobile Sales Forecasts

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Automotive sales forecasts traditionally focus on predictors such as advertising, brand preference, life cycle position, retail price, and technological sophistication. The quality of the cars' design is, however, an often-neglected variable in such models. We show that incorporating objective measures of design prototypicality and design complexity in sales forecasting models improves their prediction by up to 19%. To this end, we professionally photographed the frontal designs of 28 popular models, morphed the images, and created objective prototypicality (car-to-morph Euclidian proximity) and complexity (size of a compressed image file) scores for each car. Results show that prototypical but complex car designs feel surprisingly fluent to process, and that this form of surprising fluency evokes positive gut reactions that become associated with the design and positively impact car sales. It is important to note that the effect holds for both economy (functionality oriented) and premium (identity oriented) cars, as well as when the above-mentioned traditional forecasting variables are considered. These findings are counter to a common intuition that consumers like unusual–complex designs that reflect their individuality or prototypical–simple designs that are functional.

Key words: automobile sales; product design; processing fluency; visual prototypicality; visual complexity
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Introduction

A widespread belief in the automobile industry is that simple and prototypical designs do best with the mass consumer who values functionality, whereas unusual and complex designs do best with the premium consumer who values individuality (Sukhdial et al. 1995). Actions by car manufacturers reflect such a belief; for instance, companies generally introduce unusual and complex features (e.g., unusual colors, unique body lines) in atypical top-of-the-line products and slowly transfer them to mass market cars over time.[1] Ample research in psychology, however, contradicts such a premise. It instead suggests that prototypical and complex designs (as opposed to simple and prototypical, or complex and unusual designs) will do best in the marketplace (Bornstein 1989, Bornstein and D'Agostino 1994), and that a preference for such designs will emerge regardless of whether a car is sold for functional or image-based reasons.

These findings draw on an inherent and fundamental truth about the way the visual system operates: the idea that people's preference for any design depends on the extent to which its visual processing is surprisingly fluent. Specifically, visual processing depends on two uncorrelated aspects of a design—processing efficiency and processing expectation. Processing efficiency results whenever a design is more prototypical (versus atypical)—such designs recruit fewer neural resources and are processed quickly, and quick, efficient processing results in a gut-level positive affective response (Winkielman and Cacioppo 2001). Whenever people have a processing expectation of difficulty, this gut-level affect increases preference of a design. Processing expectation depends on visual complexity (e.g., density) of the design, and when people expect difficulty, they are unable to attribute the gut-positive affect evoked by efficient processing to specific design characteristics, and they therefore infer that the gut-positive reaction must imply that they like the design. On the other hand, when

[1] For instance, in 2006, Audi introduced a relatively functionless "daylight illumination" design feature (dotted patterns under the headlights) in the Audi S6 premium sports car that they gradually extended to their mass market cars once the feature became more common across the European market.

the processing expectation is one of ease, because a design is visually simple, people attribute the gut-level affective response that arises from processing efficiency to design simplicity, and they correct for an influence of affect on their preference toward the design (Winkielman et al. 2006). Although over 200 laboratory studies thus far attest to the robustness of fluency effects on consumer preferences (Lee 2001, Lee and Labroo 2004, Schwarz 2004), researchers have observed the effects in low-involvement situations that have modest consequences and also under tightly controlled experimental conditions. Whether (and to what extent) the fluency of processing a design exerts any influence in everyday life, especially in the context of high-involvement decisions that have real financial implications (e.g., a car purchase), is unclear.

To systematically examine this issue, we predicted six months of sales of economy (functionality-oriented compact cars) and premium (identity-based) cars in the German market (January–June 2007). We first created measures of objective visual prototypicality and of complexity that assigned equal weight to each car design and thus were independent of actual car sales. To do so, we professionally photographed, under standardized conditions, the frontal design of each car in our sample. We morphed these images using facial-morphing software and thereby developed a central representation of an economy and a premium car. The Euclidian distance of each car to its morph served as a measure of objective prototypicality. The size of an image file that resulted after a compression algorithm searched for visual redundancies served as a measure of objective complexity. It is important to note that these two measures are *not* correlated with each other, and neither correlates with other attributes of a car, such as brand preference, retail price, technological sophistication, advertising, or a product's life cycle position, all of which we also included as controls in our model to predict sales. In accordance with a fluency framework, our results show that prototypical but complex car designs garner the highest sales, regardless of whether they are economy or premium cars. Furthermore, incorporating these two design elements in forecasting models improves their prediction by up to 19%.

In demonstrating these effects, the current research makes at least three important contributions to the marketing literature. To begin with, to the best of our knowledge, it is the first to generalize past laboratory findings to real-world high-involvement decisions with real financial implications and to demonstrate a particularly large effect-size of fluency. Second, although product design has attracted much research activity (e.g., Bloch 1995, Chitturi et al. 2008), to the best of our knowledge, this paper is the first to specify which design factors impact sales, and to what extent. Third, from a modeler and practitioner perspective, these two objective design measures significantly improve sales forecasts and can help enhance the predictive power of quantitative forecasting models.

In what follows, we summarize the literature on processing fluency to predict an interactive effect of prototypicality and complexity on car sales. We then describe how we developed and validated our measures of objective prototypicality and complexity. It is important to note that both measures are exogenous with respect to sales: the measures are not affected by car sales, they do not correlate with any known predictors of sales, and they have never previously been incorporated in sales forecasts, all of which imply that manufacturers do not intuit these factors in advance of designing their cars. We then report several regression models that predict car sales from the design variables and other important controls, we evaluate the incremental fit that our variables add to traditional models, and we provide evidence of a mediating mechanism of fluency. We conclude by discussing managerial implications of our research and avenues for future research.

Theoretical Background

One of the most intriguing psychological findings to emerge in recent years is that when people are forming first impressions, they prefer prototypical stimuli (referred to as the "beauty-in-averageness" effect). Initial findings reported that people prefer a morphed face created by software that weighted all members of the sample equally over any individual face in the sample (Langlois and Roggman 1990), and researchers presumed that this preference arises because prototypicality conveys a reproductive advantage that the brain is hardwired to search out (Rhodes and Tremewan 1996). Halberstadt and Rhodes (2000), however, demonstrate similar effects with images of dogs, fish, and watches, stimuli unlikely to be associated with reproductive fitness. Investigations based on these findings suggest that people's visual memory systems store rudimentary representations of categories of products or stimuli as memory traces, and prototypical traces are activated more quickly, easily, and efficiently than nonprototypical traces. For instance, using random dot patterns, Winkielman et al. (2006) show that prototypical patterns are classified more efficiently and recruit fewer neural resources. Other laboratory studies further establish that this kind of processing fluency is inherently positive and is experienced as a gut-level affective reaction (Lee 2001, Lee and Labroo 2004, Reber et al. 1998, Winkielman and Cacioppo 2001). Researchers have also observed these gut-level affective responses toward easy-to-process line drawings, abstract paintings, pictures (Reber et al. 1998), music (Anand et al. 1988), food (Sullivan and Birch 1990), and advertising (Labroo and Lee 2006), and they observed them regardless of whether fluency was a result of repeated exposure to a visual stimulus (Zajonc 1968), exposure to related stimuli that activated visual traces of the target stimulus (Labroo et al. 2008), or of figure-ground contrast of the target stimulus (Reber et al. 1998).

