More than meets the eye? Visual storytelling and optimal distinctiveness of new ventures in online B2C markets *

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Abstract

We examine how new ventures in online B2C markets use product images for visual storytelling in their strife for optimal distinctiveness, that is, appearing as different as conformingly possible. Using machine learning approaches for object recognition and analysis on images of 1,312 entrepreneurial products offered on Amazon Launchpad, we analyze the effect of visual semantics—the meaning contained in the visual objects identified—on audience evaluation across product categories. We construe visual semantics in terms of their fit—the extent to which their meaning differs from competitors within their category, as well as their richness—the amount of meaning conveyed. We find that both effects are strongly contextualized by the product category they are used in. In non-distinct product categories—those that share frequent relations with others in the meaning system—a high semantic fit is beneficial, but this relative advantage diminishes with increasing product category distinctiveness. In distinct categories, semantic richness is evaluated favorably, but this effect diminishes with decreasing product category distinctiveness. High semantic fit and richness also mutually accentuate each other, especially in increasingly distinct categorical contexts. Our work shows that visual storytelling not only allows entrepreneurs to express differentiation and conformity, but that it also can serve as an effective tool to handle categorical contexts with heterogeneous audiences and evaluative complexities. For managers, our work provides clear guidelines for designing and using semantics in product images to appear more or less unique to consumer audiences in online B2C markets.

Keywords: Optimal Distinctiveness, Visual Semantics, Sensory Marketing
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1 Introduction

New ventures often fail during the first years of their existence (OECD, 2020). One reason for failure is the lack of a clear and compelling strategy to achieve "optimal distinctiveness"; that is, to both conform to established market norms and practices, while simultaneously standing out to generate visibility and competitive advantages (Zhao et al., 2017). For many new ventures, being distinctive is an integral and necessary part of "who and what they are" (Navis and Glynn, 2011). Yet, communicating their distinctiveness to evaluating audiences remains challenging (Glynn and Navis, 2013).

One field of research that has examined how new ventures succeed in communicating their distinctiveness is cultural entrepreneurship (Lounsbury and Glynn, 2001; Soublière and Lockwood, 2022). The cultural entrepreneurship literature proposes that new ventures use storytelling to provide meaning to evaluating audiences and to contextualize their entrepreneurial actions and products (Clarke, 2011; Navis and Glynn, 2011; Manning and Bejarano, 2017; Lounsbury and Glynn, 2001). Yet, researchers have primarily focused on how new ventures use *verbal* storytelling, such as textual narratives or spoken investment pitches, to increase the distinctiveness appeal of their products (Navis and Glynn, 2011) and favorably shape audience evaluation (Martens et al., 2007; Wry et al., 2011; Kim et al., 2016).

While verbal storytelling may be adequate in some contexts to favorably shape audience evaluation, we argue it is not the only useful semiotic mode of communication new ventures can use (Bu et al., 2022; Chan et al., 2021). *Visual* storytelling visualizes the product using carefully crafted images. Visual storytelling may help contextualize the product, convey information that cannot be conveyed through verbal storytelling (Zhang and Luo, 2022; Scheaf et al., 2018), and facilitate rapid information acquisition (Meyer et al., 2013, 2018)—a fact summarized by the phrase "A picture is worth a thousand words" (Höllerer et al., 2018). What we know about the effect of visual storytelling on audience evaluation stems primarily from investment settings with venture capitalists and crowdfunders as the focal audiences

(Chan and Park, 2015; Frydrych et al., 2016; Scheaf et al., 2018; Anglin et al., 2022; Wessel et al., 2022). But little is known about settings where *consumers* use visuals to retrieve valuable semantic meaning and quickly form an opinion of an entrepreneurial product (Shepard, 1967; Childers and Houston, 1984). In consumer settings, we propose visual storytelling to be a pervasive, salient, and well-suited strategy to manage a product's distinctiveness appeal (Childers and Houston, 1984; Boxenbaum et al., 2018; Höllerer et al., 2018; Lounsbury et al., 2018; Mahmood et al., 2019).

Because visual storytelling conveys meaning rapidly and efficiently, it may be especially important in online B2C markets (Janisch and Vossen, 2022; Kim and Jensen, 2011; Sgourev et al., 2022), where new ventures compete for consumers that typically prefer unique, distinct products (Pontikes, 2012; Taeuscher et al., 2021). Consumers are often reluctant to *read* detailed product descriptions. They rather rely on visuals (Bhakat and Muruganantham, 2013) to gain a quick impression (DelVecchio et al., 2019) and rank alternatives (Zuckerman, 2016). Thus, in B2C markets, visuals can be a critical factor in product success (Bu et al., 2022; Chan et al., 2021), making online B2C markets a great research context to examine how visual storytelling influences audience evaluation (Höllerer et al., 2019).

We build on literature on sensory marketing (Hulten et al., 2009; Krishna, 2012) and propose that new ventures can leverage two dimensions in their visual storytelling to appear more or less distinct, namely *semantic fit* and *semantic richness*. On the one hand, visual storytelling can differ in the degree to which its meaning, conveyed through interpretable objects (Dzyabura et al., 2021), aligns with consumers' expectations, which we define as semantic fit (Lee and Labroo, 2004). On the other hand, visual storytelling can differ in the amount of meaning it carries, which we refer to as semantic richness (Luffarelli et al., 2019). Consider this simplified example: A new bicycle venture that competes in the "bike" product category could use visual storytelling to portray a bicycle either as the sole focal object in front of a neutral background or embedded in a mountain scenery with a professional rider on it. While both approaches focus on the bicycle (both would score high on semantic fit, as they meet audiences' expectations for the "bike" product category), the latter case clearly carries more semantic meaning because it contains multiple objects. It thereby helps contextualize the product in terms of intended target group, product features, as well as possible use scenarios and other important factors (Rietveld et al., 2020).

In line with recent research on consumer evaluation of optimal distinctiveness in verbal storytelling (Taeuscher et al., 2022; Vossen and Ihl, 2020), we believe that the effectiveness of visual storytelling will vary across product categories. A product category not only defines the competitive context, but also groups products based on perceived features. As such, each product category conveys a specific cultural "code" associated with belonging to a category. This cultural code also includes associated behavioral expectations, which shape consumer cognition (Vergne and Wry, 2014; Vossen and Ihl, 2020). These behavioral expectations are further shaped by a product category's distinctiveness–how uncommon a product category is in relation to all other product categories in the same market (Lo et al., 2020; Taeuscher et al., 2022; Janisch and Vossen, 2022). Consequently, we ask the following two research questions: (1) How does visual storytelling's semantic fit and semantic richness influence audience evaluation of entrepreneurial products? (2) How is their effectiveness shaped by the evaluative boundary conditions defined by the respective product categories?

To answer these questions, we use four years of weekly sales data from 297 new ventures that offer 1,561 entrepreneurial products on Amazon Launchpad, a dedicated sub-section of Amazon's online B2C market for products by new ventures. To analyze visual storytelling, we collected 9,072 unique product images and analyzed their content with machine learning algorithms from image label recognition and natural language processing. This allowed us to count the number of unique image labels detected as a measure of semantic richness, and to compute those labels' typicality as a measure of semantic fit.

On average, we find that both semantic fit and richness have a positive effect on product evaluation. This effect is contextualized by the product categories in which evaluation takes place. In non-distinct product categories that overlap with other categories due to many shared properties, the positive effect of semantic fit is more pronounced, while the positive effect of semantic richness is attenuated. In distinct product categories that do not overlap or overlap slightly in their properties with other categories the effect is reversed as the effect of semantic fit is attenuated, while the positive effect of semantic richness is accentuated. However, especially in distinct product categories, semantic fit and richness mutually reinforce each other.

By adding a sensory perspective to the predominantly cognitively focused discussion on entrepreneurial storytelling we bridge two major existing literatures, namely in sensory marketing (Hulten et al., 2009; Krishna, 2012) and on audience evaluation of strategic differentiation decisions (Navis and Glynn, 2011; Smith, 2011; Zhao and Glynn, 2022). By focusing on the context of new ventures in online B2C markets, we provide meaningful insights into when and why certain visual strategies favorably affect consumer audiences' evaluation. Cultural entrepreneurship research has highlighted how entrepreneurs construct stories that will resonate with key audiences and enable new venture legitimization (Lounsbury and Glynn, 2001; Martens et al., 2007; Rindova et al., 2011). Based on a machine learning image recognition approach, we extend and rethink such research by showcasing how visual storytelling and the semantic meaning it conveys help entrepreneurs to compete in different categorical contexts.

For managers, our work provides clear-cut implications on how to incorporate visual storytelling in their appeals to consumer audiences. When designing product-promoting visuals, managers must not only take into account their basic visual properties such as illuminance, shape, or color (Sample et al., 2020; Sgourev et al., 2022), but also consider their effects on the targeted consumers' perceptual and semantic processing. Managers in online B2C markets should always consider the categorical context when deciding on their visual storytelling. By choosing the right level of semantic fit and richness for the categorical context, new ventures can ensure that there is "more than meets the eye" in their product images.

2 Theoretical background

2.1 Optimal distinctiveness and visual storytelling

Optimal distinctiveness, defined as the point(s) of strategic positioning whereby organizations seek to be as unique as legitimately possible, has received considerable attention from strategy and organizational scholars (Durand and Haans, 2022; Zhao et al., 2017; Zhao and Glynn, 2022). Usually, achieving optimal distinctiveness means finding the right balance between conforming and thus yielding to normative pressures, as well as standing out to generate competitive benefits (Haans, 2019). Not only is this trade-off very context-sensitive (Haans, 2019), but it is also especially challenging for new ventures. New ventures usually have to appeal to audiences that expect novelty (Taeuscher et al., 2021; Vossen and Ihl, 2020), which forces new ventures to find an optimal degree of "legitimate distinctiveness" (Navis and Glynn, 2011). Often, studies on optimal distinctiveness focus on the intra-category level (Lo et al., 2020), where new ventures compare themselves and their positioning with established category members such as prototypes or exemplars (Barlow et al., 2019; Zhao et al., 2018).

Both new and established ventures can influence how they are perceived by evaluating audiences by strategically using different cultural elements (Lounsbury and Glynn, 2001; Lounsbury et al., 2018). To shape the perceptions and behaviors of audiences, ventures can deploy cultural elements, such as linguistic and visual claims, or symbolic actions (Soublière and Lockwood, 2022; Meyer et al., 2018; Lounsbury et al., 2019). In terms of optimal distinctiveness, ventures can use cultural elements to both differentiate and legitimize (Martens et al., 2007; Taeuscher et al., 2022; Vossen and Ihl, 2020) by shaping them in a way that helps their products to appear more conforming or distinct (Glynn and Navis, 2013). This storytelling provides audiences with resources such as illustrations, explanations, or descriptions that support them in making sense of, evaluating, and constructing meaning (Navis and Glynn, 2011).

