Narrating optimal distinctiveness: A machine learning perspective

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Für *Marco*.

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Hätte ich vor Jahren gedacht, dass ich mal eine Dissertation verfassen werde? Nein. Bin ich froh und stolz, dass ich es getan habe? Ja, sehr. Auch wenn der Weg dorthin manchmal beschwerlich war und mir viel Ausdauer abverlangt hat, bin ich sehr dankbar für all die neuen Bekanntschaften und Freundschaften, die in dieser Zeit entstanden sind, für das, was ich Neues lernen durfte, für wunderschöne Reisen und interkulturellen Austausch, sowie für die Grenzerfahrungen, die mir geholfen haben, über mich hinauszuwachsen. Am Ende dieser aufreibenden und zugleich schönen Zeit steht eine Dissertation, in der ich von der Kraft erzähle, die unseren Worten innewohnt. Dieselbe Kraft befähigt nicht nur junge Unternehmen, sich strategisch erfolgreich am Markt zu positionieren, sondern wirkt sich auch ganz konkret auf den Alltag jedes Einzelnen aus. Sei es durch ein Wort der Ermutigung, des Ansporns, der Korrektur oder der Wertschätzung. Das durfte ich in ganz besonderer Weise in der Zeit erfahren, in der ich über meiner Dissertation geschwitzt und gegrübelt habe und manchmal das Gefühl hatte, daran zu verzweifeln.

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Abstract

Many new ventures fail to successfully establish themselves in the market or survive because they do not attract sufficiently positive evaluations from critical audiences. To ensure their survival, new ventures primarily depend on consumers, which they must convince in their multi-faceted roles of either investors, buyers, or users. However, how can new ventures try to raise their appeal to consumer audiences? One central and recent concept that aims to answer this question is optimal distinctiveness which postulates the need to be "as distinct as legitimately possible." Entrepreneurial narratives are considered a primary means of achieving such optimal distinctiveness. Despite this widespread relevance, existing research provides entrepreneurs with little clarity on how and when they can strategically rely on different modes of narratives to address consumer audiences.

This thesis offers a more fine-grained perspective on how narratives can achieve optimal distinctiveness. It showcases by which mode entrepreneurs narrate their new ventures' distinctiveness, who and against what reference levels evaluates them, influence what level of distinctiveness is optimal. As a theoretical guide, this thesis builds on existing studies on strategic differentiation and entrepreneurial storytelling as a starting point. It extends these with insights from institutional logic, sensory marketing, and organizational learning literature. Using state-of-the-art machine learning-based natural language processing methods such as doc2vec, image recognition, and speech recognition; it also provides a methodological contribution that helps identify the underlying meanings in textual, visual, and auditory narratives as critical carriers of narrative distinctiveness.

Utilizing three different empirical studies, this thesis has essential contributions that add to the literature on optimal distinctiveness and entrepreneurial narratives. First, it highlights the increasing heterogeneity within consumer audiences who differ in their expectations for distinctiveness, depending on their role as either investors, buyers, or users. Furthermore, it shows how new ventures can deploy different narrative modes they strategically benefit from. It also outlines crucial contextual factors of reference levels' multilevel and dynamic nature

that shape consumer audiences' evaluative processes. For management practice, this thesis has important implications for entrepreneurs of new ventures who use narratives to appeal to consumer audiences, especially on online platforms. The results may serve as managerial guidelines that help entrepreneurs to decide on the right way and mode to narrate their products and new ventures to consumer audiences in various roles and online settings.

1 Introduction

New ventures are the main drivers of novel, innovative products and services and the main engine of economic growth in modern economies (Schumpeter, 1939). Since new ventures are at an early stage of development and growth, they are often in the process of bringing their first products or services to market (Fisher et al., 2016). Upon market entry, entrepreneurs of new ventures face the challenge of deciding on the right market category (Barlow et al., 2019) and developing a suitable strategy to position themselves successfully therein (Haans, 2019; Vossen and Ihl, 2020; Zhao et al., 2017) to obtain sufficient financial resources and audience demand to survive in the long run. This so-called *strategic differentiation* entails the trade-off between balancing giving way to conformity and isomorphic pressures with the need to differentiate and stand out to ease competition (Deephouse, 1999). Achieving *optimal distinctiveness* in this balancing act is a challenge for new ventures.

New ventures should strive for optimal distinctiveness to appear sufficiently novel and unique, which helps them both to escape competition and to attract the attention of investors and consumers (Navis and Glynn, 2011). This is because, unlike established ventures, new ventures do not yet have a track record that would give them a leap of faith in audiences' evaluation; instead, new ventures must legitimize themselves through their distinctiveness (Taeuscher et al., 2021). Suppose this level of distinctiveness is not optimally chosen. In that case, the lack of legitimacy of new ventures, through their absent track record and the resulting higher risk and lack of differentiation, provides little incentive for evaluating audiences to consider them in their selection (Zuckerman, 2016). If a new venture appears too illegitimate (Zimmerman and Zeitz, 2002) or too different (Zhao et al., 2012), evaluators tend to choose an existing venture with a track record, making it less risky and allowing them to predict better what to expect. Because distinctiveness is critical to the strategic differentiation of new ventures, they provide an excellent environment for examining how new ventures succeed in conveying their distinctiveness and what level of distinctiveness yields superior performance and ensures continued existence (Janisch and Vossen, 2022).

Entrepreneurial narratives have proven central and influential for new ventures in successfully conveying their distinctiveness (Lounsbury and Glynn, 2001). New ventures are still in the early phase of their life cycle and thus often consist of little more than an idea or a collection of claims (Fisher et al., 2016, 2021). Because of their often novel character, they must make the unfamiliar comprehensible to the evaluating audiences and facilitate their sensemaking (Weick et al., 2005) by rationalizing who is behind the new venture, what it stands for, and why it will be successful (Navis and Glynn, 2011). Therefore, entrepreneurial narratives provide suitable means for new ventures to both differentiate and legitimize their identity through the cultural meaning they imbue: (1) by emphasizing "a core, distinctive, and enduring set of attributes, capabilities, and resources that lend strategic distinctiveness and competitive advantage" (Garud et al., 2014 p.1480), and (2) by stressing its normative appropriateness to others in the same market context (Lounsbury and Glynn, 2001). However, the high failure rate of new ventures (OECD, 2020) suggests that it is challenging for entrepreneurs of new ventures to find the right balance between distinctiveness and legitimacy claims in narratives and that they need further guidance to create an entrepreneurial narrative that optimally narrates the distinctiveness of their new venture.

This thesis, therefore, seeks to develop sound theoretical and managerial insights into three critical contextual factors that are decisive for determining the optimal level of distinctiveness in entrepreneurial narratives of new ventures: The lens of the audience evaluating a narrative (Pontikes, 2012; Fisher et al., 2017) is essential as new ventures seek to address different evaluating audiences with their narratives when asking for funding, selling a product, or increasing engagement with their contents. When considering what level of distinctiveness is optimal in these scenarios, audiences are often divided into investors and consumers. However, can new ventures assume that considering this general subgrouping of audiences when designing a narrative will create an appealing identity and mobilize sufficient resources from these evaluating audiences? This thesis challenges this assumption and investigates whether different levels of distinctiveness are optimal for *consumers as evaluating* *audiences* depending on whether they are evaluating a new venture in the role of *investors* (Taeuscher et al., 2021; Wessel et al., 2022), *buyers* (Zhao et al., 2018; Janisch and Vossen, 2022), or *users* (van Angeren et al., 2022).

Another factor influencing the optimal level of distinctiveness is the mode of narrative a new venture entrepreneur chooses to convey distinctiveness (Kaminski and Hopp, 2020). *Textual* (Taeuscher et al., 2021, 2022), *visual* (Chan et al., 2021; Bu et al., 2022), and *auditory* (Parhankangas and Renko, 2017) narratives deviate in how evaluative audiences can use these modes for their sensemaking. Most of the world comprises non-textual narrative modes, such as videos and images (Meyer et al., 2013). Videos and images especially accommodate consumers' short attention spans (DelVecchio et al., 2019) and are easy for digitally active entrepreneurs to embed in their websites.

A third critical contextual factor is the reference levels used to determine what can be deemed "optimal" regarding distinctiveness by relating a focal new venture to others (Barlow et al., 2019; Haans, 2019) or its past self (Chan et al., 2021; Janisch and Vossen, 2022). This thesis explores how comparisons to *market-based* (Haans, 2019), *category-based* (Cattani et al., 2017; Taeuscher et al., 2022), or a new venture's *past self* (Bu et al., 2022; Janisch and Vossen, 2022) as reference levels determine optimal distinctiveness. Drawing on these three key factors, the goal of this thesis is to gain a better understanding of how *evaluating audiences*, *narrative modes*, and *reference levels* affect the optimal level of distinctiveness for new ventures (Fisher, 2020; Zhao and Glynn, 2022; Glynn and Lounsbury, 2022).

Nevertheless, researching how these three factors shape optimal distinctiveness requires that distinctiveness is tangibly and quantitatively measurable based on meanings in narratives, which is inherently tricky and thus has often been limited to subjective measurements in the past. This thesis adopts doc2vec as a state-of-the-art natural language processing algorithm to address this meaning measurement problem. Doc2vec allows learning the meaning of a word by its context, using novel "word embeddings" algorithms from machine learning to incorporate the structural context of information in entrepreneurial narratives and follow the so-called distributional hypothesis: Words in the same contexts tend to bear similar meanings (Le and Mikolov, 2014). Doc2vec offers a promising, but so far under-researched in the field of optimal distinctiveness, approach to making the meanings in narratives measurable and the degree of distinctiveness more comparable to others or even to oneself at different points in time (Zhao, 2022). By no longer measuring the similarity of narratives by using identical words but by whether words appear in the same context and thus have similar meanings (Vossen and Ihl, 2020), the role of meanings in narratives for the strategic differentiation of new ventures could be further explored. In combination with image-recognition and speech-recognition algorithms, doc2vec enables the measurement of textual narratives and other modes, such as visual or auditory narratives in images and videos, through which entrepreneurs can convey the distinctiveness of their new venture (Kaminski and Hopp, 2020). By using machine learning-based measurement of meanings to assess narrative distinctiveness and simultaneously looking at the performance of a new venture, it is possible to show more effectively how distinct one should be as a new venture to succeed in the market.

Investigating from a machine learning perspective how new ventures can achieve to narrate optimal distinctiveness has three critical theoretical contributions to the theories of optimal distinctiveness and entrepreneurial narratives. First, while heterogeneity across audiences (Pontikes, 2012) or within investor audiences (Fisher et al., 2017) has been the focus in the past, this thesis shows how different levels of optimal distinctiveness apply when new ventures narrate their distinctiveness to different consumer audiences. This paper, therefore, examines heterogeneity within consumer audiences in terms of their distinctiveness preferences and shows that these need not be determined by market or category but can arise through different extents of enculturation of individual norms and values associated with particular institutional logics. Second, this thesis extends previous research's focus on how a narrative's textual mode influences the optimal level of distinctiveness to non-textual modes (Williamson et al., 2021; Glynn and Lounsbury, 2022). Different narrative modes offer the opportunity to use different dimensions to convey different aspects of a new venture and reduce evaluative complexity for audiences by facilitating sensemaking. In particular, by looking at visual narratives, this thesis shows that evaluative complexity, which has always been seen as a matter of semantic fit, is also a matter of semantic richness. Third, market-based or category-based reference levels, such as prototypes or exemplars, have been considered a further factor influencing optimal distinctiveness (Barlow et al., 2019; Haans, 2019). However, little is known about how the own portfolio or the own performance as an additional reference level influences the optimal distinctiveness of a new venture (Chan et al., 2021; Janisch and Vossen, 2022). This thesis, therefore, extends the typical suspects of reference levels. It shows that it is just as crucial for new ventures to consider their distinctiveness trajectory (Durand and Haans, 2022) and to take their last performance as an aspiration and decision tool for strategic change (Greve, 1998).

This thesis also has three important managerial implications for the strategies of new ventures to narrate optimal distinctiveness. The past literature on optimal distinctiveness and entrepreneurial narratives shows that new venture entrepreneurs should address consumers differently than investors (Pontikes, 2012; Janisch and Vossen, 2022). However, how exactly this should happen and whether all consumers should be addressed in the same way has been unclear. The results of this thesis offer entrepreneurs of new ventures insights into how consumers differ in the degree of distinctiveness they like due to a differentially entrenched institutional logic and the associated enculturation of norms and values. In terms of how new ventures should narrate their distinctiveness, lessons from past literature were mainly limited to how new ventures can differentiate themselves through textual modes, for instance, how they should design their texts for their homepage (Haans, 2019) or their investor pitch (Taeuscher et al., 2021). There has been little insight into how non-textual narratives, such as visual promotions, product images, or visual and auditory clips, should be designed to differentiate a new venture best. In this respect, this thesis provides detailed guidance on how new ventures can differentiate themselves by different narrative modes and how distinct these narratives should be depending on their mode. Furthermore, this thesis contributes to the few insights on how to evolve as a new venture strategically compared to its distinctiveness trajectory (Chan et al., 2021; Durand and Haans, 2022) and helps new venture entrepreneurs to decide when a distinctiveness change positively impacts new venture performance. Addressing these three blank spots in the literature mentioned above should help new venture entrepreneurs to succeed in the market in the long run.

Following this introduction, chapter 2 presents this thesis's central theories–optimal distinctiveness and entrepreneurial narratives. It provides a brief overview of the current state of research in these areas, highlighting in particular the central role of evaluating audience, narrative mode, and reference levels in determining the optimal distinctiveness that new ventures should narrate. Based on this theoretical overview, chapter 3 identifies the research gaps and derives appropriate research questions to close these gaps. The following chapters 4, 5, and 6 contain the studies of this cumulative thesis. Study one focuses on supporters of reward-based crowdfunding campaigns on the Kickstarter platform, so-called backers, whose primary information medium and thus means of strategic differentiation are often textual narratives that can be compared to market-based reference levels such as past and live campaigns. Backers of reward-based crowdfunding campaigns support entrepreneurial ventures financially in exchange for a reward and thus act as consumers who take on the role of investors. Study two focuses on consumers who take the role of buyers and judge products based on their images and category-based reference levels on the online marketplace Amazon Launchpad, which exists specifically for products from new ventures. In contrast to the studies one and two, which look at how audiences can use narratives for sensemaking, study three shows how entrepreneurs can measure and use the effectiveness of their auditory narratives by using their past selves as reference level. Based on the number of consumers who interacted with their auditory narratives provided for free on the online platform YouTube in their role as users, entrepreneurs can make adjustment decisions about their strategic positioning. Finally, chapter 7 summarizes and discusses this thesis's global results and theoretical and practical implications and shows how future research could address limitations.

2 Theoretical background

2.1 Optimal distinctiveness

The quest for optimal distinctiveness describes the efforts of entrepreneurs to strategically differentiate their ventures (Paolella and Durand, 2016; Janisch and Vossen, 2022) or products (Zhao et al., 2018; Barlow et al., 2019) as "different as legitimately possible" (Deephouse, 1999 p.147) in the eyes of evaluating audiences. The relevance for ventures to achieve optimal distinctiveness arises from the need to counterbalance the opposing social needs "Everyone needs to belong" to signal legitimacy, and "Everyone needs to be unique" to signal distinctiveness (Brewer, 1991 p.478) with their strategic position. Ventures achieve such an optimal strategic position when they successfully balance the benefits and costs of legitimacy and distinctiveness (Durand and Kremp, 2016). Ventures benefit from being similar to competitors because evaluating audiences are more likely to perceive such ventures as normatively appropriate. However, ventures showing a high degree of similarity to competitors may also be perceived as too mainstream and risk drowning in competition. Although standing out as different and unique helps ventures to avoid competition (Haans, 2019), being too distinct poses the risk to ventures being perceived as illegitimate by evaluating audiences (Deephouse, 1999). This consideration of distinctiveness and legitimacy as balancing forces within the theory of optimal distinctiveness can be historically located in different streams of literature that initially largely neglected the interplay of the two forces.