In these and other studies, although fluency always evokes a positive hedonic reaction toward the target stimulus, its impact on the evaluation of that stimulus depends on whether people use their affect as information or are able to discount the hedonic experience (Schwarz 2004). Studies show that people are able to correct for a biasing influence of fluency on their preferences when they become aware of a possible source of bias on their judgment (Berlyne 1966, Lee 2001). For example, when a product's design is simple and consumers expect fluent processing, people are able to correct for an influence of fluency on preference (Bornstein and D'Agostino 1994). At first, this insight might appear contradictory—visual simplicity could, for instance, have been predicted to increase processing efficiency. However, studies establish that visual complexity is a determinant of processing expectation and an overt judgment that corresponds with perceived sophistication of a design, whereas prototypicality is a determinant of processing efficiency and a gut-level response (Reber et. al 2004). Quick, efficient processing always results in a gut-level positive affective response (Winkielman and Cacioppo 2001), but this affective response increases preference of a design only when people expect difficult processing. In such situations, they are unaware of the source of their gut affective reaction and attribute it to liking the target design. In contrast, when a design is visually simple, people discount fluency because they attribute the positive gut reaction to the design's simplicity (Schwarz 2004).

The purpose of the current research is to investigate whether we observe similar effects in a real-life setting involving high financial commitment by consumers and, if we do, to investigate the size of the effect. To this end, we focus on German car sales (January–June 2007). Traditional sales forecasts include many important product characteristics such as quality, price, and image considerations (see Busse et al. 2006, Sriram et al. 2006, Zettelmeyer et al. 2006), but we expect an additional effect of design fluency. In accordance with the laboratory findings, we predict a positive effect of visual prototypicality on fluency (high processing efficiency is affective), but the effect of fluency on sales will be moderated by design complexity. Prototypicality will increase sales of visually complex cars but not of visually simple cars.[2] Moreover, in contrast to the more cognitively processed features of a car (e.g., price, quality), which show substantial differences across different consumer segments, we expect the affective fluency effects to hold irrespective of whether a car belongs to the functional economy (e.g., Honda, Renault, Volkswagon) or image-based premium (e.g., BMW, Audi, Mercedes) category.

Data Description and Validation of Variables

We divide this section into five parts. We begin with a description of the dependent variable—six months of car sales in Germany. The next two parts explain the development and validation of the independent variables: objective design prototypicality and complexity. The fourth section describes the mediator and objective fluency measures, and the final section describes traditional marketing-mix variables used as controls in the sales forecasting model.

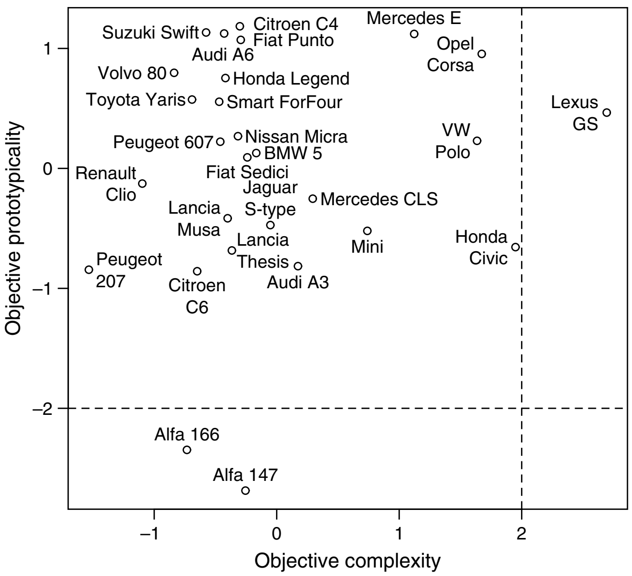
Car Sales as the Dependent Measure

We obtained six months (January–June 2007) of officially recorded car sales registration data from the German Federal Motor Transport Authority (Kraftfahrt Bundesamt (KBA)). The data set includes a total of 251,288 cars (167,382 compact cars and 83,906 premium cars) sold in the German market between January and June 2007. Included are 28 popular models. Of these, 16 are compact models that cover 56.81% of all compact car sales in the period, and 12 are premium models that cover 91.43% of all premium sales in the period (see Figure 1 for all car models in our sample).

These models cover the most important market players in each segment. Notably, we cover 91.43% of the premium segment, including models of Audi (A6), BMW (5 Series), Jaguar (S-type), and Mercedes (E, CLS) that might sell for identity-based reasons and correlate inversely with design prototypicality. However, we predict that objective visual prototypicality will increase the sales of these cars, provided the

[2] We do not make predictions pertaining to visual complexity, but it is possible that a main effect on sales will be observed, for two reasons. First, because we expect prototypicality to affect sales at high but not low levels of complexity, the interaction effect is likely to pull out a main effect of complexity. As with any main effect that is qualified by an interaction, such a main effect should be interpreted with *extreme* caution. A main effect of complexity can be interpreted as real *only* if high (versus low) complexity results in increased sales of prototypical designs *and* of nonprototypical designs. We do not expect the latter contrast to be significant, and, thus, the main effect of complexity is *not real* if it does not exist in absence of prototypicality. Second, some research (Labroo and Kim 2009) shows that when people expect to exert effort, they infer that an outcome must be more valuable. From that perspective, there is a theoretical reason to predict a direct and positive effect of complexity on sales.

Figure 1 **Distribution of the Cars on the Standardized Scores of the Two Objective Measures of Prototypicality (Euclidian Similarity) and Complexity (ZIP-Compressed File Size)**



design is also visually complex—exactly the same two variables that will also predict the sales of economy cars. Another important characteristic of this subset of cars is that it includes multiple models of cars from the same manufacturer (e.g., Honda Legend, Honda Civic). Because these cars received different scores on our objective measures of design prototypicality and complexity (see Figure 1), manufacturer reputation or other manufacturer characteristics are unlikely to drive any of our observed effects.

Objective Design Prototypicality and Complexity as Independent Variables

We procured a metallic-grey specimen car of each of the 28 car models from various dealerships. We then had the frontal design of each car photographed in a professional studio under standardized conditions. Using morphing software (Perrett et al. 1994), we created two separate morphs, one with the photographs of the 16 compact cars and another with the 12 premium cars. We first defined 50 characteristic feature points of each frontal design (e.g., vertex of headlights, grill, windshield). Next, the morphing software computed the mean position of each feature point across all models within a segment. It then warped the images of all individual cars to the prototypical proportions (see the appendix; feature points also indicated) and averaged the color values of the corresponding pixels to create the morph (Benson and Perrett 1993).

We calculated a prototypicality score for each design by summing the Euclidian distances of each of the 50 feature points of the car from the corresponding feature points in the morphed (prototypical) car and inverting the overall score. A higher score indicated a particular car was more prototypical and presumably easier (or more efficient) to process. An important aspect of this procedure is that each car in the data set received *equal* weight in the determination of what constituted a prototypical feature, and actual sales did not influence the prototypicality score.[3]

To calculate an objective measure of design complexity, we ran several computer algorithms to compress each image file. Perception research and algorithmic information theory (AIT; Donderi 2006) posit that a compressed image file can accurately measure picture complexity. The rationale is that a more complex picture is denser and has fewer redundancies, and therefore the size of a compressed image file (e.g., JPEG, ZIP) is a close approximation of the complexity of the depicted image. These measures correlate positively ($r = 0.82$) with subjective ratings of design complexity (Donderi 2006), and this approach is suited to our stimuli because the photographs of cars used in our sample were taken under standardized conditions. Thus, we can attribute any differences in the amount of information the pictures contain to differences in the cars' designs. We tested several compression algorithms, including JPEG, PNG, and ZIP, all of which yielded similar results and were highly correlated ($r \geq 0.97$, $p < 0.001$). In accordance with Baronchelli et al. (2005), we selected the scores yielded by the ZIP-compression algorithm as the objective measures of design complexity. The objective prototypicality scores were not correlated with the objective complexity scores ($r = 0.03$, $p = 0.894$), thus ensuring that our measures indeed capture two independent constructs.

