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# A COMPUTATIONAL VISUAL ANALYSIS OF IMAGE DESIGN IN SOCIAL MEDIA CAR MODEL COMMUNITIES

Jochen Wulf
*University of St. Gallen*, jochen.wulf@unisg.ch

Tobias Mettler
*University of Lausanne*, tobias.mettler@unil.ch

Stephan Ludwig
*University of Melbourne*, stephan.ludwig@unimelb.edu.au

Dennis Herhausen
*University of St.Gallen*, dennis.herhausen@unisg.ch

# A COMPUTATIONAL VISUAL ANALYSIS OF IMAGE DESIGN IN SOCIAL MEDIA CAR MODEL COMMUNITIES

*Research paper*

Wulf, Jochen, University of St.Gallen, St. Gallen, Switzerland, jochen.wulf@unisg.ch

Mettler, Tobias, University of Lausanne, Lausanne, Switzerland, tobias.mettler@unil.ch

Ludwig, Stephan, University of Melbourne, Australia, stephan.ludwig@unimelb.edu.au

Herhausen, Dennis, KEDGE Business School, Marseille, France, dennis.herhausen@kedgebs.com

## Abstract

*While user-generated images represent important information sources in IS in general and in social media in particular, there is little research that analyzes image design and its effects on image popularity. We introduce an innovative computational approach to extract image design characteristics that includes convolutional neural network-based image classification, a dimensionality reduction via principal component analysis, manual measurement validation, and a regression analysis. An analysis of 790,775 car images from 17 brands posted in 68 car model communities on a social media platform reveals several effects of product presentation on image popularity that relate to the levels of utility reference, experience reference, and visual detail. A comparison of economy cars and premium cars shows that car class moderates these image design effects. Our results contribute to the extant literature on brand communities and content popularity in social media. The proposed computational visual analysis methodology may inform the study of other image-based IS.*

*Keywords: computational visual analysis, product communities, image analysis, social media, convolutional neural networks.*

## 1 Introduction

Images assume a dominant role in technology-mediated communication on social media platforms such as YouTube, Facebook, Pinterest, or Flickr owing to the ever-increasing diffusion of camera and broadband technologies. Companies aim to benefit from the trend of customers sharing company-related experiences via text- and image-based content (Brodie et al., 2013). The image hosting and social media platform Flickr, for example, hosts a vast amount of brand-related and product-related communities, featuring more than 10 billion user-generated images (Stadlen, 2015). However, while customers share a lot of content, not everything achieves high popularity. In spite of their importance for companies' marketing efforts (Goh et al., 2013), little is known on the design-related factors of user-generated images that affect image popularity.

Prior research found that user-generated content shared on social media impacts corporate performances by influencing buying decisions (Goh et al., 2013; Dewan and Ramaprasad, 2014; Kumar et al., 2016), firm equity value (Xueming et al., 2013), and strengthening firm-customer relationships (Rishika et al., 2013). Regarding company-generated images in social media, prior research substantiated that some images are more popular than others. For example, images that carry emotional appeal stimulate user engagement (Akpinar and Berger, 2017); images that transport high levels of directiveness, in contrast, tend to attract less resonance (Ordenes et al., 2018). Prior research that analyzes user-generated content in social media largely focused on textual aspects (e.g., Goh et al., 2013). The sparse research on users' sharing of images in social media brand communities discusses strategies for word-of-mouth marketing (Kozinets et al., 2010) and user motivations (Arvidsson and Caliandro, 2016). However, there is, to the best of our knowledge, no prior study that looks at design factors of user-generated images and at how images' designs might affect their popularity in social media product communities.

The visual presentation of products plays a pivotal role in high-involvement decisions such as purchasing a car (Cox and Cox, 2002). Consumers' repeated exposure to car designs, for example, influences aesthetic liking and sales (Landwehr et al., 2013). The role of the visual context in car presentation, however, remains unknown. In order to address this research gap, we study: *How the location of a car in relation to other contextual objects within an image influences its' popularity?* Drawing on narrative transportation theory (Green et al., 2008; van Laer et al., 2012) and processing fluency theory (Reber et al., 2004), we offer new insights on three image design aspects pertinent to popularity; namely utility reference, experience reference, and visual detail.

We retrieved 790,775 car images relating to 17 brands posted in 68 car model communities from a social media platform's API[1] together with data on image view counts, image favoring counts, and user- and group-related data. We then used a residual net image classification model that was trained on Google's open images dataset (Krasin et al., 2018) in order to detect objects and conducted a principal component analysis with the object detection probabilities. We carried out a manual validation confirming that three principal components measure our theoretical constructs. A regression analysis broadly confirms the hypothesized direct and moderation effects.