The theoretical concept of optimal distinctiveness emerged from two initially very different streams of literature: Strategic management and institutional theory (Durand and Haans, 2022; Zhao and Glynn, 2022). While strategic management initially focused primarily on the advantages of distinctiveness as an inimitable resource (Barney, 1991), helping to outperform competitors (Porter, 1980), institutional theory emphasized, above all, the need to conform to isomorphic pressures and normative constraints to establish legitimacy (DiMaggio and Powell, 1983). Over the years, bridges have been built between the two streams of literature, which initially dealt with the importance of legitimacy and distinctiveness for the strategic differentiation of ventures in general (Deephouse, 1999; Zuckerman, 1999), giving rise to the contemporary optimal distinctiveness literature (Zhao et al., 2017), which has attracted increasing scholarly interest over the past decade. Only increasingly is the role of legitimacy and distinctiveness for strategic differentiation also being considered in entrepreneurial settings. Since novelty, distinctiveness, and non-conformity are expected and thus considered legitimate in entrepreneurial settings, summarized under the construct "legitimate distinctiveness" (Navis and Glynn, 2011), the question for *new ventures* is not whether they should be distinct, but what levels of distinctiveness are optimal and how they convey their distinctiveness.

Building on the counteracting forces inherent in optimal distinctiveness, previous studies have attempted to determine what level of distinctiveness leads to superior performance (Zhao et al., 2017). Achieving superior performance is stated as an entrepreneur's core motivation to shape the strategic differentiation of their ventures in a way that evaluating audiences perceive them as optimally distinct (Durand and Haans, 2022). It could be shown that ventures who are perceived as optimally distinct may benefit in multiple ways as they are evaluated more favorably (Durand et al., 2007), acquire more resources (Zimmerman and Zeitz, 2002), sell more (Zhao et al., 2018; Janisch and Vossen, 2022), and increase their likelihood to survive (Überbacher, 2014; Goldenstein et al., 2019). However, past research has shown the relevance of context in determining the optimum of a venture's distinctiveness and achievable performance in different dynamic environments.

Researching optimal distinctiveness in different contexts has led to the overall finding that the tolerated or desired distinctiveness level is context-specific (Zhao et al., 2017). The costs related to distinctiveness depend on how pronounced the evaluating audience's need is to perceive a venture as legitimate, similar, or conforming to competitors. In multiple contexts, such as in commercial banking (Deephouse, 1999), crowdfunding (Taeuscher et al., 2021; Wessel et al., 2022), in an app market (van Angeren et al., 2022), the automobile industry (Liu et al., 2017), the music industry (Askin and Mauskapf, 2017), or the gaming industry (Vossen and Ihl, 2020), it could be shown that audiences favorably evaluate intermediate levels of distinctiveness which leads to superior performance, indicating that the relationship between distinctiveness and performance follows an inverted u-shaped effect. However, in other contexts, such as the creative industry (Haans, 2019), the gaming industry (Cennamo and Santalo, 2013), the music industry (Goldenstein et al., 2019), or in an online B2C marketplace (Janisch and Vossen, 2022), audiences perceive such an intermediate positioning as blurring, they, therefore, devalue ventures using such a strategic positioning, which lowers these ventures' performances (Durand and Calori, 2006). Here, scholars observe a u-shaped effect of distinctiveness on venture performance, interpreted as a disparagement for getting "stuck in the middle" by benefiting neither from conformity nor distinctiveness (Cennamo and Santalo, 2013). Also, not all studies on optimal distinctiveness have found either an inverted u-shape or a u-shape effect of distinctiveness on venture performance. Taeuscher et al. (2022) examined the optimal level of distinctiveness in the hospitality industry and found that the effect flips depending on the distinctiveness of a venture's category. Furthermore, Bu et al. (2022) found a linear effect of distinctiveness on venture performance when looking at product designs of cars, which they explain with a limited range of distinctiveness available for product designs.

The optimal distinctiveness literature proposes three main factors to explain the contextual variability in determining the optimal level of distinctiveness for a new venture, which the following chapters will look at: The role audiences play as evaluators of optimal distinctiveness (Zhao et al., 2017; Durand and Haans, 2022; Zhao and Glynn, 2022), through which mode new ventures convey optimal distinctiveness, and the choice of reference levels (Fisher, 2020; van Angeren et al., 2022). Because entrepreneurial narratives are a primary means that new ventures can deploy to convey their optimal distinctiveness, and based on which audiences evaluate new ventures and compare them to competitors, they shape these established factors, a reason why the following chapter outlines the literature on entrepreneurial narratives.

This review of the optimal distinctiveness literature has shown that ventures face the tension of presenting themselves as both legitimate, to conform to normative pressures, and distinct from their competitors, to avoid competition. Being perceived as optimally distinct positively impacts ventures' performance, for example, by making them more favorably evaluated by audiences, more likely to survive, raise more money, or sell more. The degree to which legitimacy or distinctiveness should be weighted to achieve optimal distinctiveness has been studied in various contexts. These studies have produced conflicting results, showing that the consideration of optimal distinctiveness is context-sensitive and thus depends on who evaluates their distinctiveness, by what means ventures convey optimal distinctiveness, and the levels of reference to which they relate them. It was also shown that, particularly for new ventures, the question is not whether they should be distinct but what levels of distinctiveness are optimal and how they can convey their distinctiveness. How new ventures, whose strategic differentiation above all their identity formation is essential (Lounsbury and Glynn, 2001; Navis and Glynn, 2011), can succeed in this balancing act through entrepreneurial narratives has recently been increasingly the focus of the literature on optimal distinctiveness.

2.2 Entrepreneurial narratives

Previous research has highlighted entrepreneurial narratives as the "primary vehicle" (Zhao and Glynn, 2022 p.3) that entrepreneurs use to position their new ventures strategically. Entrepreneurs can deploy entrepreneurial narratives to make claims about their new ventures or ideas that set expectations (Martens et al., 2007; Garud et al., 2014) and create an appealing identity that attracts and mobilizes resources from evaluating audiences (Navis and Glynn, 2011; Kim et al., 2016; Krause and Rucker, 2020). This "process of storytelling that mediates between extant stocks of entrepreneurial resources and subsequent capital acquisition and wealth creation" defines what Lounsbury and Glynn (2001 p. 545) refer to as cultural entrepreneurship. According to the cultural entrepreneurship theory, entrepreneurs can become "skilled cultural operators" (Überbacher et al., 2015 p.925) when deploying narratives as cultural resources (Rindova et al., 2011) in a way that favorably shapes audiences' perceptions and evaluations. To be positively evaluated, entrepreneurs should construct narratives that resonate with audiences' cultural repertoires (Pan et al., 2020; Nielsen and Binder, 2021). These cultural repertoires, which cover a variety of cultural elements like categories, logics, identities, and beliefs, determine what audiences value, believe, or expect (Soublière and Lockwood, 2022) and differ across audiences (Fisher et al., 2017), which shapes how narratives resonate with a particular audience (Lounsbury et al., 2019).

The fact that a narrative resonates with the audience depends on how much the audience can make sense of the narrative. Entrepreneurs must facilitate sensemaking to help audiences determine whether a new venture, which is still unpredictable to them owing to a lack of a track record (Stinchcombe, 1965), matches their values and expectations and inspire audiences to take action (Navis and Glynn, 2011). The longer the process of sensemaking takes for an evaluating audience, in other words, the more difficult they perceive it to comprehend a new venture or product, the less likely audiences are to participate in an action, such as forming a favorable evaluation or mobilizing resources (Pollack et al., 2012). One effective tool that entrepreneurs can use to facilitate audience sensemaking is to craft their narratives with meanings that communicate to audiences a coherent identity and help them match whether what a new venture stands for resonates with their values and expectations (Gehman and Soublière, 2017; Lounsbury and Glynn, 2019).

The meanings and coherence that materialize through narratives have been established as decisive contributing factors to evaluating audiences' sensemaking processes (Weick et al., 2005; Navis and Glynn, 2011). Meanings conveyed through narratives help audiences to comprehend or make sense of who is behind a new venture, why these entrepreneurs are qualified, what they want to do, and why they believe they will be successful. Based on these meanings, audiences can situate a new venture in a broader web of meanings as a group member, such as a market industry or category (Wry et al., 2011; Vossen and Ihl, 2020). Hence, market and category dynamics that affect this broader web of meanings have been shown to shape how audiences perceive and classify a new venture's meanings (Zhao et al., 2017; Lounsbury et al., 2019). Furthermore, meanings imbued in narratives help audiences to evaluate whether a new venture's overall constructed identity is coherent and resonates with what they value and expect (Navis and Glynn, 2011). Perceived coherence is essential as it decreases evaluative complexities for audiences and creates a plausible identity in the eyes of evaluating audiences. In other words, through the meanings entrepreneurs convey in their narratives, they explain and rationalize their entrepreneurial activities and also enable audiences to comprehend even a market-unfamiliar endeavor (Lounsbury and Glynn, 2001), which contributes to new venture legitimization (Aldrich and Fiol, 1994; Suchman, 1995).

This review of the literature on entrepreneurial narratives has shown how essential narratives are for new ventures to facilitate audiences' sensemaking and shape their evaluations. How compelling narratives enhance audience sensemaking–a crucial process preceding the evaluation of a new venture–depends on how coherent evaluating audiences perceive the meanings conveyed in the narratives and how these meanings culturally resonate with evaluating audiences' values and expectations. Therefore, the construction of resonating meanings plays a central role for entrepreneurs in favorably shaping audiences' evaluation and motivating them to mobilize resources. Due to the importance of meanings imbued in narratives for audiences' sensemaking, this thesis focuses on how meaning shapes audience evaluation and, thus, new venture performance. The following chapter explores how entrepreneurs can use these meanings to convey through their narratives an optimal level of legitimizing and differentiating claims about their new ventures to resonate with evaluating audiences.

2.3 Narrating optimal distinctiveness

Past research has investigated the role of optimal distinctiveness in how entrepreneurs should construct narratives to resonate culturally with evaluating audiences. Choosing an entrepreneurial narrative to convey distinctiveness is an easily manageable and changeable tool for new ventures. Creating such a narrative does not have to be resource-intensive, which is essential as new ventures often have limited financial resources. Entrepreneurs need to anchor their new venture's narrative (Vossen and Ihl, 2020) by claiming category membership through culturally aligning with established precedents (Wry et al., 2011) as means of legitimacy. However, entrepreneurs should also set their new venture apart by deviating within an established range of acceptability as means of distinctiveness (Soublière and Lockwood, 2022). Entrepreneurs differentiate and legitimize the identity of their new ventures through the cultural meaning they imbue through their narratives: (1) by emphasizing "a core, distinctive, and enduring set of attributes, capabilities, and resources that lend strategic distinctiveness and competitive advantage" (Garud et al., 2014 p.1480), and (2) by stressing its normative appropriateness to others in the same market context (Lounsbury and Glynn, 2001).

Therefore, entrepreneurial narratives have attracted widespread attention in recent optimal distinctiveness research for identifying and measuring entrepreneurial efforts to straddle the trade-off between legitimacy and distinctiveness in their strife for optimal distinctiveness (Taeuscher et al., 2021, 2022). Recent studies have identified three critical contextual factors on how entrepreneurs can successfully convey their optimal distinctiveness. These include which audience evaluates a new venture based on its narrative (Taeuscher et al., 2021; Janisch and Vossen, 2022) because audiences differ in their institutional logic that shapes their values and expectations and thus influences the effectiveness of distinctiveness (Thornton et al., 2012; Fisher et al., 2017; Nielsen and Binder, 2021). It also includes how a new venture narrates its distinctiveness, as meanings are conveyed and processed differently (Krishna, 2012; Höllerer et al., 2018; Glynn and Lounsbury, 2022). Finally, choosing reference levels is also crucial, as a new venture can only be optimally distinct compared to another reference level (Barlow et al., 2019; Haans, 2019). The following subchapters show the status of research on these three factors influencing optimal distinctiveness.

2.3.1 The role of evaluating audiences

For a long time, audiences were thought to be a homogeneous group that agreed on what they considered understandable, desirable, appropriate, or valuable (Überbacher, 2014). Only in recent years has there been increasing investigation of possible heterogeneity across audiences and its consequences for their optimal distinctiveness evaluations. Through the advent of the institutional logic perspective (Thornton et al., 2012; Durand and Paolella, 2013), which looks at the norms, structures, and practices individuals take for granted (Pahnke et al., 2015), institutions are no longer seen as environments with rigid norms and expectations, but as dynamic environments to which entrepreneurs of new ventures must respond if they are to achieve or maintain optimal distinctiveness. The institutional logic an audience adopts, that is, the "socially constructed, historical patterns of material practices, assumptions, values, beliefs, and rules" (Thornton and Ocasio, 1999 p.804), shapes its normative expectations (Fisher et al., 2017; Fisher, 2020). Only a new venture that an audience perceives as legitimate as it complies with its normative expectations qualifies to be considered further and compared to other legitimate representatives by this audience (Zuckerman, 2016; Deephouse and Carter, 2005).

According to the institutional logic theory, not all audiences follow the same logic. Investor audiences, so-called market-makers (Pontikes, 2012), are particularly important for new ventures, as mobilizing financial resources from them has a decisive influence on the existence of a new venture. The primary focus of past research is how the legitimacy and distinctiveness expectations depend on the institutional logic of investor audiences. Different investor audiences exist, crowdfunding backers, government agencies, angel investors, venture capitalists, and corporate venture capitalists, who differ in their institutional logic

(Fisher et al., 2017). Whether an investor audience adopts a community logic, state logic, market logic, professional logic, or corporate logic has implications for the type of claims (contribution, technical, disruption and connection, competitive, complementary) they look for in entrepreneurial narratives.

Such claims facilitate investor audiences' sensemaking and attenuate their risks and information asymmetries, legitimizing a new venture (Martens et al., 2007; Fisher et al., 2017). The institutional logic is decisive for an audience's legitimacy expectation and tolerance for distinctiveness and novelty (Taeuscher et al., 2021). It has been shown that investor audiences have a higher tolerance for distinctiveness, especially if their sunk costs are already high or an investment seems to be without alternatives (Smith, 2011). In addition, investor audiences may perceive distinctiveness as desirable if it implies a novel, disruptive or market-changing character of the new venture (Pontikes, 2012).

In contrast to investor audiences, consumer audiences' legitimacy and distinctiveness expectations have hardly been researched. Consumer audiences, also called market-takers, look for parallels/similarities to precedents to refer to cognitive evaluation schemes they are familiar with, which facilitates their evaluation of a new venture and shapes their legitimacy perceptions (Pontikes, 2012). Hence, consumer audiences show a preference to evaluate new ventures using visual rather than textual narratives (DelVecchio et al., 2019), as they are often quicker to grasp and retain information (Childers and Houston, 1984; Matthews et al., 2007) from such narrative modes that ease consumer audiences' sensemaking (Höllerer et al., 2018). Due to their preference for easy-to-digest information, consumer audiences, on the one hand, often disfavor distinctiveness because it leads to perceived ambiguity and increased evaluation complexity, making it difficult to map a new venture to established cognitive evaluation schemes. On the other hand, distinct new ventures draw more attention from consumer audiences as distinctiveness helps to avoid competition and increases a new venture's memory value (Pieters et al., 2002). In conclusion, how audiences differ in their distinctiveness evaluations needs further exploration. However, how audiences evaluate distinctiveness describes only one influencing factor on the perceived distinctiveness of a new venture. At the same time, the question of what role what the audience evaluates, that is, the mode of a narrative, plays in this evaluation comes into focus.