However, much of the existing research on how storytelling is used to achieve optimal distinctiveness emphasizes the role of textual narratives and storytelling (Barlow et al., 2019; Haans, 2019). More recently, product design features such as the physical appearance of art, car fronts, or furniture, has also been studied in this context (Banerjee et al., 2022; Bu et al., 2022; Chan et al., 2021). Notwithstanding these results, we argue that especially for new ventures in online B2C markets, relying on textual storytelling or product design features may not be the most advisable strategy to convey optimal distinctiveness. Consumers are not necessarily willing to read through long descriptions or look at a supplier's homepage, but are primarily sight-driven (Radford and Bloch, 2011; Chan and Park, 2015; Hulten et al., 2009) and often try to gain a quick impression of a product. They are therefore particularly receptive to product visuals, from which they can extract meaning very rapidly and effortlessly (Greene and Oliva, 2009; Joubert et al., 2007; Li et al., 2003).

While product design features are undoubtedly important factors for audience evaluation, we consider visuals from a storytelling perspective that focuses not so much on the design of a certain product, but rather on the visual information and meaning conveyed to supplement the evaluation of the product (Adaval et al., 2018; Meyer et al., 2018; Mahmood et al., 2019). Our focus on these visual semantics builds on recent vision research demonstrating that the meaning contained in visual scenes is a main predictor of attention allocation, memorization, and judgment (Henderson et al., 2018, 2019). To investigate how such visually conveyed meaning can change the distinctiveness claims of new ventures' products, which in turn affect consumers' evaluation, we look at two properties of product visual semantics: The degree to which its meaning, conveyed through interpretable objects, aligns with consumers' expectations and the amount of meaning it carries. We refer to these two properties as visual *semantic fit* and *semantic richness* and deem both crucial in determining whether visual storytelling can influence audience perceptions of distinctiveness.

Visual semantic fit—the fit between the meanings contained in a new venture's visual design elements and expected semantic meanings given by the product category—influences consumers' evaluation process by facilitating their visual processing (Lee and Labroo, 2004).

Naturally, consumers derive these expected semantic meanings from the categorical norm, that is, from intra-categorical comparisons with the prototype or exemplar (Barlow et al., 2019). Consumers favorably evaluate information that is close to their expectations and more familiar, because familiarity makes information easier to process and thereby saves cognitive resources (Landwehr and Eckmann, 2020; Christensen et al., 2020; Paolella and Durand, 2016; Pontikes, 2012). Hence, presenting easy-to-process information helps new ventures appear more conforming (Smith, 2011). New ventures can provide easy-to-process information through a visual narrative that fits with consumers category expectations. Semantically fitting stimuli also facilitate consumers' visual processing as they are easier to perceive and remember (Reber et al., 1998; Labroo et al., 2008; Brasel and Hagtvedt, 2016). The overall burden of the evaluative process is also a key factor in whether distinctiveness is perceived positively or negatively by audiences (Janisch and Vossen, 2022; Paolella and Durand, 2016).

However, new ventures that adopt semantic meanings in their visual narrative that fit the category norm are less likely to stand out and reap competitive benefits. Consumer audiences interested in start-up products expect novelty and thus may devalue new ventures that fail to meet such expectations (Taeuscher et al., 2021; Vossen and Ihl, 2020). New ventures that fail to be perceived as novel and unique render themselves more interchangeable (Pocheptsova et al., 2010; Janisch and Vossen, 2022) . Deviating from the category norm in terms of visual semantic meanings can help new ventures signal such novelty and arouse consumer interest (Labroo and Pocheptsova, 2016).

Visual semantic richness—the amount of semantic meaning conveyed in visual design elements (Luffarelli et al., 2019)—influences consumers by enriching their basis for evaluating a product. Semantic richness is different from visual complexity as described by visual complexity theory (Donderi, 2006). Whereas visual complexity is defined as the extent to which a visual design element contains redundancy, either in the form of feature complexity or design complexity (Pieters et al., 2010), semantic richness refers to the depicted number of unique identifiable objects. Visuals can be visually complex but contain little meaning, and vice versa. Consumers rely on the amount of semantic meaning to fully evaluate a product, especially in highly competitive and uncertain market contexts, such as online B2C markets. Enriching consumers' basis for evaluating a product gives them a better idea of how to place a product in the competitive landscape which can reduce uncertainties and concerns (Radford and Bloch, 2011). On the one hand, a new venture that uses low levels of semantic richness in its visual narrative provides less material as an information base and may not appropriately alleviate consumers' uncertainties, which may lead to devaluation of a new venture's product and subsequently lower its sales performance (Taeuscher, 2019).

On the other hand, a new venture that uses high levels of semantic richness in its visual narrative enriches the evaluation basis of consumers through more meaning conveyed (Luffarelli et al., 2019) from which consumers may infer product features or characteristics (Adaval et al., 2018). Such added information helps consumers gain a better final impression of a new venture and its products, and facilitate comparisons against the impressions gained about competitors (Zuckerman, 1999; Barlow et al., 2019). However, a new venture that uses excessive levels of semantic richness in its visual narrative may make it more difficult for consumers to evaluate its product and possibly distract consumers from core product attributes due to the amount of information-carrying meaning (Kim et al., 2016).

These arguments show that both semantic fit and semantic richness have clear potential to be useful tools for new ventures to achieve optimal distinctiveness with consumer audiences. Past research on textual storytelling has established that the extent to which distinctiveness claims help new ventures depends on the categorical context (Haans, 2019; Janisch and Vossen, 2022). Next, we therefore discuss how semantic fit and semantic richness affect audience evaluation and product performance across different product categories and develop our hypotheses.

2.2 The contextual role of product category distinctiveness

Product categories serve as reference levels for audiences to group products based on their features and to evaluate the distinctiveness appeal of a product (Deephouse, 1999; Zuckerman, 1999). Product categories facilitate audience comparison of products (Phillips and Zuckerman, 2001), by reducing audiences' consideration sets as product categories group together products with similar characteristics such as "cultural features, values, and potential uses" (Vergne and Wry, 2014, p.68). Reduced consideration sets are particularly relevant as evaluating audiences have limited attentive and cognitive resources. Thus, categorization of products creates meaning systems that define the required characteristics and appropriate behavior for belonging to a category (Phillips and Zuckerman, 2001) and delineates these meaning systems from those of other categories.

These meaning systems represent evaluation schemes and provide an anchor for audiences (Vergne and Wry, 2014) to quickly and efficiently compare large amounts of information in order to evaluate one product in comparison to others (Cattani et al., 2017). Thus, in terms of determining optimal distinctiveness, a category should be viewed not just as a pool of competitors to differentiate from or conform to, but as a meaning system that can influence fundamental parts of product evaluation (Soublière and Lockwood, 2022; Vossen and Ihl, 2020). However, we argue that these meaning systems that categories provide to the evaluating audience depend on their own category distinctiveness, that is, their own relative position across all product category meaning systems (Lo et al., 2020). In non-distinct product categories–that is, those that frequently overlap in attributes with other categories and thus occupy a more central position across all product category meaning systems–audiences prefer conformity and effortless evaluation, which increases the penalties for nonconformity and reduces the benefits of differentiation (Janisch and Vossen, 2022). For distinct product categories, that is, those that have little or no overlap in their attributes with other categories and therefore occupy a marginal position across all product category meaning systems, audiences tend to be novelty-oriented and more willing to tolerate increased evaluation complexity if it provides them with more specialized products (Taeuscher et al., 2022).

The use of visual storytelling to fit or deliberately deviate from a product category's meaning system can affect consumers' evaluation of distinctiveness. We argue that depending on whether a product competes in non-distinct or distinct product categories, consumers' preferences for visual storytelling that adheres to or deviates from the norm of the category may differ. On the one hand, in non-distinct product categories, consumers will appreciate it when a product has a high semantic fit in its visual narrative with the category norm, as this makes it easier for them to evaluate the product quickly and effortlessly. Consumers penalize non-conformity in such a setting (Janisch and Vossen, 2022), because it is cognitively more effortful to evaluate a product that deviates from the category norm in its visual narrative (Wyer and Srull, 1989). A product in a non-distinct product category should thus adhere to consumers' expectations of conformity by using a visual narrative with semantic meaning close to the category norm.

On the other hand, in distinct product categories, consumers will expect a product to have a lower semantic fit in its visual narrative with the category norm, as they have a higher tolerance and preference for distinctiveness. Thus, particularly in contexts where audiences are specifically looking for novelty, such as in entrepreneurial consumer markets (Taeuscher et al., 2021), low levels of semantic fit can be expected to legitimize products by making them appear more novel and innovative, increasing a product's competitive advantage (Christensen et al., 2020). Novelty-expecting audiences seek innovative products which they perceive as exclusive and non-interchangeable (Pocheptsova et al., 2010). Thus, new ventures that use difficult-to-process visual storytelling might pique the interest of such audiences and increase likability (Labroo and Pocheptsova, 2016). This leads to Hypotheses 1 and 2.

Hypothesis 1: *High levels of semantic fit in visual storytelling increases performance for products in non-distinct categories.*

Hypothesis 2: *Low levels of semantic fit in visual storytelling increases performance* *for products in distinct categories.*

Depending on whether a product is active in non-distinct or distinct product categories, consumers' demand for information may differ. We argue that consumers expect less rich visual image information from products in non-distinct categories, as established evaluation criteria shaped by the category make it easier for consumers to place a product in the competitive landscape (Radford and Bloch, 2011). Too high levels of semantic richness could therefore unnecessarily complicate comparison processes for consumers and possibly distract them from core attributes due to the surplus of information-carrying meaning (Kim et al., 2016). Therefore, we expect products in non-distinct categories to benefit from communicating their conformity through restricting the semantic richness of their visual storytelling.

Conversely, we propose that products in distinct (vs. non-distinct) categories tend to be more novel, and consumers expect them to be so. In order to make sense of novel features and uses (Adaval et al., 2018), consumers tolerate and often require rich, and even hard-to-process information (Paolella and Durand, 2016). New ventures can provide such information in the form of semantically rich visual storytelling. Semantically rich visuals will facilitate and guide consumers' visual imagery and mental stimulation of product use and benefits (Nielsen et al., 2018), which is particularly important for innovative products (Zhao et al., 2009, 2012; Feurer et al., 2021). Moreover, visual storytelling that is rich in meaning may be perceived by consumers as more elaborately designed and unique instead of just being copycats imitating competitors' visuals (Van Horen and Pieters, 2012), which can serve new ventures as an additional signal of quality and differentiator. Hence, we expect products in distinct categories to benefit from clearly communicating their distinctiveness through more complex visuals, that is, using visuals that are rich in semantic meaning. This leads to Hypotheses 3 and 4.

Hypothesis 3: *Low levels of semantic richness in visuals increases performance for products in non-distinct categories.*

Hypothesis 4: *High levels of semantic richness in visuals increases performance for products in distinct categories.*

	Semantic fit	Semantic richness
Non-distinct product category	High (H1)	Low (H3)
Distinct product category	Low (H2)	High (H4)

Table 1: Summary of hypotheses

3 Empirical approach

3.1 Data

To analyze how semantic fit and richness of visual storytelling affect consumers in online B2C markets, we used sales data from products on the online B2C marketplace Amazon Launchpad (Janisch and Vossen, 2022). Online sales hold new opportunities for small brands and niche products but are also subject to intense competition due to low barriers to entry, making it difficult to capture the attention of consumer audiences. To alleviate this problem for innovative new ventures (such as small and medium brands with a unique selling point or crowdfunded products) to attract attention, Amazon initiated Amazon Launchpad in 2015. Since then, participating new ventures have benefited from Amazon's established consumer audience and its long-standing knowledge as a successful online marketplace operator on how to thrive in a highly competitive market environment.[1] Thus, the Amazon Launchpad setting provides us with a unique perspective for studying new ventures that explicitly compete in existing product markets for consumers who are particularly interested in entrepreneurial products.