Validating the Objective Prototypicality and Complexity Scores

To allow a unified analysis across the two segments as well as a meaningful interpretation of regression coefficients across the distribution of cars, and because we predict an interaction between the two design measures that requires mean-centered variables, we z-transformed the Euclidian similarity and ZIP complexity scores for each segment. Mapping the coordinates of each car on the two objective design measures

[3] To attest reliability and confirm that the measure does not depend on any particular design, we examined the effect of omitting each car from the morph. We thus built 16 (12) new morphs for the compact (premium) segment, calculated 16 (12) sets of Euclidian prototypicality scores for each of our original cars based on these newly created morphs, and correlated the scores with the initial Euclidian prototypicality scores. All correlation coefficients are above 0.98 and significant ($p < 0.001$). Thus, our measure is reliable and not dependent on any particular design.

(i.e., prototypicality and complexity) revealed three outliers (Alfa 147, Alfa 166 on prototypicality, and Lexus GS on complexity; see Figure 1). Because these outlier models are not significant players in the German market, we excluded their data from subsequent analyses. Their inclusion does not alter our results (see "Supplementary Analyses: Robustness Checks").

To confirm that the two objective measures (independent variables) depict the proposed constructs, a sample of consumers who fulfilled target consumer characteristics participated in a Web survey. Two hundred forty-two consumers ($M_{\text{age}} = 33$; $\text{SD}_{\text{age}} = 4.79$; 41.3% male) evaluated the 16 compact cars, and 322 ($M_{\text{age}} = 41$; $\text{SD}_{\text{age}} = 10.81$; 45.7% male) evaluated the 12 premium cars ($M_{\text{age}} = 37.5$; 57% male). Each consumer viewed one car at a time; we randomized the order in which images appeared across participants. After the instructions, an image of the first car appeared on the page and participants judged the design's typicality (1 = novel, unique; 7 = familiar, typical) and complexity (1 = simple, plain; 7 = complex, intricate). As we expected, the Euclidian (objective) prototypicality scores significantly correlated with subjective prototypicality ($r = 0.42$, $p = 0.037$) but not with subjective complexity ($r = -0.25$, $p = 0.23$). Similarly, ZIP (objective) complexity significantly correlated with subjective complexity ($r = 0.56$, $p = 0.004$) but not with subjective prototypicality ($r = -0.32$, $p = 0.12$).

Developing and Validating an Objective Measure of Fluency

Existing research employs response time to judge the attractiveness of a stimulus as an objective measure of gut-level affective reactions evoked by fluency of a stimulus (Winkielman et al. 2006). To create such an objective measure of design fluency, we surveyed 508 consumers ($M_{\text{age}} = 37.5$; 57% male; $N_{\text{compact cars}} = 253$; $N_{\text{premium cars}} = 255$). Each consumer viewed one car at a time; we randomized the order in which the images appeared across participants. Each consumer was asked to assess, as quickly as possible, the overall apperance of each car design. These response-time data were positively skewed and thus log transformed, and we removed outlier responses that were more than three standard deviations away from the mean response. As we expected, and replicating similar findings in other contexts (Labroo and Lee 2006, Winkielman et al. 2006), those reaction times that were aimed at objectively measuring design fluency corresponded with the Euclidian (objective) prototypicality scores ($r = 0.43$, $p = 0.03$) but not with ZIP (objective) complexity scores ($r = -0.29$, $p = 0.16$).[4]

To further ensure that (a) preexisting associations do not bias our fluency index and (b) the index captures fluent processing of the most basic visual memory traces of each design, we created 30 dot patterns, one for each of the 28 real cars and each of the morphs, composed only of the 50 feature points of the respective car design (see the appendix). We also created 30 additional dot patterns using the distributional parameters (mean, standard deviation) of the dots of all the cars in our sample, but having a random placement of the 50 dots of each design. To ensure that the random dot patterns did not differ with respect to symmetry, we drew dots for only the left-hand side and then mirrored the image at the vertical central axis. Sixty-one participants evaluated the visual fluency of the dot patterns of the 16 compact cars and their morph, as well as the random dot patterns associated with the 16 compact cars, and 61 participants evaluated the visual fluency of the dot patterns of dot the 12 premium cars' feature points, the morph's points, and the random dot patterns associated with these cars ($M_{\text{age}} = 44.1$; $\text{SD}_{\text{age}} = 15.11$; 47% male). We manipulated the three kinds of dot patterns within participants. The dot patterns appeared one at a time in random order on the screen and participants evaluated them on three fluency-related items ("Constructing a mental image of this car ...": 1 = feels difficult, is exhausting, takes a long time; 7 = feels easy, is relaxing, happens instantly; see, e.g., Labroo and Lee 2006). For the subsequent analyses, we pooled these three measures to form a fluency index for each type of dot pattern and aggregated the scores across participants where necessary.

First, we found, for the real cars, that our objective fluency measure (response times based) correlated with these most basic fluency impressions of pure dot patterns ($r = 0.38$, $p = 0.044$), suggesting that this response time measure is picking up a fundamental gut-level response to basic memory traces of each design. Second, we found that participants rated the dot pattern corresponding to the morph as more fluent than any of the dot patterns of individual cars in the market ($M_{\text{Morph}} = 4.07$, SE = 0.15; $M_{\text{Real\_Cars}} = 3.75$, SE = 0.12, $t(121) = 3.04$, $p < 0.01$).

[4] We further investigated what might underlie objective complexity. Based on research showing that processing effort expectation signals value (i.e., Labroo and Kim 2009) and might thus correspond with perceived sophistication of a design or perceived price premium of a car, participants were additionally instructed that price reflects a car's sophistication and were asked to estimate the price of each car. This estimate was subtracted from the car's actual retail price. As we expected, this price premium correlated with objective complexity ($r = 0.50$, $p = 0.011$), but not with objective prototypicality ($r = 0.01$, $p = 0.950$).

Third, we found that the extent to which the random dot patterns elicited feelings of fluency depended on their closeness to the morph; that is, the (objective) Euclidian similarity scores for the random dot patterns correlated positively with the subjective fluency evaluations ($r = 0.49$, $p < 0.01$).

To additionally ensure that our objective measures do not correspond with identity signaling, especially for premium cars, we conducted a post hoc test. Fifty-six consumers evaluated the 12 premium cars on the extent to which they were suited to signal one's identity ("This car's design can signal identity": 1 = disagree, 7 = agree) and ranked them according to this potential. Regressing these ratings or these rankings on the objective prototypicality and complexity scores and the interaction revealed no significant coefficients ($p > 0.24$), suggesting that identity-related effects may be based more on a car's brand associations than these basic design aspects.

Control Variables

Because a car's objective visual prototypicality or complexity scores might correlate with other explanatory variables predicting market success, we collected data on retail price, advertisement spending, overall technical quality, brand preferences, and position in a car's life cycle (Sriram et al. 2006) for each model, and we included these items as control variables in the analysis.[5] For the retail price, we used the lowest selling price of a new car found on http://www.autoscout24.de, Germany's largest Internet car market. According to Zettelmeyer et al. (2006), this price influences sales more than an unrealistically high list price. For ad spends per car, Nielsen Media Research GmbH, Germany's leading media research company, provided estimates (from January–June 2007). For a car's technical quality, we obtained an index from Allgemeiner Deutscher Automobil-Club (ADAC; see http://www.adac.de), Germany's largest automobile association (Tellis and Johnson 2007). The ADAC conducts tests and grades all cars for technical quality (1 = very good, 6 = inadequate), and it and countless newspapers and magazines publish these results. We measured brand-name preferences for the 16 compact and 12 premium cars in a Web survey using 284 and 509 car customers in Germany, respectively, who indicated on a seven-point scale how much they liked the brand names of each car. EurotaxGlass International AG, a leading automotive database, provided data on the time since market launch for each car (see Golder and Tellis 2004). None of these control items significantly correlated with either of our objective measures (Euclidian similarity: $-0.22 \leq r \leq 0.27$; $0.19 \geq p \geq 0.69$; ZIP complexity: $-0.15 \leq r \leq 0.27$; $0.19 \geq p \geq 0.86$).