2.3.2 The role of narrative modes

Entrepreneurs can use different narrative modes to legitimize and differentiate their new ventures through entrepreneurial narratives (Lounsbury et al., 2018). This thesis focuses on three primary narrative modes to narrate optimal distinctiveness: Textual, visual, and auditory (Kaminski and Hopp, 2020). The most frequently studied of these three modes are textual narratives. Due to the potential length and detail of information, textual narratives are of particular use for entrepreneurs that need longer descriptions, such as those that seek support from audiences, primarily investors, to launch a new venture or product which does not yet exist physically but only conceptually (Moss et al., 2018). By making claims about what the new venture or product will look like in the future and what purpose it will serve, entrepreneurs can demonstrate their ability to succeed, and thereby facilitate audiences' sensemaking, favorably shape their evaluations, and motivate them to mobilize resources (Cappa et al., 2020).

Commonly researched textual narratives through which new ventures who are still in a conceptualization phase seek to balance legitimacy and distinctiveness pressures to leverage (non-)financial support from audiences are campaign texts in crowdfunding (Williamson et al., 2021; Taeuscher et al., 2021) and game proposals in gaming platforms (Zhao et al., 2018; Vossen and Ihl, 2020). Research on these textual narratives has focused on how the language of distinctiveness and accountability used in those narratives (Kim et al., 2016), novelty or familiar framing (Pan et al., 2020), the topics (Vossen and Ihl, 2020; Taeuscher et al., 2021), or the meaning (Kaminski and Hopp, 2020), impact audience evaluations and a new venture's funding success. Also, textual narratives that present intangible products as optimally distinct to audiences have been considered, such as textual descriptions of mobile apps (Barlow et al., 2019) or vacation housing (Taeuscher et al., 2022).

In contrast to textual narratives, visual and auditory narratives have been studied less frequently. However, they are increasingly becoming the focus of researchers due to the proliferation of online platform-based entrepreneurship (Cutolo and Kenney, 2021) that strongly relies on images and videos. In addition, the evolution from previously primarily qualitative-based studies to more objective, computer-based methods for analyzing non-textual narrative modes, such as image and speech recognition, has led to a more significant consideration of visual or auditory narratives in research on entrepreneurial narratives and optimal distinctiveness in recent years (Dzyabura et al., 2021). The focus of the little research on narrating optimal distinctiveness through visual narratives has been on product designs, such as measuring the distinctiveness of automobile manufacturers' car designs using morphing technology (Bu et al., 2022) or comparing the distinctiveness of design patents to both past and contemporary design patents (Chan et al., 2021). Similarly, research on auditory narratives has been restricted to investigations of video pitches in a crowdfunding setting, such as the legitimating role of comprehensibility and plausibility achieved through using concrete and precise language (Parhankangas and Renko, 2017) or presenting an endeavor as either ongoing journey or results-in-progress (Manning and Bejarano, 2017).

The different modes of narratives provide essential sensemaking tools for evaluating audiences. Whether a narrative is textual, visual, or auditory is critical to how audiences process and evaluate the meanings of a new venture's entrepreneurial narrative. As such, the narrative mode influences narratives' ability to convey conformity and differentiation claims. From the literature on sensory marketing, we know how narratives stimulate audiences' senses and influence their perceptions and evaluations by triggering visual imagery (Wyer et al., 2008) or abstract cognitive associations (Hulten et al., 2009; Krishna, 2012; Adaval et al., 2018; Sample et al., 2020). In textual narratives, the words that the audience processes shape the overall content of the narrative and determine its linguistic style, which triggers cognitive associations related to how high the quality of a product is (Kim et al., 2016) or how well-prepared, reliable, and promising a new venture appears to be (Cappa et al., 2020; Manning and Bejarano, 2017; Voronov et al., 2022), which, in turn, has consequences for the perceived legitimacy of a new venture.

Unlike the processing of textual narratives, the processing of visual or auditory narratives is more multilayered (Cattani et al., 2017; Chan et al., 2021). Visual narratives consist of object-related and spatial pictorial information (Adaval et al., 2018; Sample et al., 2020; Dzyabura et al., 2021), shaping audiences' cognition processes. For example, research on visual narratives has shown how depicted movement in visual narratives influences perceived engagement (Cian et al., 2014), how the number of objects (Pieters et al., 2010) or disfluency (Christensen et al., 2020) contributes to perceived visual complexity, and how perceived fluency impacts as how prototypical and consequently as how legitimate a visual narrative is evaluated (Reber et al., 1998; Lee and Labroo, 2004; Labroo et al., 2008; Labroo and Pocheptsova, 2016). Although the mode of a narrative affects the extent to which narratives can convey claims of conformity and differentiation, how these claims must be balanced to create an optimally distinct narrative ultimately depends on what can be defined as "optimal" in this regard.

2.3.3 The role of reference levels

Choosing a reference level is critical to determining what "optimal" means for the narrative distinctiveness of a new venture. Without a reference level, optimal distinctiveness remains a "vacuous" (Zhao, 2022 p.29), unanchored concept. Therefore, market- or category-specific comparisons often determine the optimum of distinctiveness and represent the two most discussed sources for reference levels. Above all, the category is an essential guide in evaluating distinctiveness for both entrepreneurs and audiences. Categories group ventures based on common core attributes or characteristics (Smith and Medin, 1981). In this way, categories benefit both entrepreneurs of new ventures and the evaluating audience (Cattani et al., 2017). Entrepreneurs of new ventures can use category-based comparisons to identify their competitors, observe their behavior, and relate their distinctiveness. Audiences benefit from categories to locate competitors' narratives to whom they can compare and evaluate the narrative distinctiveness of a focal new venture (Arjaliès and Durand, 2019). Moreover, categories help audiences know what to expect from a member of a particular category (Vergne and Wry, 2014; Durand and Paolella, 2013) because they encode meanings about normative rules that determine a category-specific legitimacy threshold as well as values (Barlow et al., 2018). These coded category meanings allow audiences to place an endeavor within a broader context of meaning (Khaire and Wadhwani, 2010) and serve as cognitive filters and formal schemas by which they can judge whether what a new venture claims in its narrative can be evaluated as typical and normatively appropriate or atypical and distinct within its category (Taeuscher et al., 2022). Finally, using the formal schema of a category to pre-select sufficiently legitimate ventures assists the audience in narrowing their considerations and, in the next step, evaluating the remaining ventures (Zuckerman, 2016).

From considering the category of a new venture as a reference level, several possible modes of evaluation emerge (Gouvard and Durand, 2022) for either comparing a new venture's narrated distinctiveness to those of multiple other ventures or a single venture within the same category. When researching how new ventures should differentiate themselves from multiple others in the same category, past literature on optimal distinctiveness has often considered the overall market or the prototype of a category as a reference level. As the prototype of a category best represents what a category stands for, it has long been the primary reference level investigated when seeking to understand how audiences gauge optimal distinctiveness and evaluate a focal venture's narrative. While most scholars refer to a category prototype as the industry average (Vergne and Wry, 2014; Deephouse, 1999) or the most-average member of a category (Haans, 2019), for others, a category prototype represents the fictional average in terms of relevant attributes and features for a given category (Vergne and Wry, 2014).

The literature on optimal distinctiveness has shown that differentiating from the category prototype has negative and positive effects on a new venture's performance outcomes. Entrepreneurs who deviate too much from the category prototype with their new venture risk failing to meet the audience's normative expectations of a category and signaling valid category membership (Durand and Paolella, 2013). A new venture that signals a valid membership reduces audience confusion about its categorization (Negro et al., 2010) and may increase its legitimacy (Zuckerman et al., 2003). Since the emergence of a category prototype requires an established category with clear boundaries to other categories (Zhao et al., 2018), for categories without a transparent prototype, insufficient differentiation from the category prototype can also adversely affect new venture performance (Barlow et al., 2019). Moreover, the impact of distinctiveness on performance depends entirely on how distinct others are (Haans, 2019). In contrast to heterogeneous categories, new ventures in homogeneous categories should not adopt moderate levels of distinctiveness in their entrepreneurial narratives. Similarly, not being sufficiently distinct from the prototype has a negative impact in crowded categories because if each venture strives to be like the category prototype, the category members end up being too similar, and each venture gets lost in the crowd (Barlow et al., 2019). Deviation from the prototype can therefore provide a competitive advantage. However, too much deviation from the prototype can make it difficult for the audience to evaluate a new venture or product because there is no comparable baseline. In this case, the audience has difficulty understanding a new venture or product and may even question it and evaluate it as illegitimate (Hsu, 2006; Durand et al., 2007; Negro et al., 2010), which can lead to negative consequences for new venture performance (Pontikes, 2012; Smith, 2011).

In addition to the possible comparison with multiple other ventures in the category, the literature on optimal distinctiveness has also shown that the narrative distinctiveness of a new venture can be evaluated based on a single other venture in the category. Here, the role of the exemplar of a category, as a single other venture, has often been particularly emphasized in recent studies (Haans and Rietveld, 2022). Unlike the category prototype, a category exemplar is defined as the most salient category member or a clear market leader within a category and, therefore, likely to gain the attention of evaluating audiences (Smith and Medin, 1981; Barlow et al., 2019). Regardless of a category's maturity, audiences or entrepreneurs of new ventures can detect a category's exemplar as an exceptional category representation (Zhao et al., 2018) in terms of the most well-known, highest-performing, or best-reviewed member and use it as a cognitive reference to compare it to a focal new venture and evaluate its narrative distinctiveness.

There are differing results on how the strategic differentiation of a new venture compared to the exemplar affects its performance. Conforming to a category exemplar may create a legitimacy spillover effect (Durand and Kremp, 2016), as category exemplars are often viewed as members worth aspiring to (Durand and Paolella, 2013). Being similar to a category exemplar renders a focal venture or product a plausible candidate in audiences' consideration set (Younger and Fisher, 2020). Conforming to the exemplar creates legitimacy and distinctiveness, positively impacting new venture performance (Barlow et al., 2019). The category exemplar establishes a basis of comparison for audiences. Still, it already represents a flagship member of the category who stands out from the bulk of the category and is thus a legitimate and a distinctive member of the category. However, as category exemplars are salient members that exemplify their category and receive significant attention (Zhao et al., 2018), it is essential to be also different from the category exemplar to be competitive (Younger and Fisher, 2020). Findings show that new ventures in nascent categories benefit from being similar to exemplars and pivoting to a moderate level of distinctiveness as these categories evolve (Zhao et al., 2018).

However, recent research challenges the assumption that the evaluation of narrative distinctiveness of a focal new venture takes place exclusively based on comparisons with the prototype or exemplar of a category corresponds to reality. Instead, scholars assume that simultaneous comparison with multiple reference levels may become necessary for evaluation within the same category because a focal new venture competes simultaneously with the prototype and exemplar. These dual reference levels may influence each other. However, the extent to which such coexisting reference levels influence evaluations is poorly understood (Zhao, 2022). What we know so far from the existing literature is that new ventures should differentiate themselves from the prototype in a category when positioning themselves both against the prototype and the exemplar so as not to get lost in the crowd, but to match the exemplar, as this has a positive impact on the success of a new venture (Barlow et al., 2019). Simultaneous comparisons with multiple reference levels are also crucial in categories that have nested subcategories (Lo et al., 2020). Some categories are not delineated but consist of nested structures that group ventures into the basic and then the subcategories according to a general-to-specific hierarchy. Here, it was shown that new ventures benefit from being delineated from their basic category (Gehman and Grimes, 2017). Overall, this literature review shows the crucial role of reference levels in determining optimal distinctiveness. The following chapter discusses where there are still research gaps regarding the role of reference levels in determining optimal distinctiveness and for the factors introduced earlier–the evaluating audience and the narrative mode.

3 Research questions and research design

3.1 Research questions

The initial literature review has shown that entrepreneurial narratives are a primary cultural element and strategic tool for evaluating or achieving optimal distinctiveness. Optimal distinctiveness depends primarily on three factors: The evaluating audience as the recipient and evaluator of narratives, the narrative mode as the means of conveying optimal distinctiveness, and the reference levels as the basis for evaluation. Evaluators differ not only across audiences in the institutional logic they apply but also within audiences, as shown for investor audiences. However, the question of how consumer audiences differ in their institutional logic and how this affects their preferences for optimal distinctiveness is a blank spot in the literature. Moreover, findings on how the mode of a narrative determines optimal distinctiveness are mostly limited to a textual mode. How the optimal level of distinctiveness may differ for other narrative modes, such as visual and auditory, is relatively unexplored. What is known about the importance of reference levels for optimal distinctiveness is that audiences often compare and evaluate a new venture against competitors, usually the prototype or exemplar of a category. Entrepreneurs may use these same category-based reference levels to interpret whether they appear optimally distinct. However, little research exists on the role of a new venture's past self as a reference level for perceived optimal distinctiveness. This results in three gaps arising from the lack of knowledge about the role of heterogeneity within consumers as the evaluating audience, narrative mode-sensitive distinctiveness preferences, and a new venture's past self as a reference level in determining optimal distinctiveness. The following three subchapters describe these gaps and present the three derived research questions.

3.1.1 First research question: Heterogeneity within consumer audiences

The first research gap arises from the limited consideration of heterogeneity within consumer audiences that new ventures address with their entrepreneurial narratives and the consequences thereof for their function as evaluators of optimal distinctiveness (Fisher, 2020). In the past, entrepreneurial narratives, as a means to convey optimal distinctiveness to audiences, have primarily been researched by looking at how *investor audiences* perceive and evaluate the strategic positioning of resource-seeking new ventures (Martens et al., 2007; Smith, 2011). Findings emphasize the relevance of conformity and narrative comprehensibility to mobilize resources from investor audiences, reached by constructing unambiguous identities that attenuate risk and invoke familiarity for decreasing information asymmetry and perceived uncertainty (Martens et al., 2007). However, it has also been shown that distinctiveness can be beneficial in some cases when investors are already heavily committed due to their sunk costs resulting from the time invested in search and the trust provided or when they do not find any other option that could substitute an investment (Smith, 2011).

Nevertheless, little is known about how other audiences, other than investors, value conformity and distinctiveness, such as *consumer audiences*. Taking a more fine-grained perspective on how audiences of entrepreneurial narratives differ in their optimal distinctiveness evaluation across audiences might be insightful, as we know from the literature on institutional logic that audiences are very heterogeneous (Pontikes, 2012; Kim and Jensen, 2014). This heterogeneity affects how much a particular audience discounts illegitimacy and is willing to be confronted with evaluative complexities, which means it tolerates or expects distinctiveness (Fisher et al., 2017; Taeuscher et al., 2021). However, such heterogeneity may exist across audiences and within them, which is a blank spot in the current literature on optimal distinctiveness. Although the literature on entrepreneurial narratives in crowdfunding provides insights into how consumers as "different kind of investor" (Nielsen and Binder, 2021 p.14) evaluate the strategic position of a new venture (Anglin et al., 2022; Kaminski and Hopp, 2020; Cappa et al., 2020; Manning and Bejarano, 2017; Kim et al., 2016; Frydrych et al., 2016), these studies assume a universal view of consumer audiences.