To identify our sample, we collected information on all products on the U.S. Amazon

[1]For more detailed information on Amazon Launchpad and its program terms, please refer to https://www.amazon.com/launchpad/startups/faqs, https://sellercentral.amazon.com/gp/help/external/G202007390 and https://press.aboutamazon.com/news-releases/news-release-details/amazon-launchpad-celebrates-five-years-empowering-startups/.

Launchpad. Visual storytelling can be costly to create, and it is to be expected that storytelling quality may vary considerably across the different new ventures on Launchpad because nascent start-ups may lack funding to create high-quality visuals. In order to improve comparability, we therefore only included products who were at the point of data collection also available in all other western Amazon Launchpad summaries (France, Germany, Italy, Spain, the United Kingdom, and Canada) between February 2015 and September 2020 (292 weeks). The reasoning for this is that internationalization is a strong indication of domestic success (Joardar and Wu, 2017) as only successful new ventures have the resources to expand to additional markets, and consequently also the resources for professional imagery. To uniquely identify a product and a new venture, we used the Amazon Standard Identification Number (ASIN) as well as venture information, such as the venture name, tax number, or trade register number. We removed resellers that sell only products they do not manufacture themselves and ventures that do not qualify as new ventures due to their size or age, which left us with 1,561 products.

We used the commercial data analytics service Keepa.com to obtain panel data on price trends and sales performance, as well as information on product categories (Janisch and Vossen, 2022). Keepa.com tracks hundreds of millions of international Amazon products and allows subscribers to access this data through an API. By using the Amazon ASIN, we were able to request daily monitoring of price and sales rank changes, as well as product category information and image links for all products in our sample. We subsequently removed products from the dataset for which this data was incomplete. This entails products for which no sales data was available (10 products) or for which we had less than three daily observations (42 products). We also removed all products for which Keepa.com did not provide category (195 products) or image information (43 products). Since our observation period is very large, 2044 days, and price or sales rank changes can be very marginal from one day to the next, we aggregated the daily observations for products provided by Keepa.com on a weekly basis (van Oest et al., 2010). Since products were added but also removed from

Amazon Launchpad over the course of these 292 weeks, our panel is unbalanced.

Next to data on prices and sales, Keepa.com also collects links to product images, as well as product category tags about the respective products that play a key role in constructing variables for our analysis. Consumers can use product categories on Amazon Launchpad to find and compare products more easily. A product category on Amazon Launchpad can be understood as a nested structure of multiple tags that group products in a "general-to-specific hierarchy" (Gehman and Grimes, 2017, p.2295). We illustrate this with an example from our data set. Products such as cycling lights and a fitness watch share many features as they are both used for sport activities. Due to this feature overlap, they are both to be found in the same basic category *Sports & Outdoors* as indicated by their affiliated top tags. Although cycling lights and a fitness watch have many features in common, there are also some features they do not share. Due to this partiality of their feature overlap, these products can be further delineated as indicated by their affiliated tags further down along their hierarchically nested category structure which group them into first and second subordinate categories (Gehman and Grimes, 2017) (see Table 2).

Basic category	First subordinate category	Second subordinate category
Sports & Outdoors	Sports & Fitness	Exercise & Fitness, Accessories, Other Sports, Hunting & Fishing, Golf, Leisure Sports & Game Room, Sports Medicine, Tennis & Racquet Sports, Boating & Sailing
	Outdoor Recreation	Skates, Skateboards & Scooters, Climbing, Cycling, Water Sports, Outdoor Clothing, Camping & Hiking, Winter Sports
	Fan Shop	Sports Equipment

Table 2: Example for the nested structure of product categories on the U.S. Amazon Launchpad

We consider in our study the three first-order category tags of a product, as data exploration showed that product category tags beyond that often distinguish products only based on colors or shapes, a distinction that is too granular for investigating our question of how the effectiveness of image semantic fit and semantic richness on product sales performance is shaped by the evaluative boundary conditions set out by the respective product categories. We used a product's basic category provided by Keepa.com as reference level to compute how distinct the multiple category tags affiliated with a product are from those of all other products in the same basic category. If products do not only share the same basic category but also the first and second subordinate category, they become more likely to be direct competitors, as the more specific the categorization becomes, the smaller the set of products for consumers to compare. We therefore compared the visual storytelling of a product to that of products from the same second subordinate category. We argue that this perspective of intersecting and hierarchical category relationships helps to understand the role the category context plays for how semantic fit and richness of visual storytelling affect consumers in online B2C markets.

To investigate how visual storytelling affects products' distinctiveness appeal in online B2C markets and subsequently their sales performances, we collected all 9,072 unique images monitored by Keepa for 1,518 entrepreneurial products. We analyzed the images with *Amazon Rekognition*, a tool provided by Amazon which allows its users to detect labels, representing objects, scenes, actions, or concepts, in images with artificial intelligence using deep learning.

For each identified label, Amazon Rekognition provides a confidence score that indicates the accuracy of the label.[2] The illustrative example in Figure 1 shows the label results and confidence scores for a self-taken photograph. For the depicted mountain scenery, Amazon Rekognition suggests labels such as tent (object), mountain range (scene), camping (action), and outdoors (concept). To avoid false positives—incorrectly predicted labels—and false negatives—labels that are present in an image but not predicted, we set a threshold value. In our subsequent analyses, we only considered labels if their confidence score exceeded the threshold value. We set the threshold value to 55%, which is in line with the threshold value Amazon uses for the demo version of Amazon Rekognition.[3]

[2] For more detailed information on Amazon Rekognition, please refer to https://aws.amazon.com/rekognition/.

[3] We opted for this value in line with Amazon's own reasoning but would argue that a 55% certainty should serve as a lower bound as anything below that would basically amount to a coin toss. To further test Amazon's assumption, we conducted robustness checks with a higher certainty threshold of 80% with comparable results. Results are available from the authors upon request.

Label detected with confidence score							
Outdoors	99.1%	Tent	90.9%	Camping	81.8%	Azure sky	64.1%
Nature	98.9%	Landscape	88.4%	Water	74.7%	People	62.3%
Mountain	97.3%	Mountain range	88.1%	Field	69.4%	Glacier	62.0%
Scenery	94.8%	Ice	85.0%	Peak	69.0%	Lake	60.9%
Person	91.3%	Plant	83.0%	Sky	65.5%		
Human	91.3%	Grass	83.0%	Snow	64.5%		

Figure 1: Labels detected by Amazon Rekognition in sample image with confidence scores

3.2 Dependent variable

Our dependent variable is *Amazon sales rank*. To operationalize our dependent variable, we log-transformed and averaged the sales rank for both each product and each week during observation (Chevalier and Mayzlin, 2006; Smith and Telang, 2009; van Oest et al., 2010). A product's sales rank is market-specific and does not represent sales performance in absolute terms for a product in a smaller product market could reach a high ranking even with relatively low sales compared to a product in a broader product market. To account for this, we control for competition within a market category. For interpreting the dependent variable, it is crucial to keep in mind that while a positive coefficient implies a decrease in sales performance, a negative coefficient corresponds to an increase in sales performance. To bypass this circumstance and make interpretation of our results more intuitive, we multiplied the sales rank by negative one.

3.3 Independent variables

Our three key independent variables are *image semantic richness*, *image semantic fit*, and *product category distinctiveness*. To operationalize *image semantic richness*, we accessed all image links provided for a product by Keepa.com and analyzed it with Amazon Rekognition. For each image, we then computed the total number of unique labels identified by Amazon Rekognition that surpassed the threshold value of 55% (Overgoor et al., 2022; Dzyabura and Peres, 2019). This approach relies on the fact that labels extracted via Amazon Rekognition represent meaningful concepts that result from training on human categorization data, and we assume that the amount of meaning conveyed by an image increases monotonously with the number of labels extracted. If a new venture used multiple images for an individual product, we averaged *image semantic richness* across all images available. Thus, we compute our measure of *image semantic richness* as:

$$Image\ semantic\ richness_i = \frac{\sum_{x=1}^{X} L_{ix}}{X} \tag{1}$$

where L is the number of unique labels for an image detected by Amazon Rekognition and X represents the total number of images advertizing a new venture's product.

Image semantic richness measures the number of labels provided in visual storytelling but does not consider the extent to which the labels of the collected images are similar in their semantic meaning. Hence, we operationalized *image semantic fit* by building a visual distinctiveness variable that dynamically measures the extent to which the semantic meaning used by a new venture in its images for a product i deviates on average from the semantic meaning used by all competing products in the same second subordinate category c and week t. This means that we computed the extent to which the identified labels of, for example, the product images for a biking helmet differ in meaning from other images for cycling accessories, as they belong to the same second subordinate product category *cycling*. To do so, we measured the cosine similarity of all image labels affiliated with a product i to all other product images in the same subordinate category c and week t by using doc2vec as a machine learning-based algorithm from natural language processing (Vossen and Ihl, 2020).

Doc2vec builds on "word2vec" and follows the so-called distributional hypothesis: Words that are adjacent to the same words share the same context and thus have a similar meaning (Le and Mikolov, 2014). As the name suggests, word2vec serves to translate words into unique numeric vectors. In order to mathematically compute and recognize the context of words, the so-called word embeddings, word2vec trains a neural network that learns the semantic and syntactic qualities of a word based on a large text corpus. Finally, computing the cosine similarity of two word vectors provides information about the semantic similarity of these words. Doc2vec is an extension of word2vec and assigns a unique vector not only to each word, but also to each document with variable text length. That is, doc2vec learns not only in what context a word appears, but also whether that context is specific to a particular document. Doc2vec can be used for different types of documents, the only requirement is that the documents must be in textual form. Thus, doc2vec can also be used for similarity computation of images when converted to a textual form consisting of a string of words that reflect the objects, scenes, actions, and concepts represented in an image. Since textual information can be similar without using the exact same words, doc2vec, unlike other natural language processing methods such as n-grams, offers the possibility to measure image similarities based on shared semantic meaning. Accordingly, we deem do2vec a suitable method to investigate how new ventures can present their visual storytelling semantically similar or dissimilar to the visual storytelling of their competitors, as we can measure semantic fit between images even in cases in which new ventures use different labels to describe the same aspect of their product (Vossen and Ihl, 2020).