With our results, we contribute novel image design knowledge to the extant literature on product communities and user-generated content in social media. Further, our proposed computational visual analysis methodology may inform the study of other image-based IS, such as learning support systems, online media, and operational production systems.

In the following, we discuss the research background and develop five hypotheses. Thereafter, we present the research methodology and the results. After discussing the theoretical and practical contributions and the limitations of this research, we end with a conclusion.

# 2 Research Background

Product communities bring together customers on a platform, such as a social media site, and allow customers to form a common identity or to receive product usage support (Brodie et al., 2013). Users upload content, such as text, images, and videos, on social media because this affords self-presentation and content sharing (Karahanna et al., 2018).

Customers that engage with content in social media product communities exhibit higher levels of customer profitability, because participating within an active network of fellow customers creates the feeling of a community, which positively influences a customer's relationship with the product-

[1] We do not disclose the social media platform's name in order to protect the platform against potential negative publicity owing to the platform's open data access policy.

offering firm (Rishika et al., 2013). The level to which users engage with social media content by liking, commenting, or favoring it is referred to as popularity (De Vries et al., 2012). Content popularity is influenced by various design-related factors, such as valence, informativeness, emotional appeal, the level of entertainment, and the linguistic style (De Vries et al., 2012; Goh et al., 2013; Akpinar and Berger, 2017; Herhausen et al., 2019).

Prior research that specifically looks at images in social media product communities finds that the use of images increases a content's information richness, which leads to a higher popularity of image-based content in comparison to textual content (De Vries et al., 2012; Sabate et al., 2014). In spite of the important role of image-based content, there is relatively sparse research that addresses design-related image aspects and, more particularly, how to position a product in a visual context. One prior work on the use of social media images at the firm level analyzes the images' directiveness via manual coding and shows that higher levels of directiveness lead to lower popularity at the customer side (Ordenes et al., 2018). A second work finds that emotional appeals of image-based content in social media brand communities positively influences popularity, while informative appeals boost brand evaluations (Akpinar and Berger, 2017).

Regarding the customer-level use of social media images, a qualitative analysis of user blogs (including visual data) identifies different strategies for word-of-mouth marketing in online communities (Kozinets et al., 2010). A qualitative analysis of consumer-posted images about Louis Vuitton gathered on Twitter finds that brand references in images serve as a medium to generate publicity for diverse situations of identity (Arvidsson and Caliandro, 2016).

In summary, while prior research produces initial theories that explain user choices of image design in social media communities, there is only sparse knowledge of design attributes that affect image popularity in social media. For high-involvement decisions such as purchasing cars, the visual presentation is particularly important (Cox and Cox, 2002; Landwehr et al., 2011; Landwehr et al., 2013). The role of the visual context in car presentation, however, is under-researched. In order to address this research gap, we analyze how the location of cars in relation to other contextual objects within images influences image popularity in car model communities on a social media platform.

# 3 Theory and Hypotheses Development

In the following, we develop our research model that explains an image's popularity through a car's contextual presentation. Informed by narrative transportation theory (Green et al., 2008; van Laer et al., 2012) and by processing fluency theory (Reber et al., 2004), we hypothesize that visual objects that appear in the context of a car and the car's visual detail influence the image popularity. Figure 1 presents the research model.

## 3.1 Utility Reference

According to narrative transportation theory, when a person gets immersed in a story, this person's attitude and intention changes to reflect that story (Green et al., 2008). The level of a person's narrative transportation depends on the narration medium as well as on the narrated story (van Laer et al., 2012). Regarding the medium, image-based representations are particularly suitable for low cognition content (Green et al., 2008), such as when developing an attitude towards a physical product's appearance. Regarding the narrated story, an imaginable plot that a person can relate to and generate vivid cognitive associations increases narrative transportation (van Laer et al., 2012).

In product communities, informative content about the product may support an imaginable plot. Prior social media research has found that the level of information about a product affects the popularity of social media content about this product (Lee et al., 2018). Users in product communities appreciate product-related information because it creates a better sense of the product's relevant features (Akpinar and Berger, 2017) and reduces purchase-related uncertainties (Goh et al., 2013).