However, limiting consumers to their role as investors neglects that consumers can also take on other roles, such as buyers or users. Consumers in these different roles seek to make sense of new ventures for different reasons and motivations to evaluate them (Lehner, 2013). Consumers may base their evaluations on similar norms, values, and expectations due to a common institutional logic, but how they give final weight to these might differ within their audience (Hannan, 2010). Previous research supporting this assumption of heterogeneity within consumer groups has shown that consumers can deal with evaluative complexities differently (Pontikes, 2012). It stands to reason, therefore, that consumers might differ in how they use imbued meanings in narratives for their sensemaking and evaluate a new venture's narrated distinctiveness based on their roles as investors, buyers, or users, due to differences in conformity and differentiation preferences. This thesis, therefore, responds to a call to fill the research gap on heterogeneity within consumer audiences (Zhao, 2022) by examining the following research question:

1. *How does heterogeneity within audiences shape the effectiveness of distinctiveness claims in entrepreneurial narratives?*

3.1.2 Second research question: Narrative mode-sensitive distinctiveness preferences

The second research gap relates to the lack of understanding about how the optimal level of distinctiveness may be different depending on the mode of an entrepreneurial narrative a new venture chooses to convey its distinctiveness. As the initial literature review has shown, existing research often limits the effect of narratives on audience evaluation and new venture success to a *textual* mode (Martens et al., 2007; Vossen and Ihl, 2020). In the past, scholars predominantly used qualitative methods (Manning and Bejarano, 2017; Cappa et al., 2020; Voronov et al., 2022) or computer-aided textual analyses (CATA), such as dictionaries (Allison et al., 2013; Moss et al., 2015; Parhankangas and Renko, 2017) to make such textual narratives' content or linguistic style measurable. A few studies also viewed textual narratives as the sum of their presented topics and how much a narrative deviates from that of other narratives in the composition of its topics (Haans, 2019; Cutolo et al., 2020; Williamson et al., 2021; Taeuscher et al., 2022). As these methods are limited in their ability to capture the meanings of narratives on a large scale, which are an essential means for entrepreneurs to narrate their new ventures' distinctiveness and thus are carriers of information that audiences use in their evaluation process (Navis and Glynn, 2011), further research is needed on narratives using machine learning-based natural language processing methodologies that enable meaning-based measurement of textual narratives by looking at the contextual embedding of a word. Only recently, a few studies have adopted such methods to more objectively measure the overall semantic meaning conveyed through textual narratives (Vossen and Ihl, 2020; Kaminski and Hopp, 2020).

However, textual is only one possible mode for a new venture to present its distinctiveness. Restricting research to textual narratives neglects the influence of other modes on perceived distinctiveness, especially visual ones. The question is how visual stimuli trigger different stimuli than linguistic ones as in textual or auditory narrative modes (Höllerer et al., 2018). What is particularly challenging in quantitatively researching the impact of meaning conveyed through visual narratives on perceived distinctiveness is that they need to be translated into a textual mode as a prerequisite for computer-aided, meaning-based similarity measurements (Dzyabura and Peres, 2019; Kaminski and Hopp, 2020). Hence, little is known about how a different optimal level of distinctiveness may apply to a particular narrative mode. To date, the few studies of visual narratives that exist often refer to product designs (Chan et al., 2021; Bu et al., 2022) that can be used to measure conformity regarding narrative coherence or resonance. However, product designs are inappropriate for measuring the meanings conveyed. For instance, the displayed objects in product images might indicate semantic richness or complexity. Therefore, this thesis aims to provide deeper insight into how to make meanings measurable in non-textual narrative modes. By taking a machine learning stance towards optimal distinctiveness as a vehicle to extend measuring meaning to visual narratives, this thesis seeks to contribute to a better understanding of how narrative distinctiveness through different, also non-textual, modes can affect audience evaluation and, thus, new venture performance. This leads to the following research question:

2. How do different narrative modes impact the effectiveness of distinctiveness claims on entrepreneurial performance?

3.1.3 Third research question: A new venture's past self as the reference level

The third research gap derives from the underemphasized role of a new venture's past self as a reference level to evaluate optimal distinctiveness. In the past, the distinctiveness of a new venture was evaluated by relating it to a single, static reference level. Reference levels are crucial to estimating "optimal" distinctiveness (Zhao, 2022). However, so far, mainly competitive reference levels have been used with the focus on the overall market and a category's prototype or exemplar (Haans, 2019; Zhao et al., 2018; Taeuscher et al., 2022). Yet, these relatively generic reference levels hardly reflect the entrepreneurial reality, after which new ventures and their audiences evaluate optimal distinctiveness based on "dual or many coexisting" (Zhao, 2022 p.59) reference levels. Therefore, more recent studies examine how strategic positioning vis-à-vis multiple reference levels shape entrepreneurs' and audiences' optimal distinctiveness evaluations at a given point in time, such as considering multiple reference levels within a category (Barlow et al., 2019).

However, we know little about how simultaneous comparisons with multiple static levels of reference affect the optimal level of distinctiveness in narratives and how that level evolves dynamically. Competition-based reference levels are subject to dynamic changes in the aggregate of category members, new ones entering or leaving the market category (Cattani et al., 2017), or the salience of a venture. In addition, audience expectations of a venture's legitimacy and distinctiveness claimed in its narrative may change as it matures (Fisher et al., 2016). This suggests a dynamic view of narrative distinctiveness as a constant balancing act for entrepreneurs to multiple and changing reference levels. To this end, this thesis takes a more active stance toward optimal distinctiveness, viewing its pursuit as an ongoing balancing process (Garud et al., 2014) during which entrepreneurs need to evaluate the effectiveness of their new venture's narrative actively and, if necessary, make dynamic strategic changes (Burnell et al., 2023) motivated by comparisons with multiple reference levels (Zhao and Glynn, 2022).

Dynamically adjusting the level of distinctiveness a new venture conveys in its narratives to continue to appear optimally distinct compared to competitors also calls into question how a new venture develops in comparison to its distinctiveness trajectory (Durand and Haans, 2022). Bu et al. (2022 p.5) have shown that "competition and legitimacy pressures exist not only with other organizations but also among different products within the same organization," as new ventures face the challenge of remaining competitive with their product portfolio but also presenting a coherent overall image (Janisch and Vossen, 2022). The role within-organization distinctiveness plays in distinctiveness evaluations, such as comparing a focal new venture's current self to its past self, has largely been ignored in past research on optimal distinctiveness (Bu et al., 2022). The reasoning behind comparing a new venture to its prior distinctiveness is that new ventures, like categories, are subject to dynamic development processes that affect the evaluation of optimal distinctiveness (Durand and Haans, 2022).

Achieving optimal distinctiveness or remaining optimally distinct is a continuous balancing act and learning process for new ventures (Tracey et al., 2018) and may require changes across their life cycle (Fisher et al., 2016). These changes may, however, impact how coherent audiences perceive the overall identity of a new venture (Janisch and Vossen, 2022). To receive feedback on whether or not a strategic position is optimally distinct and decide if a change is needed, the organizational learning theory suggests that new ventures can formulate *aspirations* based on their competitors' performances to relate to their performance. An aspiration represents a lower bound for satisfactory performance (Schneider,

1992) that enables entrepreneurs of new ventures to keep track of their performance and adapt their strategic positioning when needed (Lant, 1992; Greve, 1998, 2003). Performance below aspiration (Cyert and March, 1963; Bromiley, 1991) often triggers problemistic search and leads to strategic change that aims at restoring performance to the aspired level (Jordan and Audia, 2012; Ref and Shapira, 2017; Posen et al., 2018). Accordingly, comparing their performance to their aspirations that dynamically change over time (Tracey et al., 2018) allows new ventures to constantly balance the opposing forces of conformity and distinctiveness to find an optimal strategic position. The influence of a new venture's developmental trajectory on strategic differentiation decisions and the associated experiences and learning (Greve, 2002; Kirtley and O'Mahony, 2023) represents an essential additional reference level in measuring optimal distinctiveness. Therefore, this thesis aims to shed light on how narratives can be made more comparable based on their mediated meanings to understand better the influence of different competitive reference levels and a new venture's past self as a reference level on optimal distinctiveness. This thesis, therefore, addresses the following question:

3. How does the choice of reference levels influence the evaluation of narrative distinctiveness?

3.2 Research design: Towards narrative distinctiveness through doc2vec as a machine learning algorithm

Based on the established research questions seeking to close the identified research gaps, Figure 1 provides an overview of the theoretical research design of this thesis. The three studies included in this thesis investigate how machine learning improves our understanding of the contextualizing role of evaluating audiences (3.1.1), narrative modes (3.1.2), and reference levels (3.1.3) for achieving optimal distinctiveness through entrepreneurial narratives. Each study looks at a different type of consumer audience, narrative mode, and

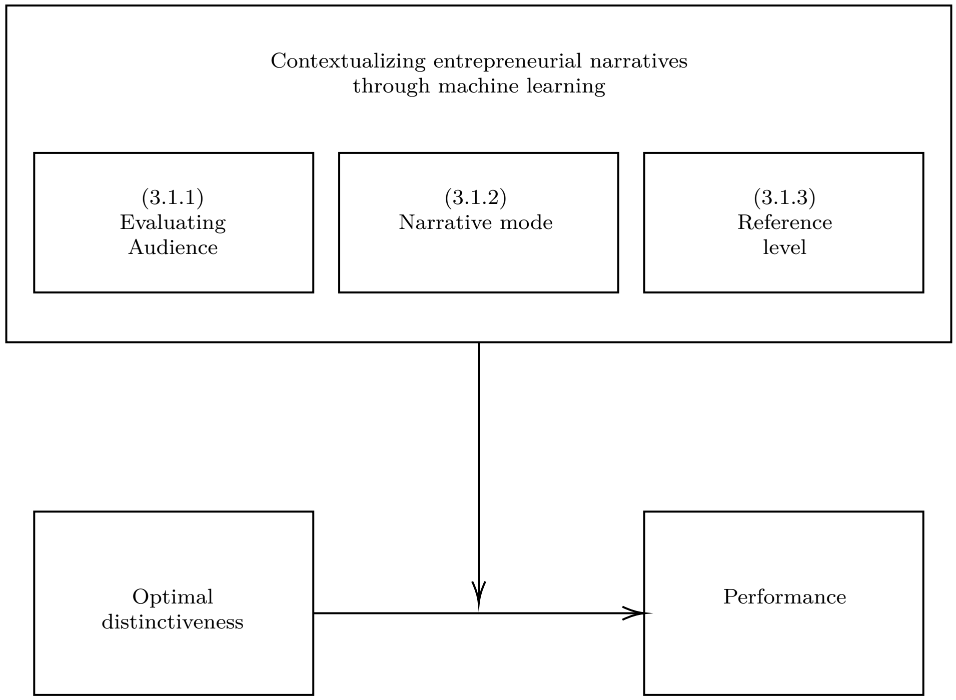

Figure 1: Theoretical research design.

reference level. In the first study, this thesis examines the project descriptions of 14,108 crowdfunding campaigns on Kickstarter. In the second study, this thesis analyzes images of 1,312 entrepreneurial products offered by 297 new ventures across 292 weeks on Amazon Launchpad, a separate B2C marketplace on Amazon for entrepreneurial products. In the third study, this thesis investigates transcript data from 1740 most-viewed videos released over a time window from 2010 to 2021 by the most-successful 348 YouTube content creators as of 14th June 2021 from 12 different channel categories. In all three quantitative studies, this thesis analyzes the effectiveness of different narrative modes on consumer audiences' evaluation and, subsequently new ventures' strategic differentiation success based on different performance measurements. The first study examines the impact of textual narratives, such as campaign descriptions, on the number of recruited first-time and repeat backers as consumer investor audiences, and the funding raised by a campaign. The second study examines the impact of visual narratives, such as product images, on consumer buyer audiences and, thus, on the sales rank of a new venture's product. The third study examines the impact of performance feedback through aspiration levels on how entrepreneurial content creators change the auditory narratives in their videos on subsequent releases to maximize their appeal to consumer user audiences. The data sets of the three studies are independently collected and compiled, consisting of publicly available data. For the statistical analyses, this thesis draws on open-source software and machine learning applications, such as Python and R.

This thesis provides a machine learning perspective on what level of distinctiveness is optimal for new ventures to narrate through meaning. To answer the question of how the evaluating audience (3.1.1), the narrative mode (3.1.2), and the reference level(s) (3.1.3) affect optimal distinctiveness in new venture narratives, this thesis employs machine learning-based natural language processing methods as means to measure distinctiveness of meaning. This thesis uses doc2vec for this purpose in all three studies. Doc2vec is a state-of-the-art machine learning algorithm from natural language processing for measuring the meaning of a narrative (Vossen and Ihl, 2020). Doc2vec builds on "word2vec." The language model word2vec, based on neural networks, was introduced in 2013 to overcome bag-of-n-grams models' inability to memorize word vectors and adjust predictions to a context (Mikolov et al., 2013a,b). Word2vec considers the context of a word, derives its meaning, and encodes it in a vector representation. In a word2vec network, each word in a corpus is represented by a fixed dimensional vector created by maximizing the probability for a word to appear in the same meaning context. The probability of a word to appearing in the same meaning context is proportional to the similarity of these so-called word embeddings. That means if two words appear in the same context, they are similar in meaning. This is called the distributional hypothesis.

Distances between vectors encode how similar words are in their meaning. In a well-trained word2vec network, the learned word embedding vectors for, for instance, APPLE and PEAR would be close, both representing fruits, whereas those for APPLE and BREAD would be further from each other in the vector space. The fact that vectors encode meanings allows for representing vector relations among themselves–how similar words are in meaning–by calculating vector similarities using cosine similarity. A cosine similarity between two vectors equal to 1 indicates a perfect alignment of two vectors, as they have a cosine angle of 0 degrees. In contrast, a cosine similarity of -1 would show that both word vectors are very distinct, as they point with their cosine angle of 180 degrees in opposite directions in the vector space.

Word2vec can be trained using two model architectures: Continuous bag-of-words-model (CBOW) and skip-gram model. While the CBOW architecture is designed to learn how to predict a focus word from given k preceding and following context words, the skip-gram model predicts these surrounding k context words one by one from a given focus word by giving higher weights to words that appear more often in context with the focus word. CBOW works better to predict frequent words, whereas the skip-gram architecture is favored for predicting rarer words. The model architecture determines how word2vec assigns a unique vector to each unique word in the corpus. To learn these vector representations, word2vec creates a word matrix W, each row representing a unique word, and a context matrix C. The dimensionality d of these matrices is often set to 50-300. Higher dimensional embedding can capture more fine-grained relationships between words, but depending on the size of the corpus, it can also deteriorate the accuracy of the model (Mikolov et al., 2013a). First, the vectors are initialized to random weights and adjusted throughout a deep learning process. This deep learning process builds on three layers: An input layer, a hidden layer, and an output layer. Depending on the model architecture, the word matrix W or the context matrix C represents the input layer. The hidden layer serves the neural network to remember proven learned and to forget incorrectly learned controlling factors, so-called weighting matrices. By repeatedly training the neural networks, word2vec aims to maximize the average log probability for these predictions and to minimize the error term using gradient descent. For this purpose, error terms resulting from comparing the output vector to the target vector are propagated back to the neural network to adjust the weighting matrices so that the output vector becomes more and more similar to the target vector.

Since word2vec is limited to capturing semantic meaning from words, in 2014, doc2vec was introduced by Le and Mikolov (2014) as an extension that captures the semantic meaning of text documents (narratives) by learning paragraph vectors (PV). Doc2vec allows text documents of any length to be converted to a predefined vector length while preserving word order and thus preserving context-specific semantic meanings. To represent a document or paragraph as a vector, doc2vec first creates a vector for each unique word of the corpus with the length of the corpus. The learned word vectors are then used to infer the paragraph vectors. Similar to word2vec, there are two different model architectures in doc2vec: Distributed bag of words (PV-DBOW) and distributed memory (PV-DM). While the PV-DBOW model architecture resembles the skip-gram approach in word2vec, the PV-DM resembles the CBOW approach. In doc2vec, the paragraph token can be considered another word that acts as a memory. Depending on the model architecture, it remembers either what is missing from the current context (PV-DM) or which context is missing from a given word (PV-DBOW).