Since doc2vec translates text of any length that uniquely identifies a document into a numeric vector representation, which in turn is used to calculate document similarities, we first had to convert the pictorial information of the product images in our data set into text form. We therefore compiled a text document for each product image in our data set, consisting of all the labels representing the objects, scenes, actions, and concepts detected by Amazon Rekognition with a confidence score equal or above to 55% which are affiliated with each of these product images. We trained the algorithm with all images of the products we identified on the U.S. Amazon Launchpad to detect the semantic relations between the labels the new ventures use in their visual storytelling and to measure the extent to which each image resembles the semantic meaning used in images by other competing products in the same subordinate category c and week t. As training parameters, we set the vector size for the word embeddings to 300 dimensions and specified that the meaning context of a label should be learned based on a local context window of three labels in order to prevent overfitting (Kaminski and Hopp, 2020).

To exemplify the underlying meaning relationships between the labels detected in the product images of our U.S. Amazon Launchpad data set, we used a t-distributed stochastic neighbor embedding (t-SNE) (van der Maaten and Hinton, 2008) that based on our trained model maps labels with similar meaning close to each other, while dissimilar labels show a greater distance. T-SNE uses a non-linear dimensionality reduction technique and allows us to visualize the 300 dimensions of the label embedding vector spaces for the image training data in a more intuitively interpretable two-dimensional space. Figure 2 shows ten sample input labels of our image training data and the three labels that were identified as those most similar in meaning for each of these input labels. As can be seen in Figure 2, the three labels most similar in meaning to, for instance, the label "bike" are "cyclist," "mountain bike," and "motorcycle." Not only can we represent clusters of similar label meanings, but we can also see how far the meanings of these clusters diverge from each other. In the concrete example shown, this means that the meaning contexts associated with the input labels "bike" and "car" are more similar since they are closer within the two-dimensional vector space than, for instance, the meaning contexts associated with the input labels "bike" and "kid." [4]

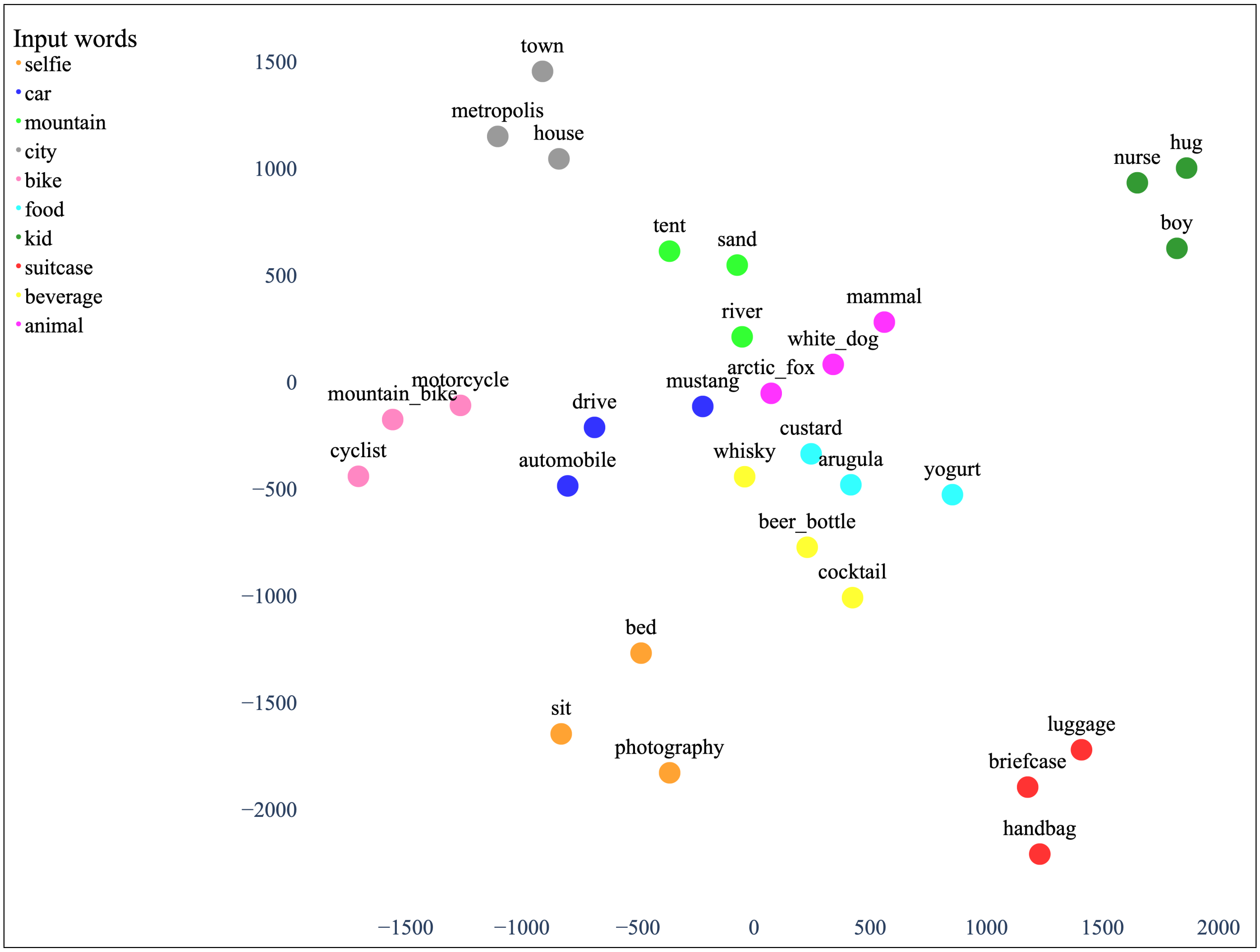

Figure 2: tSNE of image training data—ten sample labels and their three labels most similar in meaning

[4]It is important to note how our data contextualizes our approach. As with most natural language processing applications, doc2vec benefits from a rich data set. In comparison to the large data sets for which it is usually used, such as millions of news articles, our data set is small and contains few documents (9,072 images). Moreover, the dictionary Amazon Rekognition provides to identify objects only entails a few thousand words and there could be concerns that not all labels are listed. However, all our images depict products sold on Amazon and hosted by itself and thus are likely to be included in the training of their Rekognition algorithm already. This should make it highly likely that all labels get recognized and some tests at face validity confirm this. It is also important to consider that the similarities we measure relate to object labels in images and not words in textual documents. For example: While "whiskey" and "cocktail" are very similar as image labels, this only means they appear visually in the same context–think of a "hand", a "table" or a "bar". If we would anaylze news articles and measure the similarity between both words they would likely be more different from each other because "whiskey" could be more reported in the grim and dark context of drunk violence while "cocktail" could be mentioned more frequently in the fun and bright nightlife context. Despite these limitations, results show that the algorithm works quite well.

Knowing these underlying similarities between the labels and image documents allowed us to test our trained model and to operationalize the semantic fit of a venture's visual storytelling by measuring the distance between the embedding vector f of an image i and the embedding vector of another image j for all dimensions w via cosine similarity provided by *Python's Gensim* package. This results in the following equations:

$$Image\ semantic\ fit_{ij} = \left[\frac{\sum_{w=1}^{W} f_{iw}\, f_{jw}}{\sqrt{(\sum_{w=1}^{W} f_{iw}^2)} \cdot \sqrt{(\sum_{w=1}^{W} f_{jw}^2)}} \right] \tag{2}$$

We averaged all the comparisons, added and then averaged the semantic fit values of all individual images of a product i.[5]

To measure *product category distinctiveness*, we followed existing research using a similar setting (Janisch and Vossen, 2022) and analyzed the relative position of each product category in our sample (Lo et al., 2020). To do so, we considered a product's category tag combination K and measured how much it deviates from those of each other product j in the same basic product category. As only product categories with the same top tag can share tags deeper in their nested category structure, we compared a product's category tag combination only with those that share the same top tag (belong to the same basic category). For this, we coded each product i as a binary vector of every possible product category tag combination in the respective basic product category where f_{ik} equals $1/K$ if tag k is present for product i and 0 otherwise. We compared this binary vector to the vectors of all other products in that basic product category available in the same market at that point in time (Janisch and Vossen, 2022). Thus, we computed the distance between the focal product i and each other product j in the same basic product category as follows:

[5] Although prior research often conceptualizes the relationship between fit (or distinctiveness) and performance as curvilinear we do not find such a shape. Our results are in line with more recent studies that see this relationship as linear (Bu et al., 2022; Chan et al., 2021; Taeuscher et al., 2021). We would agree with the explanation of Bu et al. (2022) that the lack of a pronounced curvilinear effect is likely based upon the lack of highly distinctive product designs (in our case visual storytelling).

$$Product\ distance_{ij} = 1 - \left[\frac{\sum_{k=1}^{K} f_{ik} \, f_{jk}}{\sqrt{(\sum_{k=1}^{K} \ f_{ik}^2)} \cdot \sqrt{(\sum_{k=1}^{K} \ f_{jk}^2)}} \right] \tag{3}$$

This results in a distance vector for all products that summarizes distances between a focal product i and all other products j in the basic category available at the focal point in time. Finally, we averaged the distances and composed our measure of a product category's distinctive position i in the focal week as:

$$Product\ category\ distinctiveness_i = \frac{\sum_{j=1, j \neq i}^{N} Product\ distance_{ij}}{N} \tag{4}$$

where N stands for the total number of products in the respective week and basic product category.

To exemplify what kind of tag combination for a product's categories are non-distinct versus distinct, consider the following example from our data set: The product category (1) Grocery & Gourmet Food, (2) Beverages, and (3) Coffee, Tea & Cocoa can be considered non-distinct as its tag combination is frequently shared among products offered in the same basic category (1) Grocery & Gourmet Food. In contrast, the product category (1) Toys & Games, (2) Arts & Crafts, and (3) Clay & Dough is distinct as its tag combination is hardly shared among products offered in the same basic category (1) Toys & Games.