With regard to the visual presentation of cars, providing information about a car's utility by visualizing it in concrete usage situations may generate such an imaginable plot. Solely emphasizing a car's aesthetical appearance through displays in artificial contexts, such as car exhibitions, in contrast, may lack such a plot. Thus, we expect:

*H1: The level to which an image references a car's utility by presenting the car in concrete usage contexts, such as driving on city roads, positively affects image popularity.*

## 3.2 Experience Reference

Apart from an imaginable plot, an empathetic content, i.e. the level to which a viewer is able to emphasize with the story, influences narrative transportation (van Laer et al., 2012). Prior social media research shows that the valence of social media content affects content popularity, because emotional arousal increases social transmission (Herhausen et al., 2019). Further, emotional content, such as holiday mentions, is found to stimulate higher levels of user engagement in social media because it is more persuasive (Lee et al., 2018). Consequently, the use of emotion-eliciting strategies, such as referencing drama in social media content, increases user engagement (Akpinar and Berger, 2017).

Stressing a product's experience character targets a customer's emotional susceptibility (Desmet and Hekkert, 2007). For example, in the USA over 80% of the population lives in urban areas according to the U.S. Census Bureau (Berg, 2012). Therefore, placing a car in an outdoor context, which represents a special occasion experience, will generate emotional stimuli that will lead to a higher narrative immersion. Following this argumentation, we posit:

*H2a: The level to which an image references a car's usage experience by presenting it in special occasion contexts that are subject to positive emotions, such as outdoor trips, increases image popularity.*

Viewer characteristics as much as image characteristics, also have an impact on narrative transportation (van Laer et al., 2012). The fit between a story topic and viewer characteristics, in particular, stimulates transportation-related changes in viewer attitude and intention (Morgan et al., 2009). Regarding the presentation of cars in images, we expect differences in fit between premium cars and others car types. Premium cars, in comparison to others, are less functionally oriented and to a higher degree identity-based (Landwehr et al., 2011); thus, for premium cars, references to functional experiences will less meet a viewer's emotional susceptibility in contrast to stressing aspects of identity (such as references to a car's reputation). Therefore, we posit:

*H2b: The car class moderates the effect of experience reference on image popularity such that for premium cars this effect is weakened.*

## 3.3 Visual Detail

Apart from the context, in which an image presents a product, the level of a product's visual complexity may further influence viewer reactions. The less visual information about a product a viewer has to process, the higher is a product's processing fluency, which leads to higher levels of viewer liking (Reber et al., 2004). The positive effect of fluency on aesthetic liking implies that viewers favor less detail and complexity (Landwehr et al., 2011). Following this argumentation, we posit:

*H3a: The level of a car's visual detail that an image transports, such as depicting recognizable car parts, negatively affects image popularity.*

The impact of visual detail on image popularity, however, may be dependent on the type of product an image depicts. Viewers may be able to ignore the hedonistic experience of fluency if they become aware of this feeling's source (Schwarz, 2004); thus, when a product design is visually simple, people may discount for fluency because they attribute the positive gut reaction to the design's simplicity.

Regarding car designs, for premium cars, viewers prefer more distinct and elaborate designs that highlight the car's individuality (Sukhdial et al., 1995). Thus, we posit:

*H3b: The car class moderates the influence of the level of a car's visual detail on image popularity such that for premium cars this negative effect is weakened.*