The three studies of this thesis use doc2vec to convert entrepreneurial narratives from different modes, such as textual crowdfunding campaign descriptions, visual product images, or auditory video entertainment content, into vectors and to compare these vectors to compute narrative distinctiveness. Entrepreneurial narratives in a visual mode require an extra analysis step to achieve text formats doc2vec can process, consisting of a list of detected labels describing objects, scenes, or concepts displayed in an image. With such image recognition approaches, even visual narratives can be translated into text documents, which again can be expressed as numeric vector representations thanks to doc2vec. Based on these numeric representations, researchers can determine with established distance measures, such as Euclidean Distance or cosine similarity, if a narrative of a new venture i resembles the semantic meaning in a narrative used by a new venture y or z. Several parameters were adjusted to the nature of this thesis's data sets to improve the algorithm, such as the dimensions for the word embeddings and the local context window (Kaminski and Hopp, 2020). The dimensions for the word embeddings represent the vector lengths, implying that larger vectors can store more meaningful information. The local context window defines the threshold of neighboring words constituting the context of a focal word. To exemplify the logic underlying the word embedding vectors of the training data, this thesis uses t-distributed stochastic neighbor embeddings (t-SNE) (van der Maaten and Hinton, 2008) to map words with a similar meaning close to each other, while dissimilar words show a greater distance. T-SNE uses a non-linear dimensionality reduction technique and visualizes the dimensions of the word embedding vector spaces for the training data in a more intuitively interpretable two-dimensional space. Not only can a t-SNE represent clusters of similar label meanings, but it can also depict how far the meanings of these clusters diverge from each other.

After training the algorithm, it knows the underlying word or label similarities. It can measure a new venture's distinctiveness appeal as compared to multiple reference levels, such as its past and current competitors in the same overall market (chapter 4), its competitors in the same basic and subordinate product category (chapter 5), or the categorical prototype, exemplar, and past self (chapter 6). This thesis used cosine similarity provided by Python's Gensim package to measure the distance between the embedding vector f of a narrative i and the embedding vector of another narrative j for all dimensions w and averaged all the comparisons. Based on the averaged cosine similarity values of all comparisons, this thesis estimated in the following three studies the degree to which the narrative similarity of either an environmental crowdfunding campaign description, a new venture's product's images, or a channel's video entertainment content impacts consumer audiences' evaluations of new ventures' strategic differentiation.

Table 1 summarizes the theoretical and methodological research designs of the three studies of this thesis that are presented in the following three chapters. At the beginning of each study, this thesis provides an insight into the respective authorship contributions, the main theoretical concepts, the methodology and sample used, and the study's development and publication status.

	Study	Dancing to multiple tunes *(chapter 4)*	More than meets the eye? *(chapter 5)*	Reaching for the brightest *star* *(chapter 6)*
Theoretical	Literature	entrepreneurial narratives, OD, *institutional logic*	entrepreneurial narratives, OD, *sensory marketing*	entrepreneurial narratives, OD, *organizational learning*
	Evaluating audience	consumers (investor role)	consumers (buyer role)	consumers (user role)
	Narrative mode	textual	visual	auditory
	Reference level	past and current competitors	categorical competitors	past self
Methodological	Research context	CF: Kickstarter	Online market: Amazon Launchpad	YouTube
	Data sample	14,108 campaigns (cross-sectional data)	1,312 products (panel data)	1,392 videos (panel data)
	Narrative	campaign text	product image	audio transcript
	Main purpose of narrative	ask for funding	sell product	increase engagement with contents
	Dependent variable	number of first-time and repeat backers, funding success	product sales rank	narrative change
	Econometric approach	negative binomial, linear regression	random effects regression	fixed effects regression

Table 1: Theoretical and methodological research design.

4 Dancing to multiple tunes: Establishing legitimacy with first-time and repeat backers in crowdfunding campaigns

Authorship	Weiss, Stephanie; Vossen, Alexander.
Main theoretical concepts	Entrepreneurial narratives; optimal distinctiveness; institutional logic.
Methodology and sample	Quantitative; data set including 14,108 crowdfunding campaigns, (2011-2021).
History of the study	Presented at the Academy of Management Annual Meeting (AOM) 2020.
Publication status	Rejected after two revise and resubmits at the Journal of Business Venturing. Rejected at the Journal of Entrepreneurship Theory & Practice. Submitted to the Strategic Entrepreneurship Journal.
Contribution	In this study I was in charge of collecting all data, reviewing the literature, analyzing the data, and writing the study.

Table 2: Information about study one.

Abstract

Using 14,108 crowdfunding campaigns with diverse topics from Kickstarter's "on our radar" section, we examine three different strategies used to establish legitimacy and test their relative effectiveness in gathering support from first-time versus repeat backers: Suited narrative distinctiveness that aligns with backers' expectations of novelty, endorsement from Kickstarter staff, and campaign leadership's funding of other campaigns. While an endorsement from Kickstarter staff is more critical for first-time backers, a campaign leadership's funding of different campaigns is relevant only for repeat backers. The most pronounced differences between first-time and repeat backers exist in their evaluation of narrative distinctiveness, where campaigns face a dilemma: While a narrative that is distinct from *past campaigns* helps to attract repeat backers and to gather more resources, it simultaneously harms their efforts to attract first-time backers and subsequently grow the community. Those, in turn, can be attracted by narratives distinct from *live campaigns*, yet such narratives secure less funding. Our findings highlight and conceptualize the difference between first-time and repeat backers' evaluative processes that are critical in determining the effectiveness of a campaign's legitimization efforts and offer relevant insights into the trade-off between legitimizing and differentiating entrepreneurs face when they seek funding from crowdfunding audiences. By not exclusively focusing on technology-based campaigns, our results also showcase how past findings on legitimacy in crowdfunding generalize to additional campaign topics, such as cultural and civic ones.

Keywords: Crowdfunding; Legitimacy; Distinctiveness

JEL Codes: M13, L26, L33

4.1 Introduction

Engaging with online platform communities has become a strategically vital way to appropriate essential resources for established firms and new ventures alike (Fisher, 2019; Murray et al., 2020). New ventures, in particular, must increasingly ask themselves how to best interact with users of these platforms—as good access to them can make the difference between a successful launch and a failure (Clough et al., 2019). Therefore, it is no surprise that crowdfunding as a method of seeking funding from a large audience or group of individuals (the "crowd") for commercial, cultural, and even social entrepreneurial endeavors is becoming an increasingly popular phenomenon (Belleflamme et al., 2013; Cumming and Johan, 2017).

With its move into the mainstream, both conceptual and empirical studies on what drives those many individuals who provide resources to crowdfunding campaigns—so-called backers—have risen in prominence (Cornelis et al., 2022; Le Pendeven et al., 2022). Much of this work focuses on what drives backers of technology-based campaigns (Fisher et al., 2017; Taeuscher et al., 2021). However, on the leading platform *Kickstarter*, such campaigns account for only about ten percent of all launches (as of the writing of this work) (Kickstarter, 2022b). Do these insights generalize to the other roughly ninety percent of campaigns that entail, among others, cultural and civic topics (Josefy et al., 2017; Logue and Grimes, 2022)?

Little is known about possible differences among backers from technology-based or other campaign topics. While existing studies provide much-needed insights on established crowdfunding community members—or so-called repeat backers—successful campaigns also rely heavily on building and subsequently activating their community to recruit them as first-time backers (Murray et al., 2020). Again, on *Kickstarter*, only about a third of the overall crowd (as of the writing of this work) (Kickstarter, 2022b) funded more than one campaign and can be considered a repeat backer. Is what we know from past studies on these repeat backers also valid for these large numbers of new first-time backers?

Our work intends to address both issues, testing past findings for a broader cross-section of campaign topics and differences between first-time and repeat backers. To elaborate on these differences, we focus on how backers differ in evaluating a campaign's legitimacy, which is a necessary prerequisite of resource provision (Fisher et al., 2017) and is defined as if a campaign is "desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Suchman, 1995 p.574). While campaigns can establish legitimacy with backers via the same legitimacy mechanisms used with other resource providers (Pahnke et al., 2015), backers differ in their interpretation of those based on their institutional "community logic" (Almandoz, 2014; Fisher et al., 2017). For example, both venture capitalists and backers interpret the storytelling in a narrative as part of the campaign's identity. Still, venture capitalists perceive those as more legitimate that present themselves as competitively superior, while backers prefer those that highlight their contribution to the crowdfunding community (Nielsen and Binder, 2021).

Institutional logics, such as the community logic, are historical patterns of assumptions, values, and beliefs (Thornton and Ocasio, 1999), and it remains unclear to which extent these values and beliefs have formed in first-time backers whose focus is on the specific campaign rather than the broader platform community. Returning to the example above: Is it correct to assume that first-time backers prefer storytelling in narratives that highlight the value for a crowdfunding community of which they are not even a member (yet)? And even if so, is storytelling as essential for them as it is for repeat backers?

To offer a more fine-grained view on how campaigns establish legitimacy with both first-time and repeat backers, we argue along three essential mechanisms used to establish legitimacy with crowdfunding backers (Fisher et al., 2017): Identity mechanisms that foster understanding and align with backers' expectations of novelty and distinctiveness via narratives, associative mechanisms that indicate the endorsement of influential community actors, and organizational mechanisms that highlight campaign leadership's compliance to expected community behavior. We test the relative importance of these mechanisms in attracting funding, repeat, and first-time backers using data on 14,108 "on our radar" campaigns on

Kickstarter–an important cross-section of commercial, cultural, and civic campaigns. Replicating past research on technology-based campaigns (Fisher et al., 2017; Taeuscher et al., 2021), we find that while all three legitimacy mechanisms have a similar, positive impact on the amount of funding raised, key differences prevail in their relative importance for repeat and first-time backers. For one thing, receiving an endorsement from Kickstarter staff, and thus evidence that credible actors have vetted campaigns has a positive effect on both repeat and first-time backers that is stronger for first-time backers. In a sign that the "in-group bias" associated with crowdfunding communities is at work (Fisher et al., 2017), we find that repeat backers value campaign leadership that is actively funding other campaigns. However, this has not had any meaningful effect on first-time backers.

Repeat and first-time backers differ the most in their responses to campaign narratives. Building on the notion that crowdfunding campaigns gain legitimacy through a distinct identity (Taeuscher et al., 2021), we find that repeat and first-time backers are attracted to campaigns whose narrative differs from other campaigns. However, both backers use different cognitive referents (Zhao and Glynn, 2022), as repeat backers favor narratives distinct from past, that is, historical, campaigns. In contrast, first-time backers prefer those distinct from live and thus current campaigns (Chan et al., 2021). Campaign leadership, therefore, faces a dilemma: While a narrative distinct from past campaigns helps attract repeat backers and more funding, it harms their efforts to attract first-time backers. Making matters worse, catering to first-time backers' preference for narratives that are distinct from live campaigns reduces overall funding.

Our study helps to bring together parts of prior literature on resource provision (Fisher et al., 2017; Murray et al., 2020) by conceptualizing how repeat and first-time backers differ in their reaction to campaigns' efforts to establish legitimacy (Clough et al., 2019). We argue that both kinds of backers are not fundamentally different audiences but differ in how gained experiences and enculturation have shaped their values and beliefs as they progressed along with their membership in the crowdfunding community. By paying attention to the relative strengths of the legitimacy mechanisms, our work offers a more fine-grained perspective on the evaluative process of crowdfunding backers as investor audiences, and their use of the meaning campaigns provide them for constructing legitimacy.

From a managerial perspective, our findings help crowdfunding campaigns acquire legitimacy, primarily via a suited narrative. If the objective is to attract repeat backers, a campaign should highlight its novel contribution to the community by highlighting how it differs from past campaigns (Taeuscher et al., 2021). While such a narrative may deliver more funding, it may prevent entrepreneurs from growing their community—a trade-off relevant for serial entrepreneurs (Soublière and Gehman, 2020). Consequently, crafting the correct narrative to convey the campaign's identity requires entrepreneurs to "dance to multiple tunes."

4.2 Theoretical background

4.2.1 Establishing legitimacy in crowdfunding campaigns

"As Kickstarter does not offer refunds, we encourage backers to investigate the project idea first, vet the creator thoroughly, and assess the project's inherent risk for themselves before making a pledge."

(Kickstarter's advice to backers)

Crowdfunding platforms encourage backers to thoroughly evaluate a crowdfunding campaign to verify its legitimacy, whether it is both cognitively comprehensible and normatively appropriate or desirable (Suchman, 1995). Both aspects are of utter importance: While being cognitively comprehensible legitimates campaigns by facilitating the evaluation process for backers, being normatively desirable legitimates campaigns by aligning with backers' normative expectations. As the quote suggests, Kickstarter encourages backers not to limit this evaluation to a single aspect. In a comprehensive review (Fisher et al., 2017), existing research broadly conceptualizes three primary sources or mechanisms that new ventures, in general, and crowdfunding campaigns in particular, can leverage to establish legitimacy with possible resource providers: Identity, associative, and organizational mechanisms.

Identity mechanisms are cultural, claim-making tools such as narratives or visual representations entrepreneurs can strategically use to communicate their core attributes. Through these identity claims, entrepreneurs can create meaningful claims on "who they are," "what they do," and "why they are doing it" (Navis and Glynn, 2011). The crowdfunding literature has shown that campaigns use textual descriptions (Mitra and Gilbert, 2014) or videos (Parhankangas and Renko, 2017) to explain to backers why their idea is relevant and how it serves the community (Fisher et al., 2017). A narrative with content similar to other campaigns helps backers link it to what they know, making it easier for them to comprehend and evaluate the respective campaign (Navis and Glynn, 2011). High differentiation in this regard, however, does not provide backers with a cognitive anchor that supplies readily accessible meaning. Still, it can help a campaign stand out from competitiors and meet the preferences of an audience that values creativity and novelty (Taeuscher et al., 2021).

Associative mechanisms create legitimacy by emphasizing connectedness to the broader ecosystem (Jacobides et al., 2018) and function through evaluative endorsement from influential community actors "who share, and even espouse important community values and ideals" (Fisher et al., 2017 p.60). In crowdfunding, campaigns benefit from being vetted and validated by recognized and undisputed community members, such as the platform operator (Calic and Mosakowski, 2016; Chan et al., 2020). These influential community actors emphasize with their endorsement the best-practice status of a campaign in terms of creativity, project clarity, and appeal (Kickstarter, 2022a). By emphasizing best-practice campaigns, endorsers play the role of "value ambassadors" by thoroughly vetting a campaign's conformance to the platform community's norms, values, and ideals (Butticè et al., 2017). Thus, an endorsement by a recognized community actor legitimizes a campaign's activities and simplifies backers' evaluation process by indicating how promising a particular campaign is in the eyes of important community actors (Mollick, 2014).