[5] Some variables commonly used to predict automobile sales but unlikely to impact our objective design measures were omitted. For example, we omitted dealer characteristics (Busse et al. 2006) and seasonal/end-of-the-month effects (Zettelmeyer et al. 2006) because they are unlikely to differentially influence visual perception of a design.

Results

We first describe our main regression model, where we predict sales as a function of the two objective design measures and their interaction. We next evaluate the model's robustness against alternative model specifications. Furthermore, we explore the predictive power of our design measures in a holdout analysis that uses the sales of the first five months of our observation period to predict sales in period 6. In the final section, we implicate design fluency in a moderated mediation analysis as underlying sales.

Main Analysis: Sales as a Function of Objective Prototypicality and Complexity

We first ran a regression (ordinary least squares (OLS)) predicting sales from objective prototypicality, objective complexity, and the interaction of these two factors while controlling for the effect of segment (main model). For an individual car i, our model equation had the following form:

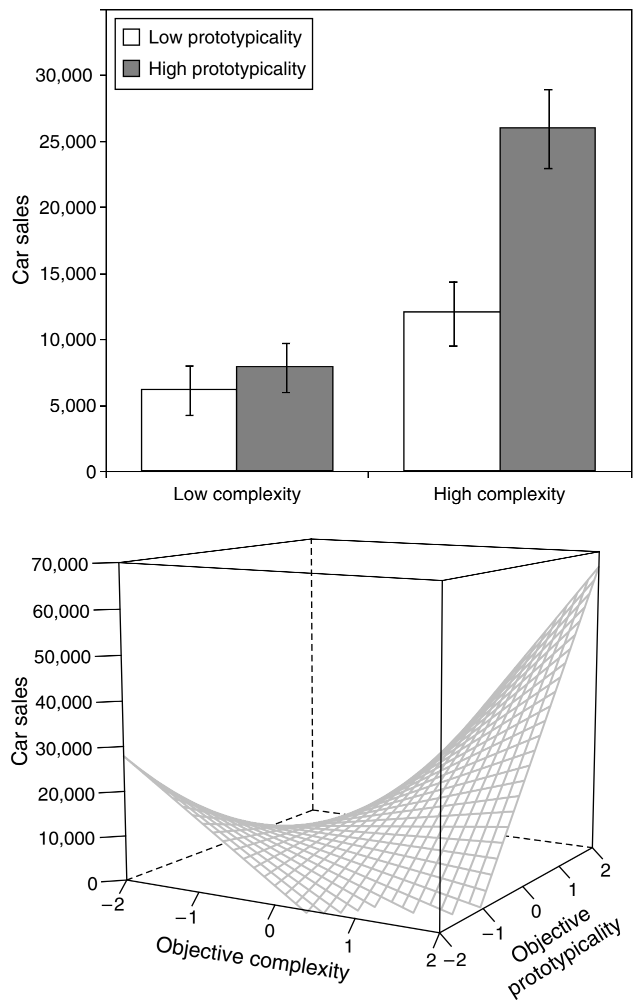
$$\begin{aligned} \text{SALES}_i = {} & b_0 + b_1 * \text{TYPICALITY}_i + b_2 * \text{COMPLEXITY}_i \\ & + b_3 * \text{TYPICALITY}_i * \text{COMPLEXITY}_i \\ & + b_4 * \text{SEGMENT}_i + e_i. \end{aligned} \tag{1}$$

Complexity was positively related to sales ($b_2 = 5{,}805.31$, $\text{SE} = 2{,}493.89$, $t = 2.33$, $p = 0.03$), as was prototypicality, although the effect was not significant ($b_1 = 3{,}861.03$, $\text{SE} = 3{,}000.88$, $t = 1.29$, $p = 0.21$). It is important to note that the predicted significant interaction ($b_3 = 8{,}820.79$, $\text{SE} = 3{,}360.93$, $t = 2.63$, $p = 0.02$) qualified these main effects, indicating prototypicality resulted in higher car sales, but only for complex designs (see Figure 2). The effect of the control variable segment was not significant ($p = 0.22$). This model explains 46% of sales variance.

Objective design aspects are usually not part of traditional forecasting models, which instead include price, advertisement spending, quality ratings, position in a product's life cycle, and brand strength. To show that the proposed objective design measures affect sales in addition to and independent of these controls, we estimated (a) a model in which we used only the five above-mentioned variables and the car segment to predict sales in the German market (null model):

$$\begin{aligned} \text{SALES}_i = {} & b_0 + b_4 * \text{SEGMENT}_i + b_5 * \text{PRICE}_i \\ & + b_6 * \text{ADVERTISEMENT}_i + b_7 * \text{QUALITY}_i \\ & + b_8 * \text{LIFECYCLE}_i + b_9 * \text{BRAND}_i + e_i, \end{aligned} \tag{2}$$

Figure 2 Sales as a Function of Objective Prototypicality (Euclidian Similarity) and Objective Complexity (ZIP-Compressed File Size), Controlling for Price, Advertisement Spending, Technological Sophistication, Brand Preference, and Time Since Market Launch



Notes. Top: data are median split on complexity, and standard errors are indicated. Bottom: mapping of continuous surface.

and (b) a model comprising, in addition to these five variables, our two objective design measures accompanied by their interaction (alternative model):

$$\begin{aligned}\mathrm{SALES}_i = {} & b_0 + b_1 * \mathrm{TYPICALITY}_i + b_2 * \mathrm{COMPLEXITY}_i \\ & + b_3 * \mathrm{TYPICALITY}_i * \mathrm{COMPLEXITY}_i \\ & + b_4 * \mathrm{SEGMENT}_i + b_5 * \mathrm{PRICE}_i \\ & + b_6 * \mathrm{ADVERTISEMENT}_i + b_7 * \mathrm{QUALITY}_i \\ & + b_8 * \mathrm{LIFECYCLE}_i + b_9 * \mathrm{BRAND}_i + e_i. \quad (3)\end{aligned}$$

The null model explained 68.6% of the variance in sales, whereas the alternative model explained 87.5% of the sales variance. The incremental F-test shows that this difference (increase in explained variance by about 19%) is statistically significant ($F(3, 15) = 7.53$; $p = 0.003$), demonstrating that the inclusion of the two objective design measures and their interaction can significantly increase the amount of explained variance compared with the traditional forecasting variables.

The alternative model further revealed that the inclusion of the five control variables did not change the direction, strength, or significance of our objective design coefficients. The same pattern of results emerged: a positive effect of prototypicality ($b_1 = 3{,}451.91$, SE $= 2{,}026.62$, $t = 1.70$, $p = 0.10$), a positive effect of complexity ($b_2 = 3{,}986.67$, SE $= 1{,}550.54$, $t = 2.57$, $p = 0.02$), and an interaction between these two factors ($b_3 = 6{,}124.58$, SE $= 2{,}090.17$, $t = 2.93$, $p = 0.01$). With respect to the control variables, we observed substantial effects of retail price ($b_5 = -0.77$, SE $= 0.26$, $t = -2.90$, $p = 0.01$) and brand preference ($b_9 = 7{,}693.61$, SE $= 1{,}881.12$, $t = 4.09$, $p < 0.01$). The other four variables did not influence sales ($p > 0.11$). Because of the high level of explained variance, we believe that the important variables are included in the model and that there is no underfitting.