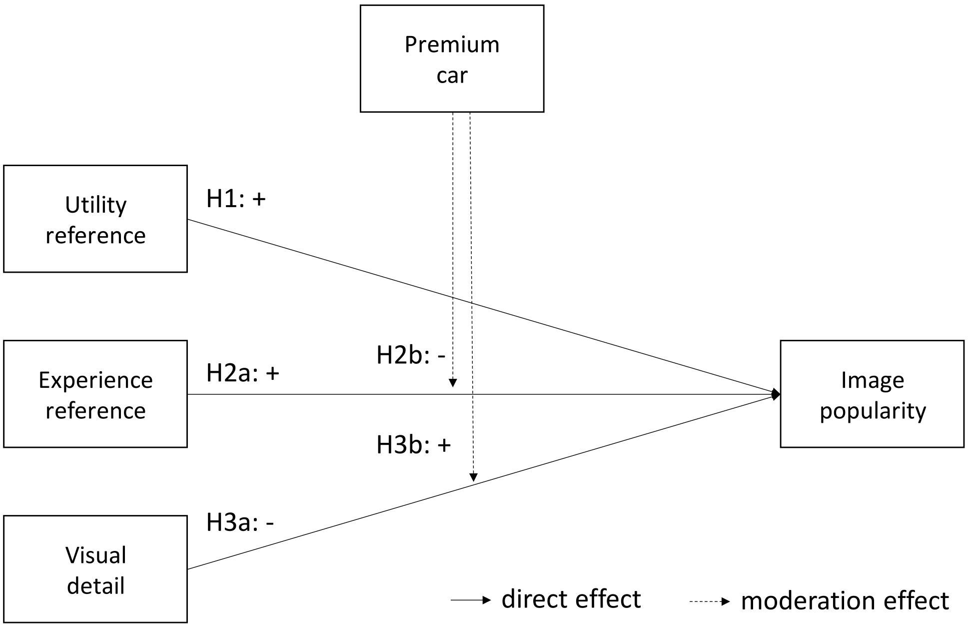



*Figure 1. Research model*

# 4 Methodology

## 4.1 Data Collection

Our analysis uses data that we collected from 68 product communities on a social media platform and that relates to car models of the 17 largest car brands. The communities either cover broadly the models of a car brand or they focus on specific car models. The product community *Volkswagen Bugs*, for example, has 950 members that share 15,200 images of the Volkswagen Bugs model. In our selection of communities, we aimed at selecting the brand's largest communities in terms of images and members and at covering both, economy and premium car model-specific communities. Table 7 in the appendix provides an overview of the car brands and communities.

Our source is a leading social media platform with over 80 million users. On this platform, users can store and share photographs; apart from image hosting, the platform includes social media functionalities such as image commenting, personal sites, user following, user contacts, and the formation of product communities. The platform's image favoring functionality enables the inclusion of a favored image in the user's favorites album, and the image's display to the user's followers.

| Name | Type | Description | Operationalization | Descriptive Statistics |
|---|---|---|---|---|
| Popularity | Dependent variable | Number of times the image was favored | Logarithm of image favorite count | mean: 1.0288<br>sd: 1.0189 |
| Views | Control | Number of times the image was viewed | Logarithm of image view count | mean: 6.1922<br>sd: 1.1608 |
| Views previous | Control | Number of times the previous image was viewed | Logarithm of image view count (previous image) | mean: 6.0160<br>sd: 1.2553 |
| Views next | Control | Number of times the next image was viewed | Logarithm of image view count (next image) | mean: 6.0127<br>sd: 1.2587 |
| Date added | Control | Image uploading timestamp | Time in seconds since 1.1.1970 00:00:00 | mean: 1382431382<br>sd: 92859168 |
| License | Control | Indicator of whether the image has a Creative Commons license and can thus be shared openly | Dummy variable | #0: 709295<br>#1: 81480 |
| Product community | Control | Product community the image is presented in (n=68) | Categorical variable | number of images<br>mean: 11629.04<br>sd: 24168.69 |
| Utility reference | Independent variable | Level to which an image references a car's utility | PCA component | mean: 1.032e-18<br>sd: .0598 |
| Experience reference | Independent variable | Level to which an image references a car's usage experience | PCA component | mean: -2.300e-19<br>sd: .0437 |
| Visual detail | Independent variable | Level of a car's visual detail that an image transports | PCA component | mean: 3.331e-18<br>sd: .1794 |
| Car class | Moderator | Differentiation of two specific car segments (economy and premium) and a general class | Categorical variable | number of images<br>economy: 91198<br>premium: 123259<br>general: 576318 |

*Table 1. Constructs and operationalization*

The platform offers an open application programming interface (API) that allows the retrieval of group-, image-, and user-specific data. We developed a custom program in order to collect images and further data for image-, user-, and group-level controls. We collected 790,775 images in total. Further, we used the European Commission's car segmentation (Commission of the European Communities, 1999) in order to distinguish the product communities that are dedicated to specific car models into economy car class (Euro segments A-D) and premium car class (Euro segments E and S). Table 1 provides an overview of the collected data.

## 4.2 Image Classification

We used a residual net image classification model (He et al., 2016) that was trained on the open images dataset (version two) and provided by the open images dataset contributors (Krasin et al., 2018). The open images dataset consists of nine million images that have been annotated with image-level labels and object bounding boxes (Krasin et al., 2017). The training set of the dataset's version two contains 5,000 trainable labels that span, among others, physical objects, species, and events. This model is particularly suitable for our image analysis task because it contains a richness of labels related to cars, car usage, and car presentation contexts such as road, highway, city, parking lot, and exhibition. The inference code takes jpeg-images as input and returns probability scores for each label.