3.4 Control variables

To increase robustness of our findings and account for other variables impacting audiences' evaluation and subsequently products' sales performance, we include the following six control variables: *product price*, *product age*, *new venture competition*, *product competition*, *product portfolio size*, and *firm-level distinctiveness.* By controlling for the logged average *product price*, we account for price related inferences on sales success. Similarly, with *product age* we control for the length of time a product has been available on the platform to account for any established customer bases, higher awareness of older products, and learning effects (Cohen and Levinthal, 1990). In addition to that, we control for *new venture competition* as well as *product competition* in a specific market category based on the shared highest level category tag (Taeuscher et al., 2021) to consider the number of new ventures and products competing at the same time. We also control for *product portfolio size* to account for the effect that new ventures offering more products might be perceived as more mature in the market than other new ventures selling only a single product. Finally, we controlled for *firm-level distinctiveness* to account for the effect that consumers may compare a product's distinctiveness appeal with the distinctiveness or conformity of a new venture's entire product portfolio (Barlow et al., 2019; Janisch and Vossen, 2022). To measure firm-level distinctiveness, we computed the cosine distance of the unique category tags affiliated with a new venture compared to the unique category tag combination of all other new ventures selling products in the same week t (de Vaan et al., 2015). As an illustrative example from our data set, a pillow spray offered by a particular new venture has the category tags (1) Health & household, (2) Health care, and (3) Sleep & snoring. The very same new venture additionally offers two other products, such as legs skin body lotion, affiliated with the category tags (1) Beauty & personal care, (2) Skin care, (3) Sunscreens & tanning products and heels rescue palm, affiliated with the category tags (1) Beauty & personal care, (2) Foot, hand & nail care, (3) Foot & hand care. Accordingly, this sample new venture is associated with a total of eight unique product market labels. Thus, we computed the distance between the category tag combination of a new venture i and the category tag combinations of all other new ventures j available at that point in time as follows:

$$Firm - level\ distance_{ij} = 1 - \left[\frac{\sum_{c=1}^{C} f_{ic} f_{jc}}{\sqrt{(\sum_{c=1}^{C}\ f_{ic}^2)} \cdot \sqrt{(\sum_{c=1}^{C}\ f_{jc}^2)}} \right] \tag{5}$$

where f_{ic} equals $1/C$ if category tag c is present for a new venture i and C equals the total number of unique category tags of a new venture, and 0 otherwise. This results in a distance vector for each new venture with its category tag combination that summarizes distances between the category tag combination of a new venture i and the category tag combinations of all other new ventures available at that point in time. Finally, we average the distances for each firm-level distinctiveness i and each week. Thus, we compose our measure of firm-level distinctiveness i in the focal week as:

$$Firm - level\ distinctiveness_i = \frac{\sum_{j=1,j\neq i}^{N} Firm - level\ distinctiveness_{ij}}{N} \tag{6}$$

where N stands for the total number of new ventures in the respective week. For a summary of all variables used within the analysis please refer to Table 3.

Variable	Variable description
Dependent variable	
Amazon sales rank	Average sales rank of product i at week t multiplied by -1. Log-transformed.
Independent variables	
Image semantic richness	Total number of unique labels used within each product image, averaged for all individual values of image semantic richness of a product i.
Image semantic fit	Cosine similarity of all image labels affiliated with a product i in the respective week t and subordinate category c using doc2vec.
Product category distinctiveness	Cosine distance based on all product category labels k affiliated with each product i in week t within own basic product category. Averaged.
Control variables	
Product price	Average price of product i at week t in USD Cent Log-transformed.
Product age	Days since introduction of product on Amazon Launchpad.
New venture competition	Count variable that counts number of new ventures j in basic category c at week t.
Product competition	Count variable that counts the number of competing products i in basic category c at week t.
Product portfolio size	Count variable that counts total number of products i offered by each new venture j at week t to account for the prominence of a new venture on the Amazon Launchpad.
Firm-level distinctiveness	Cosine distance of the unique category tags affiliated with a new venture compared to the unique category tag combination of all other new ventures selling products in the same week t.

Table 3: Variable descriptions

4 Results

Table 4 shows the descriptive statistics and correlations of all variables. Except for the variables product category distinctiveness and product competition as well as for product competition and new venture competition we find primarily low or moderate correlations. Table 5 provides the results of our hypothesis tests. Due to the structure of our data, we used a nested random-effect model. We estimate random effect models as the semantic richness variable is time-invariant and use the nested option since one new venture can have multiple products, but each product can only belong to one new venture. To account for heteroscedasticity and autocorrelation, we computed heteroscedasticity and autocorrelation consistent (HAC) estimates of the standard errors (Newey and West, 1987). Following current practice for our T of 292 weeks, we specified the number of lags L as $L \approx T^{1/4} \approx 4$ (Greene, 2018, p.960). We conducted all statistical analyses with the free statistics software *R* and the package *PLM* (Croissant and Millo, 2008).

Model 1 only includes the control variables. In Model 2-4, we stepwise introduce the terms of *image semantic fit*, *image semantic richness*, and *product category distinctiveness*. We find a significant and positive direct effect on sales performance for *image semantic fit* (b= 0.887, p= 0.002), and *image semantic richness* (b= 0.087, p= 0.037), and *product category distinctiveness* (b= 3.329, p< 0.001). [6]

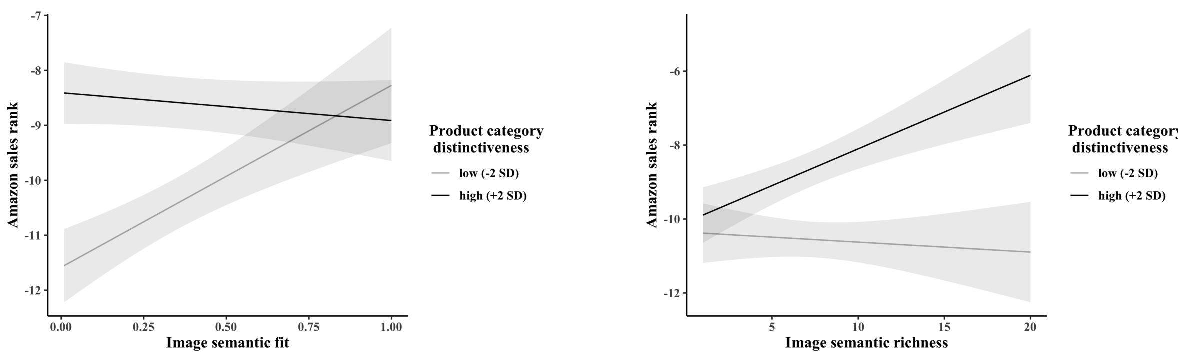

Figure 3: Effect of image semantic fit (image semantic richness) on product sales performance moderated by low (-2 SD) and high (+2 SD) product category distinctiveness. Based on model 6 (and 7) in Table 5.

To test our Hypothesis 1 that proposed a positive effect of high levels of *image semantic fit* in visual storytelling for products' performance in non-distinct categories and Hypothesis 2 that proposed a positive effect of low levels of *image semantic fit* in visual storytelling

[6]As we stated earlier, we follow Bu et al. (2022) and assume a linear relationship. To be consistent, we also tested for quadratic effects. The quadratic terms for *product category distinctiveness* (b= −0.751, p = 0.437) and *image semantic fit* (b= 0.026, p= 0.973) are insignificant, while we do find a marginally significant inverted U-shape effect for *image semantic richness* on sales performance (b= −0.015, p= 0.061).

for products' performance in distinct categories, Model 6 shows the interaction effect of *image semantic fit* with *product category distinctiveness*. The respective effect is significant and negative (b$= -6.625$, p< 0.001). This relationship is shown on the left-hand side in Figure 3. On the one hand, our results suggest that new ventures in non-distinct categories that conform in their visual storytelling to consumer expectations perform better than those that deviate from consumer expectations. On the other hand, the level of semantic fit in the visual narrative is somewhat less critical to success for new ventures in distinct categories, with success decreasing slightly as semantic fit increases.

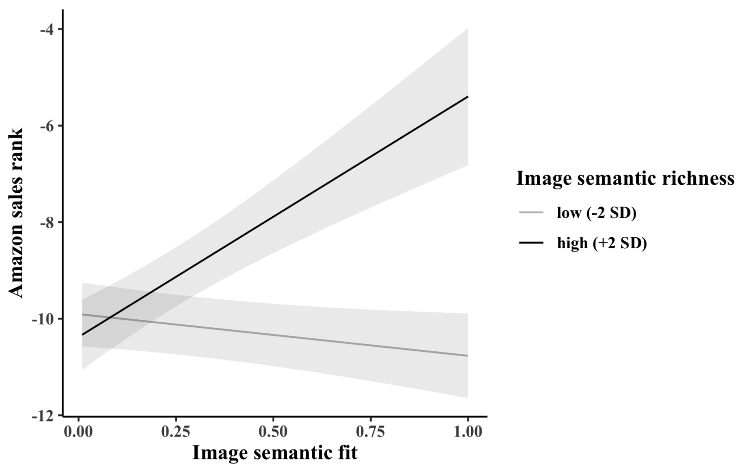

Figure 4: Effect of image semantic fit on product sales performance moderated by low (-2 SD) and high (+2 SD) image semantic richness. Based on model 8 in Table 5.

To test our Hypothesis 3 that proposed a positive effect of low levels of *image semantic richness* in visual storytelling for products' performance in non-distinct categories and Hypothesis 4 that proposed a positive effect of high levels of *image semantic richness* in visual storytelling for products' performance in distinct categories, model 7 shows the interaction effect of *image semantic richness* with *product category distinctiveness*. The respective coefficient is significant and positive (b$= 0.392$, p< 0.001). The effect is shown on the right-hand side in Figure 3. Our results suggest that new ventures in distinct category that are rich in semantic meaning in their visual storytelling perform better than those that are less rich, whereas for new ventures in non-distinct categories the level of semantic richness in their visual storytelling is less consequential for their performance success.

Although not hypothesized, we also tested for both an interaction between semantic richness and fit on sales performance, as well an interaction effect between semantic fit, richness, and product category distinctiveness. We find that semantic fit and richness mutually reinforce each other and that this effect grows in importance with increasing product category distinctiveness. While the interaction between semantic fit and richness is overall significant, the three-way interaction with product category distinctiveness is not.

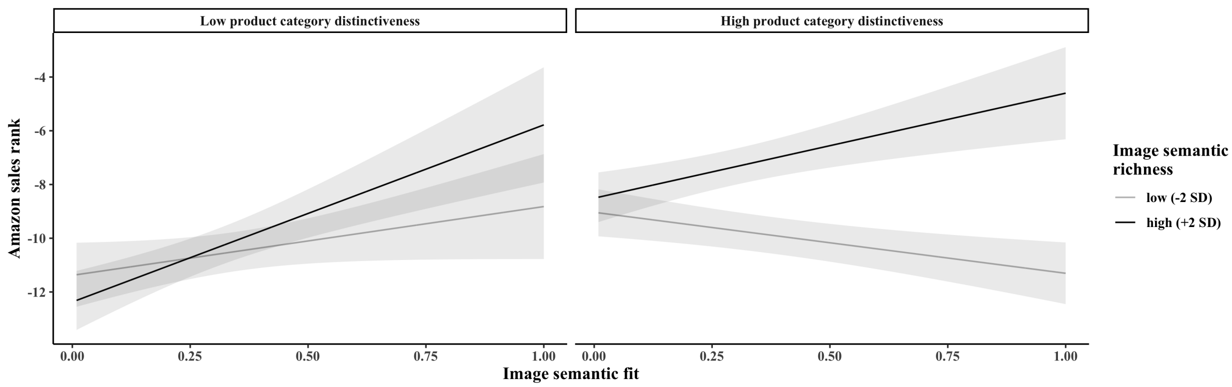

Figure 5: Effect of image semantic fit on product sales performance moderated by low (-2 SD) and high (+2 SD) image semantic richness and low (-2 SD) and high (+2 SD) product category distinctiveness. Based on model 9 in Table 5.

However, analyzing the respective plots visually showcases that the interaction effect of semantic fit and richness is not meaningful for low levels of semantic fit in Figure 4. This induces that if new ventures rely on conforming visual labels, the amount of labels used does not impact the sales rank differently. Looking at Figure 5 however shows that while there are fewer discernible differences for this interaction in low to moderately distinct product categories, there are significant differences in highly distinct product categories. Moreover, in both plots a high semantic richness is preferred to low semantic richness in most cases, especially in highly distinct product categories.