Supplementary Analyses: Robustness Checks

Based on established procedures for assessing a model's robustness (Simonsohn 2011), we estimated several additional models that differed in terms of either the estimation algorithm or the set of employed predictors (versus our main model). Our central criterion for assessing model robustness is the stability of the complexity-by-prototypicality interaction across the different models. Table 1 provides a summary of these additional models and their central characteristics.

We first conducted a robust regression analysis based on MM-estimation (Yohai et al. 1991) that included the three outlier cars because the main analysis based on OLS had excluded them (see Figure 1). This model iteratively readjusted and reduced the weights of the outliers to find an optimal solution with unbiased estimates. Besides the different estimation techniques, the model was identical to the model described by formula (1). It showed the same pattern of results and hence replicates the results of the main analysis (see Table 1).

Next, we tested whether an ideal point parameterization of our objective design measures (e.g., Elrod 1988, Kamakura and Srivastava 1986, Shocker and Srinivasan 1979) is superior to our theoretically derived model. To this end, we evaluated whether quadratic terms of prototypicality and complexity, when added to the main model, increase model fit:

$$\begin{aligned}\mathrm{SALES}_i = {} & b_0 + b_1 * \mathrm{TYPICALITY}_i + b_2 * \mathrm{COMPLEXITY}_i \\ & + b_3 * \mathrm{TYPICALITY}_i * \mathrm{COMPLEXITY}_i\end{aligned}$$

Table 1 Comparison of Model Estimates Across Different Predictors and Modeling Techniques

Model specification	Basic model			Controls-only model		Full model		Ideal-point	SEG
Regression type	OLS	MM	LMM	OLS	LMM	OLS	LMM	OLS	OLS
Dependent variable treatment	Pooled	Pooled	Discrete	Pooled	Discrete	Pooled	Discrete	Pooled	Pooled
$P(b_1)$	3,861.03 (3,000.88)	5,283.69* (1,676.02)	300.74* (160.13)			3,451.91 (2,026.61)	261.99* (130.58)	2,450.69 (3,781.04)	−412.87 (3,780.76)
$C(b_2)$	5,805.31* (2,493.89)	5,897.33* (1,776.12)	765.02* (360.82)			3,986.67* (1,550.54)	421.31* (241.24)	5,036.47 (3,175.84)	6,082.36* (2,649.08)
$P*C(b_3)$	**8,820.79*** **(3,360.93)**	**9,931.17*** **(2,285.75)**	**761.47*** **(347.16)**			**6,124.58*** **(2,090.17)**	**637.68*** **(230.99)**	**7,923.88*** **(3,629.78)**	**10,765.97*** **(3,841.40)**
$SEG(b_4)$	−5,413.24 (4,308.14)	−8,181.39* (3,362.95)	Random effect	7,498.46 (8,686.33)	Random effect	5,058.13 (6,941.55)	Random effect	−4,675.11 (4,713.69)	−7,482.54 (5,133.87)
$+P^2+C^2(b_{10}, b_{11})$								$p > 0.44$	
$+P*SEG+C*SEG+P*C*SEG(b_{12}, b_{13}, b_{14})$									$p > 0.13$
$RP(b_5)$				−0.98* (0.35)	−0.12* (0.035)	−0.77* (0.26)	−0.10* (0.027)		
$AS(b_6)$				−0.00006 (0.0003)	−0.000003 (0.00005)	−0.00004 (0.0002)	−0.000004 (0.00004)		
$QR(b_7)$				−12,592.7 (10,266.4)	−2,389.55 (1,677.05)	−9,466.04 (8,240.42)	−1,208.26 (1,367.45)		
$PL(b_8)$				−143.11 (82.88)	−11.36 (12.73)	−104.71 (62.47)	−14.34 (9.86)		
$BP(b_9)$				8,843.08* (2,488.01)	1,344.14* (406.09)	7,693.61* (1,881.12)	1,319.31* (337.37)		
No. of parameters	4	4	8	6	10	9	13	6	7
R^2/Adjusted R^2 or explained variance	0.46/0.35	0.30/0.15	0.24	0.69/0.58	0.68	0.88/0.80	0.78	0.49/0.31	0.56/0.38
Incremental F-test/Likelihood ratio vs. the basic model	Reference model							$F(2,18) = 0.46$	$F(3,17) = 1.33$
Incremental F-test/Likelihood ratio vs. the controls model				Reference model	Reference model	$F(3,15) = 7.53$*	$LR(3) = 16.99$*		

Notes. B values (SE) are presented. P, prototypicality; C, complexity; SEG, segment; RP, retail price; AS, advertising spends; QR, quality rating; PL, product life cycle; BP, brand preference rating. The predicted complexity-by-prototypicality interactions are presented in bold.
*$p < 0.05$.

$$+b_4 * \text{SEGMENT}_i + b_{10} * \text{TYPICALITY}_i^2 + b_{11} * \text{COMPLEXITY}_i^2 + e_i. \quad (4)$$

Neither the quadratic effect of complexity nor prototypicality reached significance ($p > 0.44$), whereas the theoretically predicted prototypicality-by-complexity interaction term hardly changed in direction or significance compared with the original parameterization (see Table 1). Furthermore, an incremental F-test showed that including these quadratic terms did not significantly increase the statistical fit ($F(2, 18) = 0.46$; $p = 0.64$), which indicates that the theoretically more parsimonious original model is better suited to represent the empirical data.

Third, we checked for homogeneity of our effects across segments. We argue that the impact of fluency on sales is a gut-level reaction fundamental to the basic nature of visual processing; thus, our model must hold across consumer segments, especially for consumers interested in premium cars (e.g., the Audi A6) that can signal identity.[6] On the one hand, car manufacturers appear to routinely add complex features to their most atypical models, and researchers also believe atypical and complex designs best signal identity (Sukhdial et al. 1995). We, however, believe brand associations or price are more likely to capture identity concerns and the gut-level fluency effects we observe will hold regardless of consumer segment. Thus, we extended our main model to include interactions with the segment variable:

$$\begin{aligned} \text{SALES}_i &= b_0 + b_1 * \text{TYPICALITY}_i + b_2 * \text{COMPLEXITY}_i \\ &\quad + b_3 * \text{TYPICALITY}_i * \text{COMPLEXITY}_i \\ &\quad + b_4 * \text{SEGMENT}_i + b_{12} * \text{TYPICALITY}_i * \text{SEGMENT}_i \\ &\quad + b_{13} * \text{COMPLEXITY}_i * \text{SEGMENT}_i \\ &\quad + b_{14} * \text{TYPICALITY}_i * \text{COMPLEXITY}_i \\ &\quad * \text{SEGMENT}_i + e_i. \end{aligned} \quad (5)$$

[6] Indeed, our consumer survey showed considerable differences between the typical consumers of these two segments. For example, the typical premium car buyer is older (41 versus 33 years old) and wealthier ($42,394 versus $28,314 yearly household income) than the typical compact car buyer.

This alternate model did not significantly improve the explanatory power of the main model ($F(3, 17) = 1.33$; $p = 0.30$), and none of the interactions with the segment variable was significant ($p > 0.13$); the only significant effects are those we found in the main model.