## 4.3 Dimensionality Reduction

Our approach towards dimensionality reduction of the 5,000 labels included a feature selection phase (see Table 2) and a feature projection phase (Guyon and Elisseeff, 2003). In the feature reduction phase, we manually dropped labels without relevancy to our image analysis task, such as car-brand- and car-type-specific labels. In a second step, we filtered labels where the probabilities (rounded to integer values) have an occurrence rate of 1% and above, in order to focus on labels that regularly contribute to car presentation practices. In a third step, we applied a high correlation filter with a threshold of .7 in order to avoid variable redundancies (Guyon and Elisseeff, 2003). A low variance filter did not result in a further feature reduction.

| Selection Step | Number of Labels |
|---|---|
| Starting set of image labels | 5,000 |
| Manual filtering of car-presentation-related labels | 4,784 |
| Selection of labels with greater or equal to 1% occurrence rate | 121 |
| High correlation filter (cutoff: .70) | 82 |

*Table 2. Feature selection steps*

In the feature projection phase, we applied principal component analysis (PCA) with eigenvalue decomposition in R in order to identify orthogonal components that capture most object-related variance (Husson et al., 2017). We list the first four components that account for 66% of the labels' variance and that we included in our regression analyses in Table 3.

The first component only includes the label *bumper* with a loading of above .2 and accounts for the large majority of variance. Because *bumper* has a correlation of above .7 with the dropped labels *wheel* and *grill*, this component describes the level of detail to which individual car parts are shown (*visual detail*). The second component, again, only contains one label with a loading of above .2 (*exhibition*) and account for 5.82% of the variance. The label *exhibition* refers to contexts, in which car models are exhibited to spectators in car exhibitions or showrooms. Since exhibitions are artificial, non-utilitarian presentation contexts in which cars are not presented in use and since the exhibition's loading is negative, we call this component *utility reference*. The third component includes multiple labels that describe an urban context. The fourth component includes several labels that describe an outdoor context (including *nature*, *mountain*, *leaf*, *horizon*, and *forest*). Because this component, for most users, does not describe everyday car usage situations but special nature-related experiences, we refer to this component as *experience reference*.

| ID | Construct name | Object (weight)[a] | % Var |
|---|---|---|---|
| C1 | Visual detail | Bumper[b] (.996) | 52.39 |
| C2 | Utility reference | Exhibition (-977) | 5.82 |
| C3 | / | Downtown (.524), Town (.482), Cityscape (.362), Landmark (.323), Architecture (.320) | 4.30 |
| C4 | Experience reference | Nature (.489), Mountain (.372), Reflection (.328), Leaf (.280), Horizon (.243), Flower (.235), Forest (.226), Wilderness (.225) | 3.11 |

[a] only objects with weight >.2 are exhibited, [b] >.7 correlation with wheel and grille

*Table 3. PCA components*

## 4.4 Measurement Validation

The dimensionality reduction yields four components, out of which three (C1, C2, and C4) match well with the theoretical constructs (utility reference, experience reference, visual detail) that we discussed in the theory development (see Section 3). In order to validate whether these components may serve as reliable measures for the three constructs, one author manually coded the degree to which 100 randomly sampled images exhibit low, medium, or high levels for the three constructs. Then we calculated the reliability between the automated image classification and the manual coding with Cohen's kappa. Table 4 presents the results and exemplary images. Kappa values of between .662 and .953 signal high validity of the instruments that we derived through our image classification procedure (Landis and Koch, 1977).

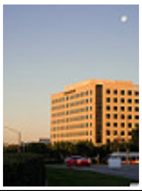
| Instrument | High (greater than .8 quantile) | Medium (between .4 and .6 quantile) | Low (below .2 quantile) | Cohen's kappa |
|---|---|---|---|---|
| Utility Reference |  |  |  | 0.953 |
| Experience Reference |  |  |  | 0.662 |
| Visual Detail |  |  |  | 0.779 |

*Table 4. Image examples and measurement validation*

## 4.5 Regression Analysis

Data collection, image classification, and dimensionality reduction produced three predictors and five controls that we include in our model. Table 5 reports the continuous variables' correlations. In order to test the five hypotheses, we calculated a linear regression model that includes as predictors utility reference, experience reference, and visual detail. Further, it includes the interactions terms of experience reference and visual detail with economy class and premium class. Considering the large size of our dataset, we followed Lin et al. (2013) recommendations for interpreting regressions with large sample sizes. We, in particular, provide standardized regression coefficients, the coefficients' 95% confidence intervals, as well as verbal interpretations of the coefficients' practical significances.