Variable	Mean	St. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Amazon sales rank	−9.609	2.519													
(2) Product price (Dollar)	3.473	1.010	-0.04												
(3) Product age (no. of weeks)	105.347	70.128	-0.06	-0.03											
(4) New venture competition (basic category)	27.317	15.609	0.09	0.11	0.15										
(5) New venture competition (subordinate category)	3.570	3.162	0.06	0.05	0.10	0.45									
(6) Product competition (basic category)	101.625	62.549	-0.01	-0.01	0.25	0.78	0.37								
(7) Product competition (subordinate category)	14.404	14.231	-0.04	-0.12	0.12	0.01	0.44	0.26							
(8) Product portfolio size	16.550	18.874	-0.07	-0.11	0.10	-0.13	-0.10	0.17	0.57						
(9) Firm-level distinctiveness	0.948	0.022	-0.10	0.03	0.06	-0.48	-0.45	-0.27	-0.23	-0.04					
(10) No. of images	6.979	3.288	0.17	0.26	0.00	-0.04	-0.04	-0.09	0.06	0.05	0.03				
(11) Image semantic fit	0.281	0.105	-0.15	0.00	-0.04	-0.23	-0.29	-0.18	-0.08	0.07	0.27	-0.09			
(12) Image semantic richness	7.108	2.594	0.12	0.02	-0.01	-0.16	0.01	-0.13	0.18	0.10	-0.04	0.25	-0.23		
(13) Product category distinctiveness	0.477	0.144	0.00	0.15	0.02	0.43	-0.13	0.35	-0.59	-0.37	0.15	-0.07	-0.05	-0.24	

Note: N=240,790.

Table 4: Descriptives and correlations

	Dependent variable:									
	Amazon sales rank									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Product price	−0.626***	−0.627***	−0.626***	−0.630***	−0.631***	−0.630***	−0.627***	−0.631***	−0.627***	−0.628***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Product age	−0.008***	−0.008***	−0.008***	−0.008***	−0.007***	−0.007***	−0.008***	−0.007***	−0.007***	−0.007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
New venture competition	0.026***	0.026***	0.026***	0.024***	0.025***	0.024***	0.024***	0.025***	0.024***	0.024***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Product competition	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Product portfolio size	0.037***	0.037***	0.037***	0.039***	0.039***	0.039***	0.039***	0.038***	0.038***	0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm-level distinctiveness	16.065***	15.750***	16.062***	14.604***	14.348***	14.246***	14.713***	14.384***	14.364***	14.323***
	(0.968)	(0.969)	(0.968)	(0.956)	(0.958)	(0.955)	(0.954)	(0.957)	(0.952)	(0.955)
Image semantic fit (ISF)		0.887***			0.748***	4.562***		−1.944***	2.052*	3.529
		(0.287)			(0.284)	(1.042)		(0.625)	(1.225)	(2.639)
Image semantic richness (ISR)			0.087**		0.098**		−0.101	−0.046	−0.211***	−0.144
			(0.042)		(0.042)		(0.063)	(0.050)	(0.068)	(0.131)
Product category distinctiveness (PCD)				3.329***	3.295***	5.514***	0.460	3.286***	2.671**	3.588**
				(0.250)	(0.249)	(0.701)	(0.754)	(0.249)	(1.058)	(1.798)
ISF X PCD						−6.625***			−6.452***	−9.076**
						(1.773)			(1.754)	(4.434)
ISR X PCD							0.392***		0.379***	0.254
							(0.093)		(0.093)	(0.222)
ISF X ISR								0.563***	0.518***	0.321
								(0.112)	(0.109)	(0.343)
ISF X ISR X PCD										0.359
										(0.576)
Constant	−23.139***	−23.087***	−23.768***	−23.360***	−24.025***	−24.452***	−22.728***	−23.352***	−23.328***	−23.792***
	(0.960)	(0.957)	(1.003)	(0.952)	(0.993)	(1.025)	(1.058)	(1.000)	(1.149)	(1.373)
Product random effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240,790	240,790	240,790	240,790	240,790	240,790	240,790	240,790	240,790	

Note: Heteroscedasticity- and autocorrelation-robust standard errors (Newey West) reported in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Results of nested (new venture) random effect regression (PLM)—image models (label recognition threshold value of 55%)

5 Discussion

The goal of this study was to gain insights into how new ventures can use visual storytelling to achieve optimal distinctiveness in online B2C markets (Lounsbury et al., 2018). To do so, we investigated how two important properties of visual storytelling, their semantic fit and richness, affect consumers' evaluation process across different product categories. We accomplish this by relying on new methods from machine learning, image label recognition, and natural language processing. We bridge two previously disconnected streams of research, namely the literature that investigates the impact of evaluative complexities and the heterogeneous preferences of relevant audiences on a venture's optimal distinctiveness on the one hand (Durand and Haans, 2022; Zhao and Glynn, 2022) and recent studies that highlight the influential role of visual perception in the management and marketing literature on the other hand (Luffarelli et al., 2019; Mahmood et al., 2019; Meyer et al., 2013, 2018; Sample et al., 2020). We find that visual storytelling offers new ventures a meaningful way to actively influence their appeal to evaluating audiences. Thus, our work extends past studies' focus on the use of textual storytelling to assist evaluating audiences in their sensemaking by contextualizing the new venture and its products (Lounsbury and Glynn, 2001; Navis and Glynn, 2011). Our focus on visual storytelling introduces a new perceptual component to the literature on optimal distinctiveness that goes beyond product design distinctiveness (Banerjee et al., 2022; Bu et al., 2022). This visual storytelling perspective is particularly relevant and consequential in online B2C markets, where audiences benefit from "seeing their product in action." Showcasing how this visual component can be strategically used by new ventures for their storytelling is our first and main contribution.

Our second contribution is to offer a more fine-grained perspective on visual storytelling as we distinguish it in terms of semantic fit, that is, the degree to which its meaning, conveyed through interpretable objects (Dzyabura et al., 2021), aligns with consumers' expectations, and semantic richness, that is, the amount of meaning it carries. On average, we find a positive effect of semantic fit and richness. Thus, on average, audiences are favorable to visual storytelling that is in line with competitors, but also to those that provide meaningful, additional context that helps sensemaking. As such, visual semantics do not only provide new ventures with suitable tools to positioning but are also effective means to contextualize the use of their products and convey helpful and meaningful information to evaluating audiences. In this regard, this work contributes to cultural entrepreneurship literature by highlighting the importance of functional properties of storytelling on audience evaluation (Navis and Glynn, 2011). Storytelling can differ not only in terms of its fit or distinctiveness, but also in the degree to it makes information appropriately available and easy to process for evaluating audiences. By utilizing semantic fit and richness, visual storytelling offers the possibility to measure and address these functional differences. Our study offers a first showcase of how state-of-the-art machine learning and image label recognition approaches may open up future research avenues in how storytelling may help to balance the need for conformity and distinctiveness (Zhao and Glynn, 2022).

Our third contribution relates to the contextual role of product categories for the effectiveness of visual storytelling. Here, our results show that visual storytelling, like textual storytelling, is strongly contextualized by the respective product category in which it is used. In line with research on textual storytelling, we explain these differences with the product categories' variance in cultural code and in audience preferences (Janisch and Vossen, 2022; Lo et al., 2020; Taeuscher et al., 2022). This also showcases that interpreting the direct average effects of both semantic fit and richness can be somewhat misleading as both have very different effects across different product categories. This is the case for semantic fit, as its positive effect predominantly manifests in non-distinct product categories, where conformity is part of the cultural code and an effortless evaluation preferred (Paolella and Durand, 2016; Smith, 2011). In distinct product categories, where audiences and the cultural code provided favor distinctiveness (Taeuscher et al., 2022), using semantic fit is rendered less effective. In such a categorical context, the benefits of semantic richness unfold as its impact on evaluating audiences is stronger in distinct product categories, while it is rendered weaker in non-distinct ones.

Differences in product category distinctiveness also affect how semantic richness and fit interact with each other. Visual storytelling with high semantic fit, benefits greatly from using semantic richness as well, and this becomes gradually more relevant in product categories with increasing distinctiveness. Thus, while the effects of semantic fit and richness are mostly independent from each other in non-distinct, mainstream product categories, their mutual effects become more relevant in more distinct categories, where a high semantic fit may meet audience approval only if the respective visual storytelling entails a high semantic richness. If these circumstances are met, semantic richness may help orchestrate (Zhao et al., 2017) the high semantic fit that usually does not appeal to audiences in distinct product categories (Vossen and Ihl, 2020). In this regard, visual storytelling differs from what we know about textual storytelling, where audience appeal is usually assumed to be more strongly related to fit (or distinctiveness) alone. The overall contribution of this paper is to show how visual storytelling can be disentangled into measures of semantic fit and richness, how both can alter audience evaluations of optimal distinctiveness and sales performance, and how their effects vary across different categorical contexts.

Our fourth contribution relates to the literature on the visual modality in organizational research and sensory marketing (Höllerer et al., 2018). We provide both empirical as well as conceptual arguments on why semantic fit and semantic richness are effective means to measure the functional properties of visual storytelling and how the semantic meanings conveyed thereby influence audience evaluation. In this way, our study extends the current focus of existing literature on low-level features of visuals, such as color schemes and patterns (Sgourev et al., 2022). Our study also adds an important facet to the ongoing discussion on the role of perceptual fluency (Lee and Labroo, 2004; Christensen et al., 2020; Labroo et al., 2008; Labroo and Pocheptsova, 2016; Landwehr and Eckmann, 2020; Mahmood et al., 2019) as well as design complexity (Kosslyn, 1975; Pieters et al., 2010) on audience evaluation.

We further provide guidelines on how semantic meanings can be measured using state-of-the-art machine learning algorithms. With the help of computer vision, our work adds an important and efficient method to the toolbox of sensory marketing scholars that intend to examine large-scale secondary data on visual storytelling, images or logos. As such, our approach may provide valuable starting points for researchers interested in utilizing more data-driven approaches in the field of sensory marketing (Golder et al., 2022).

From a managerial point of view, our results have some clear-cut implications for management practice on how to incorporate visual storytelling in their appeal to consumer audiences, an audience particularly important for entrepreneurial growth. When it comes to designing visual storytelling, managers should be especially knowledgeable about the product categories in which they intend to use them. That of course requires managers to get a good sense of consumer audiences' expectations in their target product category, in terms of the type and richness of meaning they need to convey, before designing visual storytelling. Especially in distinct product categories, managers may want to ensure that they accompany their highly fitting visual narrative with strong semantic richness also, in order to avoid audience devaluation. Although the categories themselves set out the evaluative boundary conditions for the evaluation of their visual narrative (Janisch and Vossen, 2022) and serve as meaning systems to tap in (Vossen and Ihl, 2020), managers should not underestimate the agency they have when designing their visual storytelling. If they make careful use of the fit and richness of the semantics they entail, it may strongly help them achieve optimal distinctiveness and be perceived as meaningfully different.