Finally, to assess the predictive strength of our theoretical model, we conducted a holdout validation analysis. We modeled the first five months of sales as separate observations and compared the predicted sales of that model with the actual sales of the sixth month (Fader and Lattin 1993). Because the five repeated measurements of the sales of the same set of cars are likely to lead to correlated error terms, we chose a Linear Mixed-Model (LMM) approach to adequately model the data (Fitzmaurice et al. 2004). Such a model allows us to explicitly account for unobserved but constant heterogeneity between the cars and the segments by specifying random intercepts in the model. Moreover, by specifying an autoregressive error (AR(1)) structure in the model, we additionally account for the fact that correlations between error terms are likely to be higher the closer two measurements are to each other. We estimated three models with both of these features using the lme( )-function of the nlme package of the statistic software R (Pinheiro et al. 2008). For a monthly measurement t nested within car model i nested within car segment j, all three models had the following general form in vector and matrix notation (see West et al. 2007):

$$Y_{ij} = X_{ij}b + u_j + u_{i|j} + e_{ij}, \tag{6}$$

where Y_{ij} is a 5×1 vector of sales in each of the five months, X_{ij} is the $5 \times k$ (the number of independent variables) design matrix of the values of the independent variables, b is the $k \times 1$ vector of estimated fixed coefficients, u_j is a random intercept associated with car segments, $u_{i|j}$ is a random intercept associated with cars nested within car segments, and e_{ij} is a 5×1 vector of residuals that is multivariate normally distributed with a mean of 0 and a 5×5 variance–covariance matrix $R_{i|j}$ that follows an AR(1) structure. We estimated three models based on the general structure given by formula (6) that differed with respect to the included predictors and are, in contrast to formula (6), described following standard equation notation. The first model only included the objective design measures and their interaction (main model):

$$\begin{aligned}\mathrm{SALES}_{tij} = {} & b_0 + b_1 * \mathrm{TYPICALITY}_{ij} + b_2 * \mathrm{COMPLEXITY}_{ij} \\ & + b_3 * \mathrm{TYPICALITY}_{ij} * \mathrm{COMPLEXITY}_{ij} \\ & + u_j + u_{i|j} + e_{tij}.\end{aligned} \tag{7}$$

This model yields significant coefficients for prototypicality ($b_1 = 300.74$, SE $= 160.13$, $t = 1.88$, $p = 0.06$), complexity ($b_2 = 765.02$, SE $= 360.82$, $t = 2.12$, $p = 0.05$), and the interaction term ($b_3 = 761.47$, SE $= 347.16$, $t = 2.19$, $p = 0.03$), and a significant increase in fit compared to an intercept-only model (likelihood ratio (LR) $= 10.87$, df $= 3$, $p = 0.01$). This model's fit statistics are log-likelihood (LL) $= -1{,}024.93$, Akaike information criterion (AIC) $= 2{,}065.85$, and Bayesian information criterion (BIC) $= 2{,}088.22$. These results closely resemble the results we previously described for an aggregated sales variable over the six-month period.[7] The second model included only the five control variables (null model):

$$\begin{aligned}\mathrm{SALES}_{tij} = {} & b_0 + b_5 * \mathrm{PRICE}_{ij} + b_6 * \mathrm{ADVERTISEMENT}_{ij} \\ & + b_7 * \mathrm{QUALITY}_{ij} + b_8 * \mathrm{LIFECYCLE}_{tij} \\ & + b_9 * \mathrm{BRAND}_{ij} + u_j + u_{i|j} + e_{tij}.\end{aligned} \tag{8}$$

We compared it to a third model that added the two design measures and their interaction to the variables included in the null model (alternative model):

$$\begin{aligned}\mathrm{SALES}_{tij} = {} & b_0 + b_1 * \mathrm{TYPICALITY}_{ij} + b_2 * \mathrm{COMPLEXITY}_{ij} \\ & + b_3 * \mathrm{TYPICALITY}_{ij} * \mathrm{COMPLEXITY}_{ij} \\ & + b_5 * \mathrm{PRICE}_{ij} + b_6 * \mathrm{ADVERTISEMENT}_{ij} \\ & + b_7 * \mathrm{QUALITY}_{ij} + b_8 * \mathrm{LIFECYCLE}_{tij} \\ & + b_9 * \mathrm{BRAND}_{ij} + u_j + u_{i|j} + e_{tij}.\end{aligned} \tag{9}$$

A likelihood-ratio test showed that adding the design measures and their interaction to the null model significantly increased fit to the data (LR $= 16.99$, df $= 3$, $p < 0.001$). Furthermore, the coefficients of the design variables showed similar patterns to the earlier models, with positive effects for prototypicality ($b_1 = 261.99$, SE $= 130.58$, $t = 2.01$, $p < 0.05$), complexity ($b_2 = 421.31$, SE $= 241.24$, $t = 1.75$, $p = 0.09$), and their interaction ($b_3 = 637.68$, SE $= 230.99$, $t = 2.76$, $p = 0.007$). Furthermore, with respect to the control variables, we observed significant effects for price ($b_5 = -0.10$, SE $= 0.03$, $t = -3.66$, $p = 0.002$) and brand preference ($b_9 = 1{,}319.31$, SE $= 337.37$, $t = 3.91$, $p = 0.001$). All other effects were not significant ($p > 0.15$). This model's fit statistics are LL $= -1{,}006.13$, AIC $= 2{,}038.25$, and BIC $= 2{,}074.05$. This pattern of results closely resembles results obtained for the aggregated sales variable over the six-month period.

We also looked at the predictive strength of each of these models to forecast actual sales in the sixth month. Whereas the first model (main model)

[7] We also compared our theoretical main model to the alternative ideal-point parameterization (LR $= 0.30$, df $= 2$, $p = 0.86$) and segment heterogeneity (LR $= 5.67$, df $= 3$, $p = 0.13$) models and found again, using likelihood-ratio tests, that neither of these alternatives is significantly superior to our theoretical model.

explained 24% of the sales variance in the sixth month, the second model (null model) explained 68%. Finally, the alternative model, including design variables and control variables, explained 78% of sales variance; that is, the two design variables and their interaction significantly improved the predictive strength of a traditional forecasting model ($F(3, 111) = 15.93$; $p < 0.001$).

Fluency as Mediating Mechanism

We conducted a moderated mediation analysis (Muller et al. 2005) to investigate whether prototypicality evokes fluency, but design complexity moderates the effect of fluency on sales. The analysis employed the objective measures of design prototypicality and of design complexity, as well as their interaction as independent variables, the objective response time measures of design fluency as the mediator, and the disaggregated monthly sales as the dependent variable. We estimated all models using Linear Mixed Models.

First, as already outlined in the previous section, the model given by formula (9) reveals a significant interaction between prototypicality and complexity ($b_3 = 637.68$, SE $= 230.99$, $t = 2.76$, $p = 0.007$). This result demonstrates that sales are a function of the interactive effect of prototypicality and complexity. Second, we estimated a model where we predict objective fluency from objective prototypicality, objective complexity, their interaction, and controlling for the segment as a random factor:

$$\begin{aligned}\text{FLUENCY}_{ij} &= b_0 + b_1 * \text{TYPICALITY}_{ij} + b_2 * \text{COMPLEXITY}_{ij} \\ &\quad + b_3 * \text{TYPICALITY}_{ij} * \text{COMPLEXITY}_{ij} \\ &\quad + u_j + u_{i|j} + e_{ij}. \end{aligned} \tag{10}$$

The results of this second model show that only the effect of prototypicality is significant ($b_1 = 0.47$, SE $= 0.18$, $t = 2.54$, $p = 0.019$; other p values > 0.07). Hence, prototypicality increases fluency, regardless of complexity. Third, we estimated a model where we predict sales from objective prototypicality, objective complexity, and the interaction between prototypicality and complexity, controlling for our five control variables as fixed effects and for the segment as a random effect, and we include fluency and the interaction between fluency and complexity:

$$\begin{aligned}\text{SALES}_{tij} &= b_0 + b_1 * \text{TYPICALITY}_{ij} + b_2 * \text{COMPLEXITY}_{ij} \\ &\quad + b_3 * \text{TYPICALITY}_{ij} * \text{COMPLEXITY}_{ij} \\ &\quad + b_5 * \text{PRICE}_{ij} + b_6 * \text{ADVERTISEMENT}_{ij} \\ &\quad + b_7 * \text{QUALITY}_{ij} + b_8 * \text{LIFECYCLE}_{tij} \\ &\quad + b_9 * \text{BRAND}_{ij} + b_{15} * \text{FLUENCY}_{ij} \\ &\quad + b_{16} * \text{FLUENCY}_{ij} * \text{COMPLEXITY}_{ij} \\ &\quad + u_j + u_{i|j} + e_{tij}. \end{aligned} \tag{11}$$