| | Popularity | Views | Date added | Views previous | Views next | C3 | Utility Reference | Experience Reference | Visual Detail |
|---|---|---|---|---|---|---|---|---|---|
| Popularity | 1 | 0.64* | 0.3* | 0.54* | 0.54* | 0.03* | 0.03* | 0.03* | -0.07* |
| Views | 0.64* | 1 | 0.04* | 0.84* | 0.84* | 0.03* | 0.01* | 0.02* | 0.03* |
| Date added | 0.3* | 0.04* | 1 | 0.08* | 0.07* | 0.01* | 0* | -0.01* | -0.11* |
| Views previous | 0.54* | 0.84* | 0.08* | 1 | 0.83* | 0.02* | 0.01* | 0.02* | 0.01* |
| Views next | 0.54* | 0.84* | 0.07* | 0.83* | 1 | 0.02* | 0* | 0.02* | 0.01* |
| C3 | 0.03* | 0.03* | 0.01* | 0.02* | 0.02* | 1 | 0 | 0 | 0 |
| Utility Reference | 0.03* | 0.01* | 0* | 0.01* | 0* | 0 | 1 | 0 | 0 |
| Experience Reference | 0.03* | 0.02* | -0.01* | 0.02* | 0.02* | 0 | 0 | 1 | 0 |
| Visual Detail | -0.07* | 0.03* | -0.11* | 0.01* | 0.01* | 0 | 0 | 0 | 1 |
| Notes: *:p<.001 | | | | | | | | | |

*Table 5. Correlations*

# 5 Results

Table 6 reports the regression's standardized regression coefficients, standard errors, p-values, and 95% confidence intervals. The adjusted r-squared value of .50 (F-statistic: 9825, p-value: < 2.2e-16), according to Cohen (1988, p. 413), suggests a high level of explained variance in behavioral sciences. A one standard deviation change in the effect sizes of the predictors and the moderation terms, with one exception, lead to a 1% change or more in popularity. Following the practice in prior research (e.g. Saboo et al., 2016), we consider these effect sizes sufficiently large to proceed with interpreting the standard coefficients' p values and confidence intervals.

Regarding the predictors, utility reference has a positive coefficient of .03 with a p-value below .001. This confirms H1: The level to which an image references a car's utility by presenting the car in concrete usage contexts, such as driving on city roads, positively affects image popularity. The coefficient for experience reference similarly has a positive value of .029 with a significant p-value (<.001), which confirms H2a: The level to which an image references a car's usage experience by presenting it in special occasion contexts that are subject to positive emotions, such as outdoor trips, increases image popularity. The coefficient for visual detail has a significant negative value of -.044 (p-value < .001). This confirms H3a: The level of a car's visual detail that an image transports, such as depicting recognizable car parts, negatively affects image popularity.

Regarding the moderators, the interaction term of experience reference with the premium car class (coefficient: -.012, p-value: <.001) is significant and negative. This confirms H2b: The car class moderates the influence of the level of a car's visual detail on image popularity such that for premium cars this negative effect is weakened. The interaction term of visual detail with premium class (coefficient: .009, p-value < .001) is significant and positive. This confirms H3b: The car class moderates the influence of the level of a car's visual detail on image popularity such that for premium cars this negative effect is weakened.

| Variable | Coeff | SE | p | 95% CI | Interpretation |
|---|---|---|---|---|---|
| *Controls* | | | | | |
| Views | 0.573 | 0.0011 | 0.0000 | (0.57,0.575) | |
| Date added | 0.000 | 0.0000 | 0.0000 | (0,0) | |
| License | -0.079 | 0.0027 | 0.0000 | (-0.084,-0.074) | |
| Views previous | -0.019 | 0.0013 | 0.0000 | (-0.022,-0.017) | |
| Views next | -0.011 | 0.0013 | 0.0000 | (-0.014,-0.008) | |
| C3 | 0.007 | 0.0008 | 0.0000 | (0.005,0.008) | |
| *Predictors* | | | | | |
| Utility reference | 0.030 | 0.0008 | 0.0000 | (0.028,0.032) | (H1 supported) A 1 SD increase in utility reference is associated with an average 3% increase in popularity, all else constant. |
| Experience reference | 0.029 | 0.0010 | 0.0000 | (0.027,0.031) | (H2a supported) A 1 SD increase in experience reference is associated with an average 2.9% increase in popularity, all else constant. |
| Visual detail | -0.044 | 0.0010 | 0.0000 | (-0.046,-0.042) | (H3a supported) A 1 SD increase in visual detail is associated with an average 4.4% decrease in popularity, all else constant. |
| *Moderators* | | | | | |
| Premium class * experience reference | -0.012 | 0.0026 | 0.0000 | (-0.017,-0.007) | (H2b supported) A 1 SD increase in experience reference in the premium class is associated with an average -1.2% lower increase in popularity than in the general class, all else constant. |
| Economy class * experience reference | -0.003 | 0.0020 | 0.1769 | (-0.007,0.001) | |
| Premium class * visual detail | 0.009 | 0.0022 | 0.0001 | (0.004,0.013) | (H3b supported) A 1 SD increase in visual detail in the premium class is associated with an average .9% lower decrease in popularity than in the general class, all else constant. |
| Economy class * visual detail | 0.003 | 0.0028 | 0.2436 | (-0.002,0.009) | |
| Notes: Coeff=coefficients (standardized for all continuous variables), SE=standard error, CI=confidence interval, SD=standard deviation, product community controls are not reported for reasons of clarity | | | | | |