6 Limitations, outlook, and conclusion

Like all scientific studies, this study has limitations that could be addressed in future work. We have argued for many good reasons why the influence of visual storytelling is critical to consumers' evaluation of new ventures and subsequently new ventures' performance, especially in the realm of online B2C markets. Future work could investigate whether the implications of our findings for how new ventures can design their visual storytelling in order to be perceived as meaningfully different in online B2C markets can be extended to online B2B markets. With our setting, we specifically examine how entrepreneurial products, which are inherently more novel and innovative, appeal to consumers who are more tolerant of novelty and even more likely to expect it (Kim and Jensen, 2011; Paolella and Durand, 2016; Taeuscher et al., 2021). To increase the generalizability of our findings, future research could replicate our study in an environment with non-entrepreneurial products. Given the widespread use of rank variables (Barlow et al., 2019; Pontikes, 2012) and the longitudinal nature of our study, we legitimize our use of sales rank as a dependent variable. Nevertheless, rank variables have the limitation that they may also be partially affected by market dynamics, as a product's own rank may improve as a result of a decline in competitors' performance (Chevalier and Mayzlin, 2006; Smith and Telang, 2009).

To make visual storytelling measurable and thus map visual processing by consumers, we applied novel machine learning-based algorithms. Follow-up studies could find out whether this procedure can be confirmed by experimental evidence. For this purpose, subjects could be asked to confirm which labels they can actually recognize in an image or video by means of a list of labels. Future work could also explore how the machine learning-based algorithms we adopt in our study could be used to measure other functions of cultural elements, for instance, narrative coherence or narrative resonance (Navis and Glynn, 2011). While our approach has the great benefit of showing how semantic fit and semantic richness help new ventures achieve optimal distinctiveness in online B2C markets, future work could focus on other facets of semantic meaning contributing to this effect. Due to the API policy by Amazon, we could not collect text information on the products. Collecting information on different cultural tools, such as written text or spoken text and images in videos, provides avenues for future research to add to the discussion of multimodal sensemaking by looking at the effectiveness of semantic fit and semantic richness across communication modes (Höllerer et al., 2018) and would be particularly interesting for settings where videos are the main tool to convey information. Another limitation of this work is that we unfortunately could not collect data on whether new ventures changed their images over time. This could provide additional insight into how new ventures dynamically adapt their visuals to market conditions in order to appear as attractive as possible to consumers.

We set out to find how new ventures' choice and design of visual storytelling influences audience evaluation of new ventures' products in online B2C markets and to which extent their effectiveness is shaped by evaluative boundary conditions set out by the product categories in which the evaluation takes place. To do so, we explained with longitudinal data on different observational levels why visual stimulus properties made measurable through state-of-the-art machine learning algorithms, such as semantic fit and richness, can impact a product's appeal perceived by evaluating consumer audiences differently for different levels of product category distinctiveness and different visual modes, namely images and videos. We believe that our work will particularly help new ventures operating in distinct product categories to ensure that they also accompany their highly fitting visual narrative with strong semantic richness to be perceived as meaningfully different.

References

Adaval, R., Saluja, G., and Jiang, Y. (2018). Seeing and thinking in pictures: A review of visual information processing. *Consumer Psychology Review*, 2:50–69.

Anglin, A. H., Reid, S. W., and Short, J. C. (2022). More Than One Way to Tell a Story: A Configurational Approach to Storytelling in Crowdfunding. *Entrepreneurship Theory and Practice*, 0(0):1–34.

Banerjee, M., Cole, B. M., and Ingram, P. (2022). "Distinctive from What? And for Whom?" Deep Learning-Based Product Distinctiveness, Social Structure, and Third-Party Certifications. *Academy of Management Journal*, 1:1–53.

Barlow, M. A., Verhaal, J. C., and Angus, R. W. (2019). Optimal distinctiveness, strategic categorization, and product market entry on the Google Play app platform. *Strategic Management Journal*, 40:1219–1242.

Bhakat, R. S. and Muruganantham, G. (2013). A Review of Impulse Buying Behavior. *International Journal of Marketing Studies*, 5(3):149–160.

Boxenbaum, E., Jones, C., Meyer, R. E., and Svejenova, S. (2018). Towards an Articulation of the Material and Visual Turn in Organization Studies. *Organization Studies*, 39(5-6):597–616.

Brasel, S. A. and Hagtvedt, H. (2016). Living brands: Consumer responses to animated brand logos. *Journal of the Academy of Marketing Science*, 44(5):639–653.

Bu, J., Zhao, E. Y., Li, K. J., and Li, J. M. (2022). Multilevel optimal distinctiveness: Examining the impact of within- and between-organization distinctiveness of product design on market performance. *Strategic Management Journal*, 43(9):1793–1822.

Cattani, G., Porac, J. F., and Thomas, H. (2017). Categories and competition. *Strategic Management Journal*, 38(1):64–92.

Chan, C. S. and Park, H. D. (2015). How images and color in business plans influence venture investment screening decisions. *Journal of Business Venturing*, 30(5):732–748.

Chan, T. H., Lee, Y. G., and Jung, H. (2021). Anchored Differentiation: The Role of Temporal Distance in the Comparison and Evaluation of New Product Designs. *Organization Science*, 32(6):1523–1541.

Chevalier, J. A. and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3):345–354.

Childers, T. L. and Houston, M. J. (1984). Conditions for a Picture-Superiority Effect on Consumer Memory. *Journal of Consumer Research*, 11(2):643–654.

Christensen, B. T., Ball, L. J., and Reber, R. (2020). Perceptual fluency effects in judgments of creativity and beauty: Creative objects are perceived fluently yet they are visually complex. *Journal of Cognitive Psychology*, 32(1):45–66.

Clarke, J. (2011). Revitalizing Entrepreneurship: How Visual Symbols are Used in Entrepreneurial Performances: How Visual Symbols are Used by Entrepreneurs. *Journal of Management Studies*, 48(6):1365–1391.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1):128–152.

Croissant, Y. and Millo, G. (2008). Panel Data Econometrics in R: The plm Package. *Journal of Statistical Software*, 27(2):1–43.

de Vaan, M., Vedres, B., and Stark, D. (2015). Game changer: The topology of creativity. *American Journal of Sociology*, 120(4):1144–1194.

Deephouse, D. L. (1999). To be different, or to be the same? It's a question (and theory) of strategic balance. *Strategic Management Journal*, 20(2):147–166.

DelVecchio, D. S., Jae, H., and Ferguson, J. L. (2019). Consumer aliteracy. *Psychology and Marketing*, 36(2):89–101.

Donderi, D. C. (2006). Visual complexity: A review. *Psychological Bulletin*, 132(1):73–97.

Durand, R. and Haans, R. F. J. (2022). Optimally Distinct? Understanding the motivation and ability of organizations to pursue optimal distinctiveness (or not). *Organization Theory*, 3(1):1–16.

Dzyabura, D., El Kihal, S., and Peres, R. (2021). Image Analytics in Marketing. In Homburg, C., Klarmann, M., and Vomberg, A. E., editors, *Handbook of Market Research*, pages 1–29. Springer International Publishing, Cham.

Dzyabura, D. and Peres, R. (2019). Visual Elicitation of Brand Perception. *Journal of Marketing*, 85(4):44–66.

Feurer, S., Hoeffler, S., Zhao, M., and Herzenstein, M. (2021). Consumers' response to really new products: A cohesive synthesis of current research and future research directions. *International Journal of Innovation Management*, 25(08):2150092.

Frydrych, D., Bock, A. J., and Kinder, T. (2016). Creating Project Legitimacy – The Role of Entrepreneurial Narrative in Reward-Based Crowdfunding. In Méric, J., Maque, I., and Brabet, J., editors, *International Perspectives on Crowdfunding*, pages 99–128. Emerald Group Publishing Limited.

Gehman, J. and Grimes, M. (2017). Hidden badge of honor: How contextual distinctiveness affects category promotion among certified b corporations. *Academy of Management Journal*, 60(6):2294–2320.

Glynn, M. A. and Navis, C. (2013). Categories, Identities, and Cultural Classification: Moving Beyond a Model of Categorical Constraint: Categories, Identities, and Cultural Classification. *Journal of Management Studies*, 50(6):1124–1137.

Golder, P. N., Dekimpe, M. G., An, J. T., van Heerde, H. J., Kim, D. S. U., and Alba, J. W. (2022). Learning from Data: An Empirics-First Approach to Relevant Knowledge Generation. *Journal of Marketing*, page 002224292211292.

Greene, M. R. and Oliva, A. (2009). The Briefest of Glances: The Time Course of Natural Scene Understanding. *Psychological Science*, 20(4):464–472.

Greene, W. H. (2018). *Econometric Analysis*. Pearson Education Limited, London, eighth edition.

Haans, R. F. J. (2019). What's the value of being different when everyone is? The effects of distinctiveness on performance in homogeneous versus heterogeneous categories. *Strategic Management Journal*, 40(1):3–27.

Henderson, J. M., Hayes, T. R., Peacock, C. E., and Rehrig, G. (2019). Meaning and Attentional Guidance in Scenes: A Review of the Meaning Map Approach. *Vision*, 3(2):19–29.

Henderson, J. M., Hayes, T. R., Rehrig, G., and Ferreira, F. (2018). Meaning Guides Attention during Real-World Scene Description. *Scientific Reports*, 8(1):13504.

Höllerer, M. A., Jancsary, D., and Grafström, M. (2018). 'A Picture is Worth a Thousand Words': Multimodal Sensemaking of the Global Financial Crisis. *Organization Studies*, 39(5-6):617–644.

Höllerer, M. A., van Leeuwen, T., Jancsary, D., Meyer, R. E., Andersen, T. H., and Vaara, E. (2019). *Visual and Multimodal Research in Organization and Management Studies*. Routledge, New York, NY.

Hulten, B., Broweus, N., and VanDijk, M. (2009). *Sensory Marketing*. Palgrave Macmillan, London, UK.

Janisch, J. and Vossen, A. (2022). Categorically right? How firm-level distinctiveness affects performance across product categories. *Journal of Business Venturing*, 37(4):106228.

Joardar, A. and Wu, S. (2017). Liabilities and benefits: Examining the two sides of the foreignness coin from entrepreneurial perspective. *International Business Review*, 26(6):1157–1167.

Joubert, O. R., Rousselet, G. A., Fize, D., and Fabre-Thorpe, M. (2007). Processing scene context: Fast categorization and object interference. *Vision Research*, 47(26):3286–3297.

Kaminski, J. C. and Hopp, C. (2020). Predicting outcomes in crowdfunding campaigns with textual, visual, and linguistic signals. *Small Business Economics*, 55(3):627–649.

Kim, B. K. and Jensen, M. (2011). How Product Order Affects Market Identity: Repertoire Ordering in the U.S.Opera Market. *Administrative Science Quarterly*, 56(2):238–256.

Kim, P. H., Buffart, M., and Croidieu, G. (2016). TMI: Signaling Credible Claims in Crowdfunding Campaign Narratives. *Group and Organization Management*, 41(6):717–750.

Kosslyn, S. M. (1975). Information representation in visual images. *Cognitive Psychology*, 7(3):341–370.