Using organizational mechanisms creates legitimacy by emphasizing the role of organizational leadership and demonstrable success (Fisher et al., 2017). This mechanism works by highlighting professionalization through leadership (team) credibility (Cohen and Dean, 2005; Packalen, 2007) or by revealing critical internal structures or milestones (Wiklund et al., 2010). In crowdfunding, campaigns accomplish this by highlighting their leadership(s)' connections to previous campaigns to bolster their in-group status and demonstrate "strong ties to, and membership in the community" (Fisher et al., 2017 p.60). Backers tend to distinguish community outsiders from insiders based on campaign leaderships' "social engagement" or community activity (Zvilichovsky et al., 2013). Because of the vital role of reciprocity in crowdfunding (Mitra and Gilbert, 2014), campaign leaders who prove to be outstanding members through their strong engagement within the platform community (Zvilichovsky et al., 2013) are perceived favorably for their high sense of commitment to the community. Such behavior legitimizes campaign leadership in the eyes of backers and improves a campaign's chances of success (Williams and Shepherd, 2021).

When leveraging identity, associative, and organizational mechanisms, crowdfunding campaigns must be careful to use them in a way that appeals to the institutional logic of backers to be perceived as legitimate (Fisher et al., 2017). Institutional logics are socially constructed, historical patterns of assumptions, values, and beliefs about "what is meaningful and appropriate in a setting" (Pahnke et al., 2015 p.597), providing decision-makers with guiding rules for "action, interaction, and interpretation" (Thornton and Ocasio, 1999 p.804). In crowdfunding, these assumptions, values, and beliefs center around shared values of and commitment to the crowdfunding community and the intention to advance the platform community (Almandoz, 2014; Fisher et al., 2017). This so-called "community logic" guides backers in their actions, such as how to "act in their relationships with others" (Pahnke et al., 2015 p.597) and in how to interpret others' actions, such as cognitively comprehending their actions and constituting what can be considered as normatively desirable behavior. The current literature on community logic in crowdfunding assumes a homogeneously applied community logic among backers. However, the definition derived from institutional theory suggests that institutional logic, including community logic, is historically shaped and socially constructed, suggesting a dynamic evolution over the progression of a backer's membership in the crowdfunding community, reflecting various past experiences and interactions, and different contexts (Mutch, 2021). The subject of the next section will be how backer heterogeneity influences the effectiveness of the three different mechanisms used to establish legitimacy.

4.2.2 Differentiating between first-time and repeat backers

Although the recent literature on community logic in crowdfunding emphasizes that community logic is the logic of repeat backers who have contributed more than once to a campaign on the platform, they do account for only about a third of the crowd (as of the writing of this work) (Kickstarter, 2022b). Indeed, campaigns build their relevant community by seeking funding from both repeat and first-time backers, so campaigns must target both groups simultaneously and publicly (Burtch et al., 2016). First-time backers have never contributed to a campaign on the platform before (Murray et al., 2020) and engage initially because they are attracted to a focal campaign. For repeat backers, this locus becomes somewhat de-centered as they become committed to the ethos of crowdfunding and "buy" into crowdfunding itself by contributing to "collective memory making" (Ocasio et al., 2016 p.677) because of their greater past experiences and more frequent past interactions within the platform community.

Repeat backers experience and observe developments and changes within the crowdfunding community, which enables them to recognize trends and constantly reshape their expectations (Parhankangas and Renko, 2017). Because they have supported multiple campaigns on the platform in the past, they more frequently interacted with campaign creators and other backers. On the other hand, first-time backers' social interactions are restricted to backers from the same campaign and lack past experiences with other backers and campaign

	Level of analysis	Repeat backers	First-time backers
Community logic	Pattern of values and beliefs		
	-*Historically shaped (through past experiences)*	From evaluating multiple campaigns in the past	From funding single campaign in the presence
	-*Socially constructed (through past interactions)*	From interacting with backers and creators across multiple campaigns	From interacting with backers and creators centered on activity of one campaign
Legitimacy evaluation	Importance of the campaign's		
	-*Identity mechanism (Narrative distinctiveness)*	Appreciate distinctiveness from past campaigns	Appreciate distinctiveness from live campaigns
	-*Associative mechanism (Kickstarter endorsement)*	Less important, can substitute endorsement with own platform experience	More important, cannot substitute endorsement due to lack of platform understanding
	-*Organizational mechanism (Status as community insider)*	More important, ensures that leadership has appreciated insider status	Less important, have no specific preferences for community insiders due to own outsider status

Table 3: Key differences in legitimacy evaluation between repeat and first-time backers.

creators. This raises the question of the extent to which different legitimacy mechanisms work for either repeat or first-time backers whose values and beliefs have been shaped differently by experience and interactions as they progress along their membership in the crowdfunding community (Thornton and Ocasio, 1999). In the following, we discuss how these differences affect backers cognitively and normatively in their legitimacy evaluations. Table 3 summarizes this discussion of the key commonalities and differences between repeat and first-time backers regarding their community logic and legitimacy evaluation.

We propose that repeat and first-time backers are the most similar in their reaction to associative mechanisms. Associative mechanisms, defined as endorsements by influential community actors, such as the Kickstarter staff, showcase that a campaign is normatively desirable (Packalen, 2007) but also cognitively comprehensible (Calic and Mosakowski, 2016; Courtney et al., 2017). By definition, endorsements on Kickstarter are granted when a campaign shows commitment to Kickstarter's core normative goal of fostering creative projects and also provides a "clear and detailed description" (Kickstarter, 2022a) of how to achieve that commitment. A campaign presented in an accessible and understandable way makes it easier for backers to evaluate it. As repeat backers know from past experiences with the platform about its norms and values and how difficult it is for a campaign to receive endorsements from Kickstarter staff, they can value those appropriately. Although endorsements are normatively important to repeat backers, they are less comprehensively relevant because the past experience gained by repeat backers throughout their community membership enables them to evaluate campaign content more independently.

For first-time backers, in contrast, such endorsements are more important as they are relevant for evaluation and understanding. First-time backers learn to understand the norms and values of the platform by trusting the assessment of influential community actors (Murray et al., 2020). Thus, similar to repeat backers, they share the need for the normative desirability the endorsement guarantees. Unlike repeat backers, however, first-time backers lack experience on the platform that helps to comprehend campaigns. This renders endorsements more critical to them as an endorsement from an influential community actor indicates a high-quality campaign (Soublière and Gehman, 2020). Due to the additional, comprehensive importance for first-time backers, we argue that endorsements have a more substantial positive effect on first-time backers than repeat backers. Thus,

Hypothesis 1: *The effect of receiving a Kickstarter staff endorsement is stronger for first-time than repeat backers.*

We postulate that repeat and first-time backers react less similarly to organizational mechanisms, such as expected community behavior by campaign leadership. To both normatively evaluate and cognitively comprehend campaign leadership behavior, it is necessary to be knowledgeable about the community—or, more preferably, be a community insider (Fisher et al., 2017). Repeat backers mostly earn insider status within the community through their past interactions on the platform across multiple campaigns. Given the commonly assumed in-group bias (Brewer, 1999), repeat backers evaluate campaign leadership as more legitimate whom they believe have a more profound sense of commitment (Bateman et al., 2011) through increased engagement and social participation (Zvilichovsky et al., 2013) and excel at creating a shared sense of community (Block et al., 2018). As a result, repeat backers value the behavior of campaign leaders who play both sides of the market—through their dual roles as backer and campaign leaders—as normatively desirable. Such behavior ensures the platform's continued existence by placing supportable campaigns and satisfying the platform's requirement for reciprocal behavior (Mitra and Gilbert, 2014).

Unlike repeat backers, first-time backers have not actively participated in the community. They thus may be considered community outsiders, making them less likely to both normatively evaluate and cognitively comprehend the desirability of campaign leadership behavior. First-time backers are less inclined to show an in-group bias as they are not community insiders themselves (Brewer, 1999). Although first-time backers can generally match campaign leadership activity in supporting others with social characteristics (Zvilichovsky et al., 2013), it will be difficult for them to distinguish normal from exemplary community insider behavior. While first-time backers should have no objection to campaign leadership engaging with the community, we believe both factors make them less likely to rely on such information when evaluating campaigns. Therefore, we hypothesize campaign leaders' community insider status to be more relevant for repeat than first-time backers. Hence,

Hypothesis 2: *The effect of desirable campaign leadership behaviors is stronger for repeat than first-time backers.*

We propose that repeat and first-time backers differ the most in evaluating campaign identities communicated through narratives. The cultural entrepreneurship literature has shown that cultural tools which strongly resemble prototypical identities of the market category in which an entrepreneur operates facilitate audiences' evaluation by activating familiar cognitive templates (Pan et al., 2020). Through institutional classification, activating such familiar templates accesses meanings that would otherwise be incomprehensible (Glynn and Navis, 2013). Deviating from one's market category in these identity claims can, however, also trigger interest in novelty and may be normatively desirable since claims that are too conventional can be perceived as not entrepreneurial enough (Vossen and Ihl, 2020).

Particularly in a crowdfunding setting, expressing high novelty through a distinct campaign narrative has garnered legitimacy. Distinctiveness increases a campaign's expressive value (Chan et al., 2021), emphasizing its uniqueness. Perceiving a campaign as unique appeals to backers who can be deemed a novelty-expecting audience for whom the "competitive and normative benefits of distinctiveness exceed the potential cognitive liabilities of distinctiveness" (Taeuscher et al., 2021 p.153). However, evaluating cultural tools and their distinctiveness is often subject to different benchmarks and dynamics, and time-contingent (Zhao and Glynn, 2022). Thus, campaigns can be distinct not only from their "historical ancestors" such as past campaigns that aired before them but also from their contemporaries, such as other live campaigns seeking funding simultaneously (Chan et al., 2021).

We assume that first-time and repeat backers differ in their cognitive referents and, thus, in their preference for distinctiveness regarding past and live campaigns. Repeat backers deem a campaign narrative desirable that differs in meaning from other narratives they have encountered in the past and that meets their expectations for novelty (Parhankangas and Renko, 2017; Navis and Glynn, 2011). As such, they do not require conformance because repeat backers can also comprehend a focal campaign using existing familiar cognitive templates (Navis and Glynn, 2011) derived from more frequent social interactions and campaign experience. Their knowledge from past experiences and interactions on the platform also renders their approach to distinctiveness more "anchored" (Chan et al., 2021) and their funding decision less reliant on contemporary live campaigns. Repeat backers also feel much more familiar with institutional practices and can rely on that when contrasting a new campaign against the status quo of past campaigns (Zhao and Glynn, 2022). This effect of distinctiveness from past campaigns may therefore be much stronger for repeat than for first-time backers, which may still rely on a degree of conformance to past campaigns to foster their campaign comprehension and understanding (Glynn and Navis, 2013).

In contrast, we propose that first-time backers may favor distinctiveness from live, contemporary campaigns. First-time backers' past experiences result from lurking activities (Malinen, 2015), limiting their ability to comprehend a focal campaign's novelty and uniqueness, and compare it to past campaigns. This lack of knowledge could be overcome if first-time backers educate themselves and carefully study past campaigns. However, we deem this unlikely as the sheer volume of past campaigns could act as a deterrent, and there is no incentive for first-time backers to engage with campaigns that have already run and whose outcome they can no longer influence.

As the evaluation of identity claims always includes the weighing of decision alternatives (Durand and Haans, 2022; Haans, 2019), we propose that first-time backers find these in live, contemporary campaigns, which are not only a much more manageable number of alternatives to consider but also alternatives where first-time backers' support could still have an impact. We, therefore, expect first-time backers to perceive a focal campaign as more legitimate whose narrative is different in meaning from live campaigns and thus perceived by them as unique and distinct (Chan et al., 2021). In this regard, the distinctiveness of live campaigns is also more critical for first-time than repeat backers, who know past campaigns and do not need to rely on contemporary campaigns to determine a campaign's narrative distinctiveness.

Therefore, we propose that both backers differ in the cognitive referents they use to evaluate a campaign narrative. Repeat backers favor narratives distinct from past campaigns and match their normative expectations of novelty and distinctiveness (Seigner et al., 2022; Vossen and Ihl, 2020). Because repeat backers can use their past experiences gained throughout their community membership as a reference, they do not necessarily need to consider live campaigns. On the other hand, first-time backers prefer narratives different from other contemporary live campaigns, as these are displayed more prominently on the platform than older campaigns and thus form a more quickly grasped reference level. This leads us to the following hypothesis,

Hypothesis 3: *The effect of a narrative distinct from past (live) campaigns is stronger* *for repeat (first-time) backers.*

4.3 Empirical approach

4.3.1 Sample and data collection

As a data source, we consider the crowdfunding platform Kickstarter in this study, as it provides insights into the overall number of attracted backers to a campaign and distinguishes between the number of attracted repeat and first-time backers. To double-check our assumptions on legitimacy mechanisms, we contacted ten backers and ten creators via the Kickstarter messaging system to get some initial impressions and gather qualitative insights to inform our analysis. On Kickstarter, backers can pledge to campaigns from various categories for a non-monetary reward. To improve the chance of being discovered by backers, campaign leaders must assign their campaign to one of Kickstarter's primary categories and optionally select one of the primary subcategories. Additionally, campaign leaders can notify Kickstarter of their intent to be listed in the platform's "on our radar" section. Kickstarter's "on our radar" section hosts 13 different tag groups[1], representing significant trend groups identified by the community or Kickstarter staff. Kickstarter individually checks each application and allows the tag to be assigned only if the check is satisfactory. Unlike traditional categorization, tags allow for a more thematic subdivision of campaigns by grouping campaigns that share a common philosophy, subject matter, or theme (Kickstarter, 2013)

To exemplify this tag-based grouping, consider the tag group "Environmental," in which campaigns are grouped that share a common passion for sustainability. Because of the many ways a campaign can incorporate sustainability considerations, campaigns tagged as environmental can be very heterogeneous and often span multiple primary categories and subcategories of Kickstarter's classical categorization system. While an environmental cam-

[1]The 13 tag groups include the following tags: Affordable art, bikes, DIY (do-it-yourself), environmental, for kids, lqbtqia+, magic & divination, public benefit, robots, RPGs (role-playing games), sci-fi and fantasy, stem (projects encouraging youngsters to develop an interest in science, technology, engineering, or mathematics subjects), zine quest (magazines featuring rpg-related content) (as of November 2022).

paign might pursue to manufacture sustainable sandals made from 100 percent recycled tires and thus be tied to the main category "fashion" and the subcategory "footwear," a campaign pitching solar-powered cell phone chargers would also appear in the same tag group due to its sustainable nature. However, from a classical categorization perspective, its main category "technology" and the subcategory "gadgets" would not coincide with the categories of sustainable sandals.

To build our data set, we collected information on all campaigns in all tag groups in Kickstarter's "on our radar section." By doing so, we focus on a subset of campaigns that we deem suited due to multiple reasons. First, the "on our radar" section ensures that all campaigns in our sample have been vetted for relevance for Kickstarter and its community. Secondly, the focus on tags ensures that our selected subset of campaigns is not limited to a single category. Still, campaigns are both comparable and sufficiently different from each other. This cross-categorical setting allows us to test further the generalizability of findings from technology-based campaigns (Taeuscher et al., 2021) to broader, more diverse campaign topics that entail cultural and civic topics (Josefy et al., 2017; Logue and Grimes, 2022).[2]

The campaigns published in this subset cover a period from June 2009 to January 2022. From this data set, we excluded 49 campaigns that were still running at the time of data collection. We also excluded 275 campaigns with most of their narrative embedded in pictures by manually examining all narratives with less than 200 words (which we classified as a low word count (Soublière and Gehman, 2020)). Due to methodological reasons related

[2]Next to the theoretical arguments provided above, we also took empirical steps to test the appropriateness and suitability of the "on our radar" campaigns. First, we checked that the "on our radar" section contains campaigns from all main categories, which it does. Then, we compared the relative category prominence to the Kickstarter totals. Some differences are notable; for example, games and art campaigns are more strongly represented, and film and music campaigns are less prominent. Technology-based or publishing campaigns are more or less equally represented. Intuitively, the "on our radar" campaigns are more successful than the overall average. By definition, only those campaigns included by Kickstarter are compelling in their rigor and relevance for the platform. However, as we collect information on all "on our radar" campaigns and only compare them with themselves, we deem this not overly troublesome for interpreting our results. Second, and more importantly, Models 1-6 in Table 7 intend to replicate existing research on campaign legitimacy from both an early full sample from Kickstarter (Soublière and Gehman, 2020) and a sample of technology-based campaigns only (Taeuscher et al., 2021). As the results are comparable, we would deem this an additional indication of the appropriateness of our sampling approach.

to analyzing the narrative, we also dropped 93 non-English campaigns. To identify those campaign narratives which were not available in English, we used a language detection tool from *Python's nltk* package and calculated for 23 different languages the probability of being part of a campaign's narrative. We then manually checked those campaign narratives that did not have English as the highest probability score. We also excluded 16 campaigns from our data set that had been canceled and had no narrative.