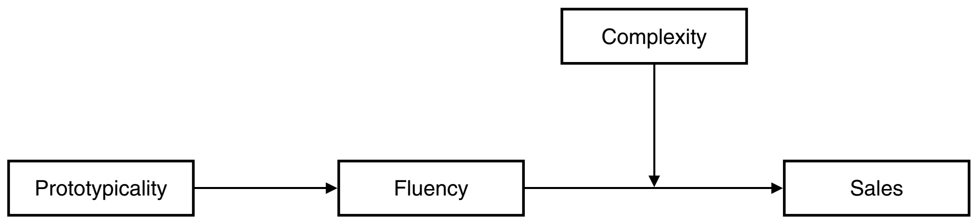
The results of this third and final model show that the interaction between prototypicality and complexity became nonsignificant ($b_3 = 89.90$, SE $= 233.40$, $t = 0.39$, $p = 0.701$) compared with the first model in this section, but the interaction between fluency and complexity was significant ($b_{16} = 1{,}017.30$, SE $= 280.09$, $t = 3.63$, $p = 0.002$, Sobel $z = 2.08$, $p = 0.04$). This third result shows that fluency mediates the effect of prototypicality on sales, but complexity moderates the effect of fluency on sales (see Figure 3).

To investigate whether an effect of fluency on sales is observed for high but not low levels of complexity, we conducted a further analysis after splitting the data on complexity. As expected, we observed a positive effect of fluency on sales ($b_{15} = 1{,}397.64$, SE $= 437.82$, $t = 3.19$, $p = 0.024$) for high levels of complexity; a similar effect of fluency on sales did not emerge ($b_{15} = -635.37$, SE $= 484.70$, $t = -1.31$, $p = 0.247$) for low levels of complexity.

General Discussion

Although design is a key aspect of automotive sales, our investigation is the first to use psychological theory to predict which design features will matter and to develop objective measures of those design features for future use in sales forecasts. It is also the first to provide an estimate of the extent to which these design factors can affect real-world sales of an important purchase. Past laboratory studies have reported that prototypical stimuli are judged to be easier to process than nonprototypical stimuli (Winkielman et al. 2006). Consistent with those findings, we found that in our tests of moderated mediation, the coefficient for prototypicality is positive—thus providing evidence for a positive correlation between prototypicality and fluency. Past laboratory studies on fluency have also found that fluently processed stimuli are positively evaluated (Halberstadt and Rhodes 2000), provided that fluency is experienced as surprising and people are not aware of the source of fluency (Schwarz 2004). Consistent with those findings, we found a significant positive effect of prototypicality on sales (various models), although the effect is not always significant, as we expect, because we predict and find that this effect will be moderated by complexity. The links of what we proposed had been shown in over 200 laboratory experiments, but our contribution is in testing these propositions on actual sales of a large-ticket item in the marketplace. This test is a very important contribution to the fluency literature, because we not only demonstrate for

Figure 3 **Moderated Mediation Analysis: The Effect of Objective Prototypicality (Euclidian Score) on Sales Mediated by Objective Fluency (Response-Time Measures) and Objective Fluency on Sales Moderated by Objective Complexity (ZIP Score)**



	P	C	$P \times C$	F	$F \times C$	RP	AS	QR	PL	BP
Sales (main model)	261.99	421.31	**637.68**			−0.10	−0.00	−1,208.26	−14.34	1,319.31
	(130.58)*	(241.24)	(**230.99**)*			(0.03)*	(0.00)	(1,367.45)	(9.86)	(337.37)*
Fluency (mediator)	**0.47**	−0.34	0.11							
	(**0.18**)*	(0.18)	(0.18)							
Sales (moderated mediation)	113.18	838.24	**89.90**	291.85	**1,017.30**	−0.13	0.00	−1,789.25	−16.01	1,220.95
	(132.23)	(229.85)*	(**233.40**)	(224.19)	(**280.09**)*	(0.04)*	(0.00)	(1,066.29)	(8.07)	(260.90)*

Notes. B values (SE) are presented. Relevant coefficients per Muller et al. (2005) are presented in bold. All models include a constant term. P, objective prototypicality (Euclidian distance); C, objective complexity (ZIP compression); F, objective fluency (response-time measure); RP, retail price; AS, advertising spend; QR, quality rating; PL, product life cycle; BP, brand preference rating.
$^{*}p < 0.05$.

the first time, to our knowledge, that fluency effects can be found outside of a tightly controlled laboratory setting, but we also show that the effect size is large. We also contribute to the literature on product design, because we use theory to show which aspects of design will affect sales and the extent to which they will affect sales. Because our theoretically driven design factors tap into gut-level human nature and are fundamental to the basic manner in which the visual system functions, the applicability of our factors is likely to extend to all types of products and consumers. By specifying a concrete way to measure these design factors, we also offer practitioners a better way to predict product sales.

In particular, we show evidence in a real-market setting that visually complex but prototypical car designs exert a pervasive and considerable effect on sales—a purchase people presumably contemplate a great deal. These two design aspects are independent of each other and of retail price, technological rating, brand associations, advertising, and length of time the car has been in the market, and they can explain up to 19% more sales variance than traditional forecasting models. It should be noted that the critical model estimates are robust against different estimating techniques (OLS, robust MM-estimation, and LMM) as well as against different sets of predictors (inclusion of control variables, ideal-point parameterization, and segment heterogeneity), attesting to the model's reliability. We also provide direct evidence of processing fluency as the underlying mediating mechanism affecting sales outside of a well-controlled laboratory setting to attest to its everyday relevance.

An important note is that we constructed the two objective design measures independent of sales, because the morphing software assigned equal weight to each car regardless of a car's actual sales. The only way the measures might not be exogenous with respect to sales is if manufacturers somehow intuit their impact on sales, but such a possibility seems unlikely. First, if the impact of these two design factors were common knowledge among marketers, why no marketer to date has included these simple factors in forecasting models to improve the predictability of forecasts by up to 19% is unclear. In addition, if some manufacturers intuit the importance of these design factors, then those manufacturers should systematically be equipping their top cars with the best features, and one of those features should be a superior design. However, such an argument would necessitate that *at least some* of our control variables should have correlated with *at least one* of our objective design measures. Instead, our design measures did not correlate with any of the control measures or with each other for either economy or premium cars. Third, if some manufacturers systematically intuited a positive value of complex and prototypical designs, we should have found a clustering of brands on high prototypicality for complex designs but less clustering (more variance in dispersion) on prototypicality for simple designs (where prototypicality does not matter). That is, if manufacturers intuit the importance of increased prototypicality of complex designs, then a majority of complex designs should be highly prototypical (low variance), but prototypicality should not matter when a design is simple (more variance). The location of brands in a prototypicality × complexity mapping, however, proved to be purely random (see Figure 1). A supporting Wald test investigating heteroscedastic dispersion of brand locations further revealed nonsignificant effects ($z = 0.00$, $p = 0.99$), validating the randomness of dispersion of brands. Thus, our measures appear to be exogenous with respect to sales—they are constructed independent of sales and do not correlate with any measures that would suggest manufacturers intuit the superiority of these particular design aspects (and their combination) over others. This field study thus retains the major advantage of laboratory studies, the exogeneity of independent variables, but additionally takes the main findings of fluency laboratory studies into the real world.