Krishna, A. (2012). An integrative review of sensory marketing: Engaging the senses to affect perception, judgment and behavior. *Journal of Consumer Psychology*, 22(3):332–351.

Labroo, A. A., Dhar, R., and Schwarz, N. (2008). Of frog wines and frowning watches: Semantic priming, perceptual fluency, and brand evaluation. *Journal of Consumer Research*, 34(6):819–831.

Labroo, A. A. and Pocheptsova, A. (2016). Metacognition and consumer judgment: Fluency is pleasant but disfluency ignites interest. *Current Opinion in Psychology*, 10:154–159.

Landwehr, J. R. and Eckmann, L. (2020). The nature of processing fluency: Amplification versus hedonic marking. *Journal of Experimental Social Psychology*, 90:103997.

Le, Q. and Mikolov, T. (2014). Distributed representations of sentences and documents. *31st International Conference on Machine Learning, ICML 2014*, 4:2931–2939.

Lee, A. Y. and Labroo, A. A. (2004). The effect of conceptual and perceptual fluency on brand evaluation. *Journal of Marketing Research*, 41(2):151–165.

Li, F. F., VanRullen, R., Koch, C., and Perona, P. (2003). Natural scene categorization in the near absence of attention: Further explorations. *Journal of Vision*, 3(9):331.

Lo, J. Y., Fiss, P. C., Rhee, E. Y., and Kennedy, M. T. (2020). Category viability: Balanced levels of coherence and distinctiveness. *Academy of Management Review*, 45(1):85–108.

Lounsbury, M., Cornelissen, J., Granqvist, N., and Grodal, S. (2018). Culture, innovation and entrepreneurship. *Innovation: Management, Policy and Practice*, 21(1):1–12.

Lounsbury, M., Gehman, J., and Ann Glynn, M. (2019). Beyond *Homo Entrepreneurus* : Judgment and the Theory of Cultural Entrepreneurship. *Journal of Management Studies*, 56:1214–1236.

Lounsbury, M. and Glynn, M. A. (2001). Cultural entrepreneurship: Stories, legitimacy, and the acquisition of resources. *Strategic Management Journal*, 22(6-7):545–564.

Luffarelli, J., Mukesh, M., and Mahmood, A. (2019). Let the Logo Do the Talking: The Influence of Logo Descriptiveness on Brand Equity. *Journal of Marketing Research*, 56(5):862–878.

Mahmood, A., Luffarelli, J., and Mukesh, M. (2019). What's in a logo? The impact of complex visual cues in equity crowdfunding. *Journal of Business Venturing*, 34(1):41–62.

Manning, S. and Bejarano, T. A. (2017). Convincing the crowd: Entrepreneurial storytelling in crowdfunding campaigns. *Strategic Organization*, 15(2):194–219.

Martens, M. L., Jennings, J. E., and Jennings, P. D. (2007). Do the Stories They tell get them the Money They Need? The Role of Entrepreneurial Narratives in Resource Acquisition. *Academy of Management Journal*, 50(5):1107–1132.

Meyer, R. E., Höllerer, M. A., Jancsary, D., and Van Leeuwen, T. (2013). The Visual Dimension in Organizing, Organization, and Organization Research. *The Academy of Management Annals*, 7(1):487–553.

Meyer, R. E., Janscary, D., Höllerer, M. A., and Boxenbaum, E. (2018). The Role of Verbal and Visual Text in the Process of institutionalization. *Academy of Management Review*, 43(3):392–418.

Navis, C. and Glynn, M. A. (2011). Legitimate Distinctiveness and The Entrepreneurial Identity: Influence on Investor Judgments of New Venture Plausibility. *Academy of Management Review*, 36(3):479–499.

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703–708.

Nielsen, J. H., Escalas, J. E., and Hoeffler, S. (2018). Mental simulation and category knowledge affect really new product evaluation through transportation. *Journal of Experimental Psychology: Applied*, 24(2):145–158.

OECD (2020). “Venture capital investments”, structural and demographic business statistics (database). *https://doi.org/10.1787/60395228-en*, Accessed:2020–11–06.

Overgoor, G., Rand, W., van Dolen, W., and Mazloom, M. (2022). Simplicity is not key: Understanding firm-generated social media images and consumer liking. *International Journal of Research in Marketing*, 39(3):639–655.

Paolella, L. and Durand, R. (2016). Category spanning, evaluation, and performance: Revised theory and test on the corporate law market. *Academy of Management Journal*, 59(1):330–351.

Phillips, D. J. and Zuckerman, E. W. (2001). Middle-Status Conformity: Theoretical Restatement and Empirical Demonstration in Two Markets. *American Journal of Sociology*, 107(2):379–429.

Pieters, R., Wedel, M., and Batra, R. (2010). The Stopping Power of Advertising: Measures and Effects of Visual Complexity. *Journal of Marketing*, 74(5):48–60.

Pocheptsova, A., Labroo, A. A., and Dhar, R. (2010). Making Products Feel Special: When Metacognitive Difficulty Enhances Evaluation. *Journal of Marketing Research*, 47(6):1059–1069.

Pontikes, E. G. (2012). Two sides of the same coin: How ambiguous classification affects multiple audiences’ evaluations. *Administrative Science Quarterly*, 57(1):81–118.

Radford, S. K. and Bloch, P. H. (2011). Linking innovation to design: Consumer responses to visual product newness. *Journal of Product Innovation Management*, 28:208–220.

Reber, R., Winkielman, P., and Schwarz, N. (1998). Effects of perceptual fluency on affective judgments. *Psychological Science*, 9(1):45–48.

Rietveld, R., Van Dolen, W., Mazloom, M., and Worring, M. (2020). What you Feel, Is what you like Influence of Message Appeals on Customer Engagement on Instagram. *Journal of Interactive Marketing*, 49(1):20–53.

Rindova, V., Dalpiaz, E., and Ravasi, D. (2011). A Cultural Quest: A Study of Organizational Use of New Cultural Resources in Strategy Formation. *Organization Science*, 22(2):413–431.

Sample, K. L., Hagtvedt, H., and Brasel, S. A. (2020). Components of visual perception in marketing contexts: A conceptual framework and review. *Journal of the Academy of Marketing Science*, 48(3):405–421.

Scheaf, D. J., Davis, B. C., Webb, J. W., Coombs, J. E., Borns, J., and Holloway, G. (2018). Signals’ flexibility and interaction with visual cues: Insights from crowdfunding. *Journal of Business Venturing*, 33(6):720–741.

Sgourev, S. V., Aadland, E., and Formilan, G. (2022). Relations in Aesthetic Space: How Color Enables Market Positioning. *Administrative Science Quarterly*.

Shepard, R. N. (1967). Recognition memory for words, sentences, and pictures. *Journal of Verbal Learning and Verbal Behavior*, 6(1):156–163.

Smith, E. B. (2011). Identities as lenses: How organizational identity affects audiences’ evaluation of organizational performance. *Administrative Science Quarterly*, 56(1):61–94.

Smith, M. D. and Telang, R. (2009). Competing with free: The impact of movie broadcasts on DVD sales and internet piracy. *MIS Quarterly*, 33(2):321–338.

Soublière, J.-F. and Lockwood, C. (2022). Achieving cultural resonance: Four strategies toward rallying support for entrepreneurial endeavors. *Strategic Management Journal*, 43(8):1499–1527.

Taeuscher, K. (2019). Reputation and new venture performance in online markets: The moderating role of market crowding. *Journal of Business Venturing*, 34(6):105944.

Taeuscher, K., Bouncken, R., and Pesch, R. (2021). Gaining Legitimacy by Being Different: Optimal Distinctiveness in Crowdfunding Platforms. *Academy of Management Journal*, 64(1):149–179.

Taeuscher, K., Zhao, E. Y., and Lounsbury, M. (2022). Categories and narratives as sources of distinctiveness: Cultural entrepreneurship within and across categories. *Strategic Management Journal*, 43(10):2101–2134.

van der Maaten, L. and Hinton, G. (2008). Visualizing Data using t-SNE. *Journal of Machine Learning Research*, 9:2579–2605.

Van Horen, F. and Pieters, R. (2012). When high-similarity copycats lose and moderate-similarity copycats gain: The impact of comparative evaluation. *Journal of Marketing Research*, 49(1):83–91.

van Oest, R. D., van Heerde, H. J., and Dekimpe, M. G. (2010). Return on roller coasters: A model to guide investments in theme park attractions. *Marketing Science*, 29(4):721–737.

Vergne, J.-P. and Wry, T. (2014). Categorizing Categorization Research: Review, Integration, and Future Directions: Categorizing Categorization Research. *Journal of Management Studies*, 51(1):56–94.

Vossen, A. and Ihl, C. (2020). More than words! How narrative anchoring and enrichment help to balance differentiation and conformity of entrepreneurial products. *Journal of Business Venturing*, 35(6):106050.

Wessel, M., Thies, F., and Benlian, A. (2022). The role of prototype fidelity in technology crowdfunding. *Journal of Business Venturing*, 37(4):106220.

Wry, T., Lounsbury, M., and Glynn, M. A. (2011). Legitimating Nascent Collective Identities: Coordinating Cultural Entrepreneurship. *Organization Science*, 22(2):449–463.

Wyer, R. S. and Srull, T. K. (1989). *Memory and Cognition in Its Social Context*. Lawrence Erlbaum Associates, Inc., Mahwah, NJ, first edition.

Zhang, M. and Luo, L. (2022). Can Consumer-Posted Photos Serve as a Leading Indicator of Restaurant Survival? Evidence from Yelp. *Management Science*, pages 1–26.

Zhao, E. Y., Fisher, G., Lounsbury, M., and Miller, D. (2017). Optimal distinctiveness: Broadening the interface between institutional theory and strategic management. *Strategic Management Journal*, 38(1):93–113.

Zhao, E. Y. and Glynn, M. A. (2022). Optimal Distinctiveness: On Being the Same and Different. *Organization Theory*, 3(1):1–15.

Zhao, E. Y., Ishihara, M., Jennings, P. D., and Lounsbury, M. (2018). Optimal Distinctiveness in the Console Video Game Industry: An Exemplar-Based Model of Proto-Category Evolution. *Organization Science*, 29(4):588–611.

Zhao, M., Hoeffler, S., and Dahl, D. W. (2009). The Role of Imagination-Focused Visualization on New Product Evaluation. *Journal of Marketing Research*, 46(1):46–55.

Zhao, M., Hoeffler, S., and Dahl, D. W. (2012). Imagination Difficulty and New Product

Evaluation: Imagination Difficulty. *Journal of Product Innovation Management*, 29:76–90.

Zuckerman, E. W. (1999). The Categorical Imperative: Securities Analysts and the Illegitimacy Discount. *The American Journal of Sociology*, 104(5):1398–1438.

Zuckerman, E. W. (2016). Optimal Distinctiveness Revisited: An integrative framework for understanding the balance between differentiation and conformity in individual and organizational identities. In Pratt, M. G., Schultz, M., Ashforth, B. E., Ravasi, D., and Zuckerman, E. W., editors, *The Oxford Handbook of Organizational Identity*. Oxford University Press.