This left us with 15,319 campaigns we used to compile our narrative distinctiveness measures. We later excluded 936 campaigns that did not provide data on how many first-time and repeat backers contributed to their campaigns. Nevertheless, because these campaigns represented real competition for campaigns that had run, we included them in calculating our competition measures and dropped them afterward. Our final sample consists of 14,108 unique campaigns. We averaged its competitive measures when a campaign appears in multiple tag groups. For example, a game that introduces children to programming is listed in both the "For Kids" and the "Stem" tag group as it thematically fits both tag groups, making the game compete with other campaigns from both tag groups. Therefore, we averaged the measures derived from both tag groups.

4.3.2 Dependent variables

Our primary dependent variables are *repeat backers*, *first-time backers*, and the *amount of funding pledged*. We collected the total number of repeat and first-time backers a campaign attracted from the campaign websites. Both variables consist of non-negative integers. We also measure a campaign's funding success, using the logged total amount of funding pledged to a campaign after it ended (Calic and Mosakowski, 2016; Soublière and Gehman, 2020). To allow cross-country comparisons, we converted all currencies to U.S. dollars based on the exchange rates when a campaign ended. Since Kickstarter is based on an "all-or-nothing" principle, the funds raised are only paid out to campaigns that were able to reach their funding goal. This means that if the funding goal is not reached after the campaign period, the campaign leadership will not receive any funding. As our goal is to identify the extent to which campaigns can attract backers regardless of their funding success, recoding those campaigns that failed to meet their funding goal to 0 would equate them with campaigns that could not attract any backers at all, introducing possible bias in our analysis. Hence, we included campaigns regardless of their ultimate funding success but also introduced a dummy variable that controls whether a campaign failed.

4.3.3 Independent variables

Our three key independent variables representing the three different legitimacy mechanisms are *staff pick* (an associative mechanism), *community insider* (an organizational mechanism), *past narrative distinctiveness* and *live narrative distinctiveness* (an identity mechanism). Previous studies have shown that the legitimacy of a campaign is increased when the campaign is “associated with, or endorsed by a prominent community member” (Fisher et al., 2017 p.60). We argue that as platform hosts, Kickstarter’s staff is a prominent member of the overall Kickstarter community and can help a campaign appear more legitimate by showing their evaluative approval for a campaign through their endorsement. According to Kickstarter, endorsed and thus legitimized campaigns are well-designed campaigns that are described clearly and in detail and presented in an engaging, creative manner (Kickstarter, 2022a). Consistent with previous studies that measured evaluative endorsement based on third-party endorsement as a dichotomous variable (Mitra and Gilbert, 2014; Mollick, 2014), we operationalized the variable *staff pick* with a dummy variable indicating whether or not Kickstarter endorsed a campaign i (Taeuscher et al., 2021).

Prior literature has also shown that backers deem campaigns more legitimate if their leadership has “actively participated in the community in the past” and can thus be perceived as a “community insider” (Fisher et al., 2017 p.60). To operationalize the variable *community insider*, we counted the number of campaigns supported by the campaign leadership as of the time of data collection and logged it.

A recent study has demonstrated that backers consider campaigns legitimate that construct a distinct narrative (Taeuscher et al., 2021). The literature on optimal distinctiveness has also shown that distinctiveness can be evaluated based on different reference levels (Chan et al., 2021). Our study analyzes how past and live campaigns as two different reference levels impact the legitimacy evaluation of the identity mechanism by repeat and first-time backers. To operationalize the variables *past narrative distinctiveness* and *live narrative distinctiveness*, we examined the textual narratives presented in a campaign's story section and compared their similarity using "word embeddings" (Vossen and Ihl, 2020). Each text document, in our case, the textual campaign narrative, was translated into a numeric vector representation with the help of a machine learning-based algorithm from natural language processing called "doc2vec" or "paragraph vector" (Le and Mikolov, 2014). Doc2vec is a machine learning algorithm from natural language processing that builds on "word2vec" and follows the so-called distributional hypothesis: Words that appear close to the same words and, therefore, in a similar context have a similar meaning. In this way, we can measure the similarity between campaign narratives even in cases where campaign leaders use different terms to describe the same campaign aspect (Vossen and Ihl, 2020). For example, campaign one may refer to "team," while campaign two may refer to "staff" and campaign three to "crew." All words are distinct (and would be measured as such by more traditional text analysis). Still, since they likely appear in a similar word context (close to the same other words), they also share a similar meaning that the algorithm can measure. We preprocessed all textual data by tokenizing, filtering for stop words, excluding punctuation, special characters, and word frequencies below five, and stemming the corpus. With this preprocessed corpus, we trained the algorithm to detect semantic relations across Kickstarter campaign narratives. We set 100 dimensions for the word embeddings and specified four words for the local context window to prevent overfitting (Kaminski and Hopp, 2020).

To exemplify the logic underlying the word embedding vectors of Kickstarter campaigns in tag groups, we used a t-distributed stochastic neighbor embedding (t-SNE) (van der

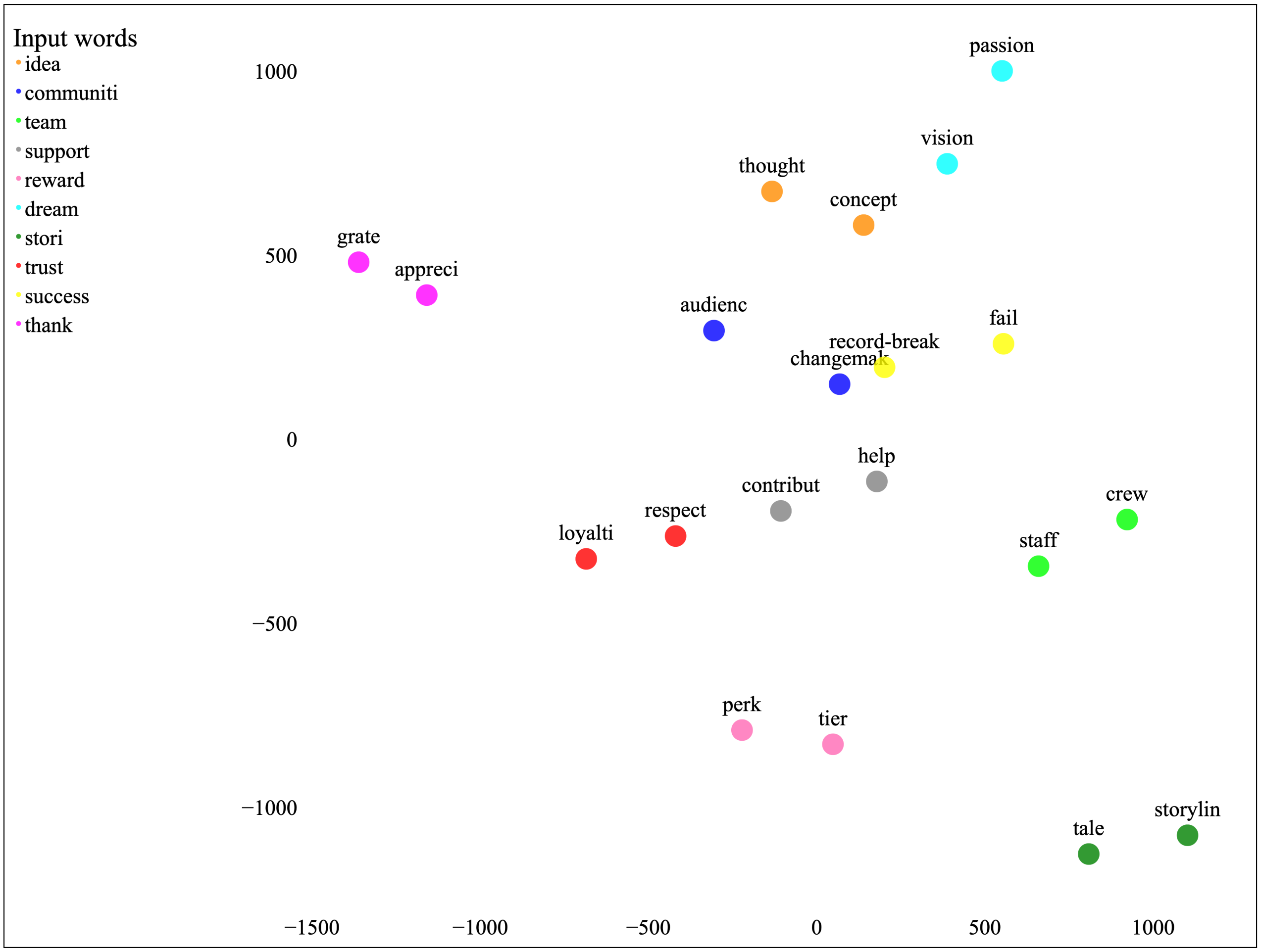

Figure 2: t-SNE of word2vec word embeddings—ten sample words and their two words most similar in meaning (words are stemmed).

Maaten and Hinton, 2008). T-SNE maps words with similar meanings close to each other, while distinct words show a greater distance. This statistical method for visualizing high-dimensional data uses a non-linear dimensionality reduction technique. It allows us to visualize the 100 dimensions of the word embedding vector spaces for the campaign narratives in a more intuitively interpretable two-dimensional space. Figure 2 shows ten sample input words of our training data set and the two words used in the most similar meaning context for each of these input words. As exemplified in Figure 2, the two words most similar in meaning to the word "community" are "audience" and "changemaker." We cannot only represent clusters of similar word meanings but also see how far these clusters diverge. In the concrete example shown, this means that the meaning contexts associated with the input words "community" and "support" are more similar since they are closer within the two-dimensional vector space than the meaning contexts associated with the input words "community" and "story."

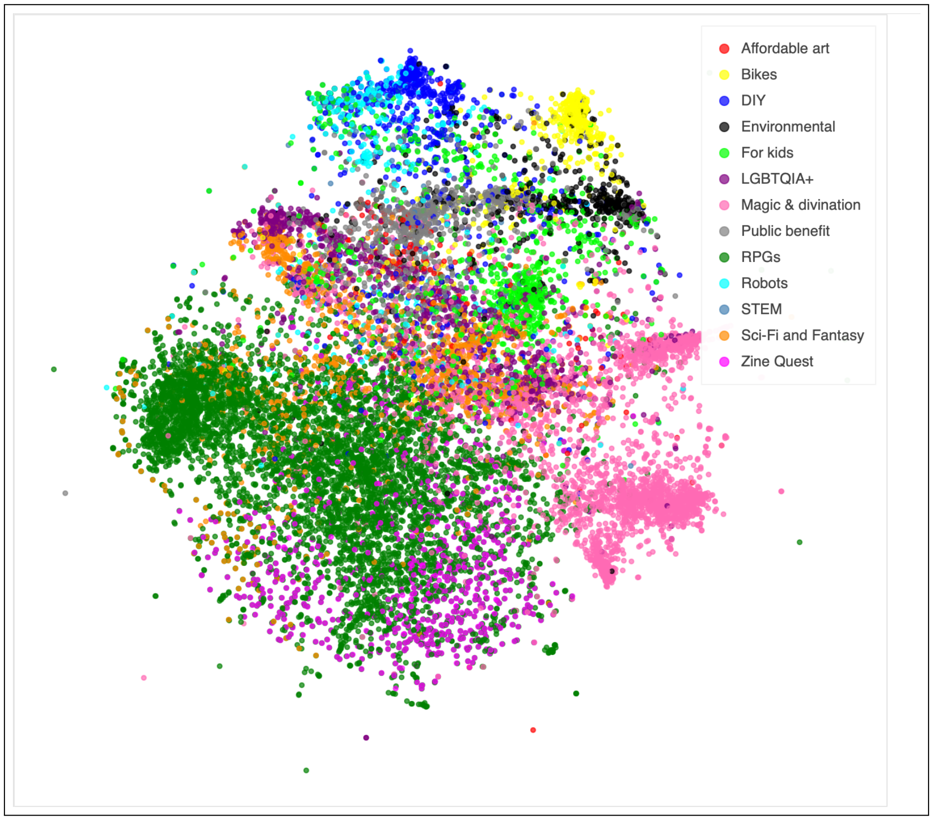

Figure 3: t-SNE of doc2vec embeddings of campaigns across tags.

Knowing these underlying word embeddings allowed us to test our trained model with the 15,319 Kickstarter narratives by measuring the distance between the embedding vector f of a tagged Kickstarter campaign i and the embedding vector of a past (live) Kickstarter campaign from a tag group j for all dimensions w via cosine similarity provided by *Python's Gensim* package. This results in the following equation:

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

Finally, we averaged all the comparisons and computed the inverse cosine similarity.

$$Narrative\ distinctiveness_{ij} = 1 - \frac{\sum_{j=1,j\neq i}^{N} Narrative\ similarity_{ij}}{N}, \tag{2}$$

where N is the total number of campaigns j.[3] Figure 3 visualizes the document embeddings of our data set's 15,319 textual campaign narratives in the vector space clustered by their tag group. Neighboring tag group clusters in Figure 3 are more similar in the meaning they use in their textual campaign narratives than tag group clusters. For instance, the textual campaign narratives in the tag group "RPGs" are in general more similar to the meaning used by textual campaign narratives in the tag groups "Zine Quest" and "Sci-Fi and Fantasy" than to those from the tag groups "Environmental" and "Bikes."

4.3.4 Control variables

Consistent with prior work (Soublière and Gehman, 2020), we controlled for campaign-, category-, and platform-level variables. As a high funding goal has been shown to negatively affect crowdfunding success (Mollick, 2014; Calic and Mosakowski, 2016), we included the logged *funding goal* as one control variable. We also considered whether a campaign was *updated* during its launch (No=0, Yes=1), as updates signal preparedness and interaction between campaign leaderships and backers, and, therefore, positively affect crowdfunding success (Chan et al., 2020; Mitra and Gilbert, 2014). In addition, narrative length and the presence of a *video* signal preparedness and mitigate informational asymmetries (Moss et al., 2018)—a reason why we additionally controlled for *low word count* campaigns with fewer than 200 words (No=0, Yes=1) (Soublière and Gehman, 2020) and available video information (No=0, Yes=1). Furthermore, campaign leaders familiar with setting up crowdfunding campaigns are also associated with being well-prepared and engaged in a platform-internal social network (Skirnevskiy et al., 2017; Butticè et al., 2017). Since this has been found to

[3]Following the argument that campaigns gain legitimacy by being distinct rather than losing it (Taeuscher et al., 2021), we perceive the effect of distinctiveness on performance linearly and not as a multiplicative effect (Bu et al., 2022; Chan et al., 2021).

decrease insecurities for backers and to result in a higher likelihood of crowdfunding success (Cholakova and Clarysse, 2015), we created a dummy indicating whether a campaign leadership is a first-time (=0) or a serial creator (=1) of a tag group-related campaign. We also controlled for the gender of the primary campaign creator (Gafni et al., 2021; Greenberg and Mollick, 2017; Seigner et al., 2022).