Arguments pertaining to whether the results apply only to certain segments in the market or to the market as a whole are also questionable. One should exercise caution while making an argument that two sets of consumers are in the market—some who give greater weight to technological characteristics or price and others who give weight to product aesthetics—and that our results apply only to design-valuing consumers who buy visually prototypical and complex cars. If this assumption were true, we would expect stronger effects for our objective design measures within the premium car segment because people are more likely to purchase these cars for hedonic aspects such as aesthetics. However, we did not find any support for this premise. The interactive effect of design prototypicality and complexity on sales held across both of the car segments and the two design factors did not interact with car segment in any way. Our data specifically showed that design is a major determinant of sales, regardless of whether a car is an economy or premium one. Furthermore, a moderated mediation analysis showed that gut-level response-time measures mediated the effect of prototypicality on sales, but as we predicted, design complexity moderated the effect. Taken together, our data thus suggest that fluency effects that arise during the visual processing of a design are basic gut-level psychological reactions that occur for all prototypical designs, but an impact on sales depends on whether people can attribute the gut reaction to design, and, as we predict, these effects are independent of car segment.

Of course, this finding does not preclude the possibility that certain segments in the market intentionally discount their feelings toward a design and weight other aspects more strongly. One such consumer segment might be consumers who exhibit a strong tendency to signal their own identity. Such consumers might be seeking unusual, unique designs to better express their individual identity. By definition, such consumers buy products that have a low prevalence in the market (Berger and Heath 2007), which would imply that an analysis of the market as a whole would reveal low sales for such a preference pattern. Thus, if a subset of consumers exists with a strong tendency to signal identity, our model appears to be in perfect accordance with such an assumption because atypical designs have been shown to only account for a low amount of sales. Note, however, that identity signaling did not correlate with our design measures. Also, from a theoretical point of view, the potential to signal one's own identity is more likely to be communicated through brand associations or pricing strategy (Aaker 1996). Thus, our findings should not be interpreted as saying identity signaling is not important for automobile sales; rather, we expect that our control measures pertaining to brand association (or even price) may have captured this factor. If so, identity signaling may have a more cognitive/motivational component to it, and our effects might be more instantaneous, relying on the immediate ease of processing the most rudimentary design patterns.

We should note some promising avenues for future research. First, a design's complexity is probably not the only design characteristic that sets up a processing expectation, and other design characteristics may also moderate the fluency effects visual typicality triggers. For instance, the extent of prior exposure to a stimulus might affect processing expectations, and future research could explore this possibility. Second, the strength of the effects and the relevance of these visual dimensions may depend on the product category under consideration. As described, cars constitute a category characterized by a considerably high investment, motivating consumers to carefully weight descriptive attributes and come up with a deliberate decision. Thus, the extent of effects we observed is noteworthy, but the impact of design prototypicality is likely to be even higher for less expensive durable goods, such as wristwatches, mobile phones, MP3 players, or digital cameras. However, the effects could also be considerably smaller for products for which design considerations only play a minor role, such as medicine bottles. Furthermore, prototypicality may not be the only determinant of the fluency in categories in which individual products also vary in terms of other fluency-eliciting characteristics such as symmetry and figure-ground contrast. Exploring this relationship for other product categories and for other fluency determinants is an important avenue for future research.

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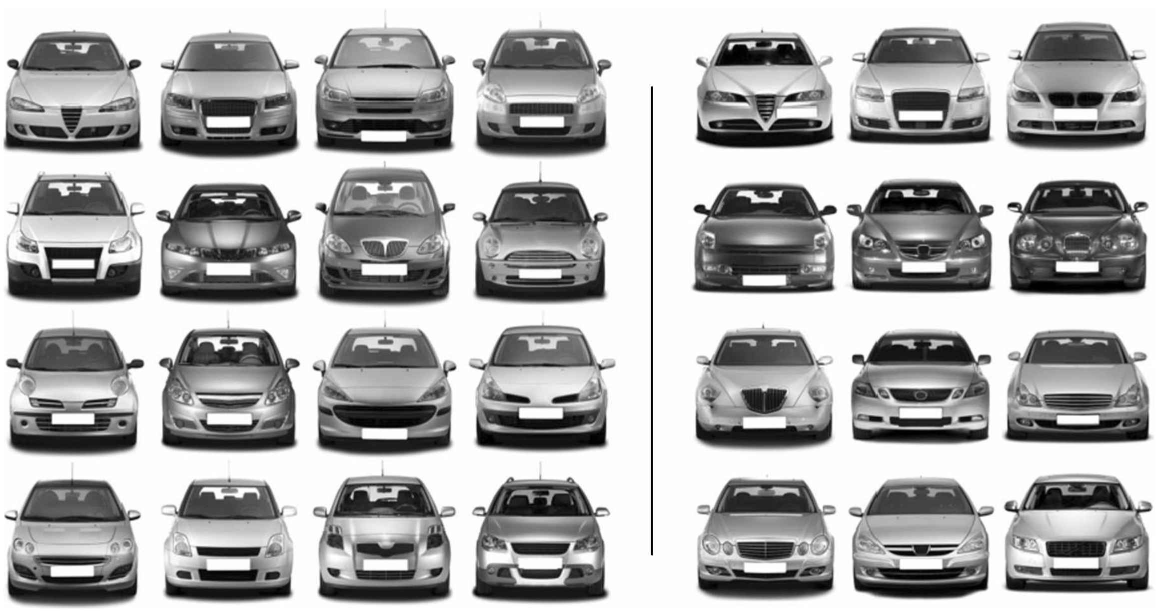
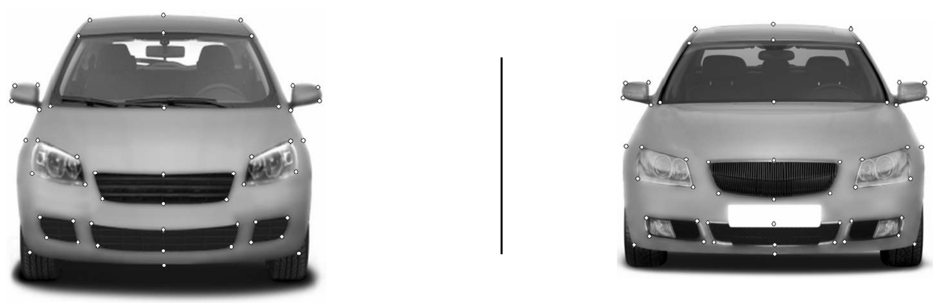
Appendix

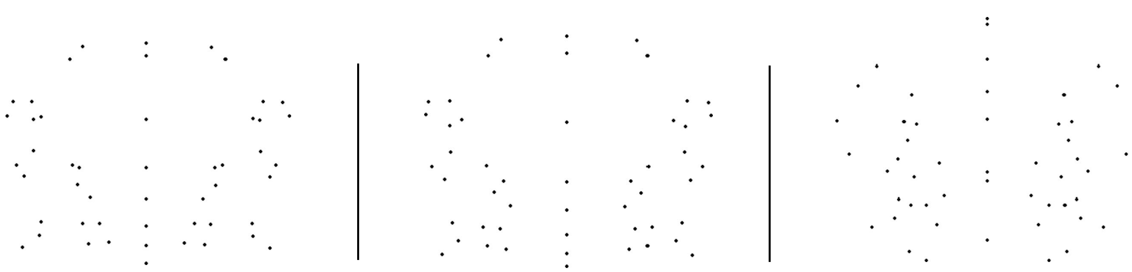
The 16 compact cars (left panel) and the 12 premium cars (right panel)



The morph of the 16 compact cars (left panel) and the 12 premium cars (right panel) with the positions of the feature points indicated



Sample dot patterns employed to validate fluency measures: left panel, feature points of the VW Polo; middle panel, feature points of morph; right panel, random feature points



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