*Table 6. Regression results*

# 6 Discussion

## 6.1 Contribution to Social Media Research

From a theory development perspective, we contribute to the sparse research on effects of user-generated image design in social media product communities on image popularity. Prior research on firm-generated images elaborated on the roles of an image's directiveness (Ordenes et al., 2018) and on an image's emotional and informative appeals (Akpinar and Berger, 2017). Our developed theory that is informed by narrative transportation theory (Green et al., 2008; van Laer et al., 2012) newly introduces the notions of utility and experience references and shows that both design aspects influence an image's popularity. On the theoretical basis of fluency theory (Reber et al., 2004), we further introduce the notion of processing fluency to image analysis in social media. Our results suggest that, comparable to visual product perceptions in print media (Pieters et al., 2010) and in experimental setups (Landwehr et al., 2013), visual complexity negatively affects a viewer's liking to different extents depending on the viewer's context and expectations.

## 6.2 Methodological Contribution to IS Research

Even though computational methods of image analysis are a main subject of research in computer science (Krizhevsky et al., 2012; He et al., 2016), the application of such methods in IS research is still relatively scarce, particularly compared to computational text analysis approaches (Abbasi et al., 2018). Visual research in IS largely employs qualitative research methods (Andrade et al., 2015). Schultze, for instance, uses a photo diary to study how individual identities are created on virtual worlds (Schultze, 2012). Vaidya interprets photographs in a qualitative study on the introduction of information systems in rural settings (Vaidya, 2012). Díaz Andrade, and Urquhart rely on photo documentations in their study of the dissemination of computer-mediated information (Díaz Andrade and Urquhart, 2009).

Among the sparse IS research that applies computational methods of image analysis, one research stream uses design science research approaches, e.g., for the analysis of street pavements (Chatterjee et al., 2017), textural eye patterns (Alhasawi et al., 2018), and pigmented skin lesions (Di Leo et al., 2017). The other stream of research deduces features from computational image analysis, which are used in quantitative empirical models. Wang et al., for example, employ a Scale-Invariant Feature Transform algorithm in order to compare the similarity of app icons in their analysis of mobile app copycats (Wang et al., 2018). Wang and Li use image processing algorithms that allow extracting color-, complexity-, and symmetry-related information in their aesthetic analysis of app icons (Wang and Li, 2017). Zhang et al. use techniques from deep learning and computer vision to build a dedicated supervised learning classifier that classifies Airbnb property images into high or low quality (Zhang et al., 2017).

In summary, prior IS researchers' approaches to image analysis allow the analysis of diverse image facets. However, the IS community has, to the best of our knowledge, not taken advantage of general-purpose data and convolutional neural networks that allow the broad detection of objects in an image for exploratory purposes. Google's open images dataset, for example, allows the construction of object detection algorithms that cover over 5,000 objects (Krasin et al., 2017; Krasin et al., 2018). In contrast to manual image coding, these technologies enable a scalable exploratory analysis of images that supports statistical models with large data volumes.

In this research, we newly introduce a computational method for the object-based exploratory analysis of images. This method is informed by state-of-the-art computer science research on convolutional neural networks (Krizhevsky et al., 2012; He et al., 2016) and builds on a multi-purpose image classification model (Krasin et al., 2018) and dimensionality reduction techniques in the development of measurement instruments that address the object-related context of a car's positioning in an image. This computational method can potentially be transferred to a variety of application scenarios in IS research that rely on object identification tasks.

## 6.3 Contributions to Practice

Our results provide several practical implications relating to image design for users and managers of social media car model communities that aim to improve image popularity. First, cars should be depicted in real use contexts, rather than in artificial contexts, in order to emphasize the car's utility. Second, one should not overly focus on the visual detail of a car, but rather allow a fluent processing of the car's visual appearance. Third, the car's visual presentation should be adapted to whether it targets an economy or a premium segment. One should position economy cars in special occasion contexts such as outdoor trips. Premium cars may less highlight such experiences because customers more strongly focus on identity and emphasize, for example, discriminating visual features (Sukhdial et al., 1995).

## 6.4 Limitations

This research is subject to several limitations. First, our empirical approach focusses on a single image hosting and social media platform. Other social media platforms provide different functionalities that shape user interaction; Facebook, for example, offers no favoring functionality but a liking mechanism. Generalizing our findings further thus requires supplementary empirical efforts that look at brand communities that are hosted on alternative social media platforms. Second, our findings may be biased by the 5000 trained objects that the chosen image classification model is able to recognize (Krasin et al., 2018). However, we were able to successfully validate the proposed object-based measurement approach and to show that we can measure the three focal theoretical constructs. Third, our findings may not be generalizable to other products apart from cars, because we collected data from car-related product communities only. A further generalization, therefore, requires empirical research that systematically includes other B2C products.

# 7 Conclusion

In this research, we introduced an innovative computational approach to extracting image design characteristics. This approach involves convolutional neural network-based object identification, a feature reduction via principal component analysis, manual feature validation, and a regression analysis. An analysis of 790,775 images of economy and premium cars of the 17 largest brands posted in 68 car communities on a social media platform revealed several effects of product presentation on image popularity that relate to the levels of utility reference, experience reference, and visual detail. A distinguishing of economy cars and premium cars showed that car class moderates image design effects. Our results contribute a visual product presentation theory to the extant literature on social media brand communities.

Regarding future research, the proposed computational visual analysis methodology may inform the study of other image-based IS. One potential research area is the impact of image design on learning success in learning support systems. A second area is the impact of image design on readership in online media. A third area is the design of visual work instructions and the impact on work outcomes in operational production systems. Another avenue for further research is the use of the presented research methodology for the study of visual communication in brand communities to analyze other products and other social media platforms.

# Appendix

| Brand | Number of communities | | | Images | | | Community members | | |
|---|---|---|---|---|---|---|---|---|---|
| | Economy | Premium | General | Total | Min | Max | Total | Min | Max |
| Audi | 0 | 3 | 1 | 46469 | 1464 | 24767 | 4708 | 321 | 1801 |
| BMW | 1 | 3 | 1 | 41839 | 1855 | 28972 | 4968 | 405 | 2763 |
| Chevrolet | 1 | 1 | 1 | 133836 | 1396 | 126245 | 5205 | 101 | 4669 |
| Chrysler | 1 | 0 | 2 | 40745 | 863 | 25333 | 1796 | 178 | 971 |
| Fiat | 3 | 0 | 0 | 7564 | 1365 | 3105 | 1321 | 141 | 621 |
| Ford | 2 | 1 | 0 | 20767 | 1327 | 14992 | 1812 | 313 | 921 |
| Honda | 0 | 0 | 2 | 31965 | 3199 | 28766 | 2597 | 253 | 2344 |
| Hyundai | 1 | 1 | 2 | 11081 | 882 | 7025 | 1133 | 105 | 736 |
| Mazda | 1 | 2 | 2 | 22783 | 922 | 8870 | 2884 | 173 | 1483 |
| Mercedes | 0 | 3 | 2 | 57690 | 1407 | 40146 | 3207 | 117 | 1780 |
| Nissan | 1 | 2 | 1 | 65111 | 6563 | 31418 | 5318 | 566 | 2110 |
| Peugeot | 2 | 0 | 3 | 36831 | 852 | 27214 | 5133 | 133 | 2300 |
| Porsche | 0 | 5 | 2 | 184284 | 969 | 151627 | 13132 | 253 | 9406 |
| Renault | 4 | 0 | 1 | 18484 | 1038 | 12091 | 762 | 16 | 397 |
| Suzuki | 1 | 0 | 2 | 8869 | 1211 | 5646 | 998 | 174 | 573 |
| Toyota | 1 | 1 | 1 | 28927 | 3522 | 21001 | 3057 | 176 | 2354 |
| Volkswagen | 4 | 0 | 0 | 33520 | 1545 | 14685 | 3480 | 286 | 1818 |

*Table 7. Car brands and communities*

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