Measuring the impact of gender on campaign success is generally quite tricky, as some work in teams or self-identify as queer or non-binary. We, therefore, decided to limit ourselves to determining the gender of the leading campaign creator whose identity profile is linked to the campaign. To determine the gender of the leading campaign creator, we used *Python's gender_guesser* package. A test trial on a subset of 509 observations from our data set yielded 89.8 percent accuracy for the gender_guesser package. The gender_guesser package subdivides gender determination into male, female, predominantly male, predominantly female, androgynous, or name could not be found. We manually checked the predominantly male and predominantly female names. Campaign leaders that identified themselves as queer among these were classified as "other," as were androgynous or undeterminable name results. Our operationalization thus yielded a categorical variable for gender (0=male, 1=female, 2=other).

As time period effects have been found to impact crowdfunding success (Mollick, 2014; Calic and Mosakowski, 2016), we controlled for *campaign duration* and *tag age*. Since the tag groups have been launched at different points in time, the latter measures the period in days between the introduction of a specific tag and a campaign's launch date, accounting for increased tag popularity over time. We log-transformed both variables. We also controlled for whether or not a campaign was canceled before its official ending date. Prior literature has also observed that certain regions, such as Silicon Valley, can positively impact crowdfunding success since superior performance and quality are associated with that region (Mollick, 2014). We control for a campaign's origin (*country control variable*) to account for these geography-related effects on crowdfunding success.

Variable	Variable description
Dependent variables	
Amount pledged	Total sum pledged (USD, log) by a campaign i.
Repeat backers	No. of repeat backers a campaign i attracted.
First-time backers	No. of first-time backers a campaign i attracted.
Independent variables	
Staff pick	Dummy indicating whether or not Kickstarter's staff endorsed a campaign i (0=No, 1=Yes).
Community insider	No. of campaigns supported by the main creator w of a campaign i (log).
Past narrative distinctiveness	1-average of cosine similarities between the document vector of a campaign i and the document vectors of all older campaigns in all tag groups.
Live narrative distinctiveness	1-average of cosine similarities between the document vector of a campaign i and the document vectors of all live campaigns in all tag groups.
Campaign-level controls	
Funding goal	Own funding goal of a campaign i (USD, log).
Updated	Dummy indicating whether or not a campaign i made any updates during launch (0=No, 1=Yes).
Failed	Dummy indicating whether or not a campaign i failed to reach its funding goal (0=No, 1=Yes).
Low word count	Dummy indicating whether or not a campaign i's narrative has fewer than 200 words (0=No, 1=Yes).
Prior experience	Dummy indicating whether or not a creator w of a campaign i is a serial creator of tagged campaigns (0=No, 1=Yes).
Canceled	Dummy indicating whether or not a campaign i was canceled before it reached its duration end (0=No, 1=Yes).
Campaign duration	No. of days, possibly up to 60 days, that a campaign i was open for pledges (log).
Tag age	Time period in days between the introduction of a tag group g and a campaign i's launch date (log).
Video	Dummy indicating whether or not a campaign i provides video information (0=No, 1=Yes).
Gender	Categorical variable of a campaign creator w's gender (1=female,2=male,3=other).
Country	Categorical variable of campaign origin i.
Category-level controls	
Tag concurrent launches	Number of concurrent launches in the first week of a campaign i in its relevant tag group g.
Tag prior performance	Log of the average amount successfully raised in the preceding 90 days of the tag group g of a campaign i.
Tag maturity	Cumulative number of unique individuals who had contributed to a tag group g prior to a campaign i's launch (log).
Tag growth	Cumulative number of unique campaigns that had been launched in a tag group g prior to a campaign i's launch.
Platform-level controls	
Season	Categorical variable of the season in which a campaign i was launched (1-4=spring-winter).
Weekday	Categorical variable of the day on which a campaign i was launched (1-7=Monday-Sunday).

Table 4: Variable descriptions.

Due to the importance of the first week of a campaign in mobilizing backers, we controlled for *tag concurrent launches*, which is the number of campaigns competing during this time in the same tag group of a focal campaign. We also controlled for the tag group's average *tag prior performance* by calculating the logarithm of the average amount successfully raised for each day in the previous 90 days (Soublière and Gehman, 2020). To control for the *tag maturity* in terms of activity, we calculated the "day-by-day total number of all backers who had pledged their support to each category" (Soublière and Gehman, 2020 p.483). We also controlled for *tag growth* by counting the cumulative number of unique campaigns in a specific tag group launched before a focal campaign in the same tag group.

Backer activity on Kickstarter is subject to seasonal fluctuation, evidenced by systematically lower values in winter and on weekends and higher values during the rest of the year and in the middle of the week. We accounted for these *season*-specific and *day-of-the-week* effects on crowdfunding success by creating a dummy for each of the four seasons (1-4=spring-winter) and each of the seven days of the week (1-7=Monday-Sunday) (Soublière and Gehman, 2020). Table 4 summarizes all variables used and their measurement.

4.4 Results

Table 5 and Table 6 show the descriptive statistics and correlations of all variables. We analyzed all statistics using the free statistics software R and Stata 17. As *first-time* and *repeat backers* are both non-negative integers, we used a negative binomial model for the regression analyses to account for overdispersion (Cameron and Trivedi, 1990).[4] We also used robust standard errors to account for heteroscedasticity. Table 7 reports the results of the multiple linear regression with the amount pledged as the dependent variable and the negative binomial regressions with first-time and repeat backers as dependent count variables. Models 1, 7, and 13 represent the baseline models. Models 6, 12, and 18 in Table 7 show the full models, including all independent variables. The remaining models assess the direct effects of *staff pick*, *community insider*, *past narrative distinctiveness*, and *live narrative distinctiveness* on the *amount pledged* and a campaign's ability to enlist *repeat* or *first-time backers*.

[4] See O'Hara and Kotze (2010) on why such an approach should be favored over a log-transformed DV.

Variables	Mean	St. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13
Dependent variables															
1. Amount pledged (Log)	9.09	1.65													
2. Repeat backers	434.97	1,494.15	0.43												
3. First-time backers	104.08	663.47	0.29	0.75											
Independent variables															
4. Staff pick	0.44	0.50	0.35	0.12	0.10										
5. Community insider	40.35	97.78	0.03	0.06	-0.02	-0.06									
6. Past narrative distinctiveness	0.88	0.02	-0.06	0.03	-0.05	-0.17	0.19								
7. Live narrative distinctiveness	0.87	0.03	0.04	0.05	0.01	0.02	0.07	0.38							
Control variables															
8. Funding goal (Dollar, log)	8.61	1.70	0.58	0.23	0.19	0.31	-0.14	-0.23	0.06						
9. Updated (0=No, 1=Yes)	0.97	0.18	0.21	0.05	0.02	0.05	0.07	0.07	-0.01	-0.04					
10. Failed (0=No, 1=Yes)	0.14	0.35	-0.33	-0.10	-0.05	-0.09	-0.11	-0.11	0.00	0.21	-0.29				
11. Low word count (<200 words)	0.03	0.18	-0.15	-0.04	-0.02	-0.05	-0.04	-0.04	-0.03	-0.12	-0.08	0.02			
12. Prior experience (0=No, 1=Yes)	0.72	2.22	0.09	0.09	-0.02	-0.09	0.34	0.15	0.06	-0.08	0.05	-0.11	-0.03		
13. Canceled (0=No, 1=Yes)	0.05	0.21	-0.13	-0.05	-0.03	-0.06	-0.04	-0.04	0.00	0.15	-0.04	-0.09	0.01	-0.03	
14. Campaign duration (Days, log)	3.40	0.35	0.17	0.02	0.05	0.13	-0.20	-0.20	0.13	0.37	-0.06	0.14	-0.01	-0.22	0.07
15. Tag age (Days, log)	7.73	0.55	0.06	0.04	-0.02	-0.10	0.05	0.35	-0.02	-0.08	0.04	-0.06	-0.04	0.18	0.02
16. Video (0=No, 1=Yes)	0.76	0.43	0.25	0.07	0.07	0.26	-0.11	-0.16	0.17	0.40	0.00	0.07	-0.08	-0.10	0.04
17. Gender	1.95	0.64	-0.02	0.03	0.02	-0.04	0.01	-0.07	0.11	0.15	-0.06	0.19	-0.01	-0.01	0.14
18. Country	20.51	7.64	0.03	0.02	0.01	0.04	0.08	-0.04	0.06	0.03	0.00	-0.01	0.01	0.05	-0.02
19. Tag concurrent launches	17.89	26.68	-0.17	0.00	-0.04	-0.26	0.13	0.27	-0.30	-0.29	0.03	-0.05	-0.02	0.12	-0.01
20. Tag prior performance (Log)	10.17	0.93	0.19	0.06	0.03	0.12	-0.02	-0.04	0.09	0.18	0.01	0.02	-0.05	0.02	0.03
21. Tag maturity (Log)	83.31	94.57	-0.10	0.08	-0.03	-0.33	0.20	0.36	0.12	-0.20	0.03	0.00	-0.06	0.32	0.06
22. Tag activity	1,558.57	1,507.83	-0.10	0.07	-0.04	-0.33	0.18	0.37	0.01	-0.23	0.03	-0.02	-0.04	0.31	0.05
23. Season	2.52	1.13	-0.08	0.01	0.00	-0.07	0.05	0.06	-0.03	-0.13	0.02	-0.03	0.02	0.01	-0.03
24. Weekday	4.36	2.13	0.09	0.04	0.02	0.06	0.02	-0.02	0.01	0.07	0.02	-0.01	-0.01	0.02	0.01

N= 14,108.

Table 5: Descriptive statistics and correlation matrix.

Variables	14	15	16	17	18	19	20	21	22	23
Control variables										
15. Tag age (Days, log)	-0.15									
16. Video (0=No, 1=Yes)	0.27	-0.18								
17. Gender	0.08	-0.15	0.12							
18. Country	0.04	-0.20	0.07	0.05						
19. Tag concurrent launches	-0.37	0.23	-0.29	-0.01	-0.05					
20. Tag prior performance (Log)	0.09	0.26	0.14	0.04	-0.04	-0.19				
21. Tag maturity (Log)	-0.22	0.47	-0.17	0.08	-0.07	0.49	0.05			
22. Tag activity	-0.24	0.56	-0.22	0.02	-0.10	0.53	0.01	0.97		
23. Season	-0.12	-0.01	-0.12	-0.01	0.01	0.27	-0.14	0.06	0.05	
24. Weekday	0.02	0.03	0.04	-0.01	0.00	-0.03	0.05	0.01	0.00	-0.02

N= 14,108.

Table 6: (continued).

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	Linear regression DV: Amount pledged							*Negative binomial* DV: Repeat backers						*Negative binomial* DV: First-time backers				
Control variables																		
Funding goal (Log)	0.747***	0.729***	0.749***	0.749***	0.746***	0.732***	0.407***	0.382***	0.416***	0.413***	0.407***	0.395***	0.590***	0.562***	0.590***	0.588***	0.592***	0.561***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Updated (0=No, 1=Yes)	0.711***	0.705***	0.701***	0.707***	0.708***	0.685***	1.024***	1.031***	1.001***	1.012***	1.026***	0.989***	0.283***	0.254***	0.284***	0.290***	0.287***	0.273***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.063)	(0.062)	(0.063)	(0.061)	(0.063)	(0.059)	(0.059)	(0.061)	(0.060)	(0.060)	(0.059)	(0.061)
Failed (0=No, 1=Yes)	-2.266***	-2.216***	-2.256***	-2.263***	-2.270***	-2.207***	-2.036***	-1.955***	-2.004***	-2.024***	-2.034***	-1.918***	-2.064***	-1.974***	-2.064***	-2.066***	-2.062***	-1.977***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)	(0.037)	(0.037)	(0.036)	(0.037)	(0.037)	(0.036)	(0.043)	(0.044)	(0.043)	(0.043)	(0.042)	(0.044)
Low word count (0=No, 1=Yes)	-0.309***	-0.297***	-0.294***	-0.304***	-0.310***	-0.277***	-0.340***	-0.316***	-0.291***	-0.324***	-0.341***	-0.255***	-0.130	-0.078	-0.132	-0.135	-0.136	-0.096
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.080)	(0.078)	(0.085)	(0.081)	(0.080)	(0.083)	(0.098)	(0.102)	(0.097)	(0.097)	(0.096)	(0.098)
Prior experience	0.051***	0.051***	0.042***	0.051***	0.051***	0.044***	0.054***	0.055***	0.032***	0.053***	0.054***	0.035***	-0.031**	-0.033***	-0.031**	-0.031**	-0.032**	-0.034***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
Canceled (0=No, 1=Yes)	-2.328***	-2.270***	-2.320***	-2.325***	-2.333***	-2.265***	-2.018***	-1.943***	-2.000***	-1.995***	-2.015***	-1.911***	-2.231***	-2.145***	-2.231***	-2.238***	-2.224***	-2.144***
	(0.047)	(0.046)	(0.047)	(0.047)	(0.047)	(0.046)	(0.064)	(0.062)	(0.064)	(0.065)	(0.064)	(0.062)	(0.070)	(0.068)	(0.070)	(0.071)	(0.070)	(0.069)
Campaign duration (Log)	0.037	0.053*	0.055**	0.039	0.042	0.085***	-0.212***	-0.187***	-0.166**	-0.192**	-0.214***	-0.114	0.185*	0.187*	0.183*	0.180*	0.177*	0.163*
	(0.028)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.077)	(0.072)	(0.079)	(0.077)	(0.077)	(0.074)	(0.103)	(0.100)	(0.102)	(0.104)	(0.103)	(0.098)
Tag age	0.207***	0.198***	0.208***	0.193***	0.218***	0.187***	0.332***	0.346***	0.339***	0.275***	0.328***	0.297***	-0.015	-0.007	-0.015	0.009	-0.027	0.007
	(0.026)	(0.025)	(0.026)	(0.027)	(0.026)	(0.026)	(0.042)	(0.039)	(0.042)	(0.046)	(0.042)	(0.042)	(0.057)	(0.052)	(0.057)	(0.054)	(0.057)	(0.050)
Video (0=No, 1=Yes)	-0.031	-0.064***	-0.023	-0.031	-0.026	-0.045**	-0.048	-0.108***	-0.051	-0.052	-0.051	-0.106**	0.396***	0.321***	0.397***	0.393***	0.390***	0.307***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.043)	(0.042)	(0.043)	(0.044)	(0.043)	(0.041)	(0.075)	(0.073)	(0.075)	(0.075)	(0.074)	(0.072)
Tag concurrent launches	-0.000	0.000	-0.000	-0.000	-0.001	-0.001**	0.001	0.002**	0.001*	0.001	0.001*	0.000	-0.004**	-0.004***	-0.004**	-0.004**	-0.004**	-0.003*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Tag prior performance (Log)	0.080***	0.072***	0.081***	0.083***	0.076***	0.073***	0.045**	0.029	0.046**	0.054**	0.046**	0.039*	0.030	0.015	0.030	0.026	0.033	0.014
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.022)	(0.021)	(0.022)	(0.025)	(0.023)	(0.023)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Tag maturity	-0.003***	-0.002***	-0.003***	-0.003***	-0.002***	-0.002***	0.006***	0.007***	0.005***	0.005***	0.006***	0.006***	-0.001	-0.000	-0.001	-0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tag growth	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Independent variables																		
Staff pick (0=No, 1=Yes)		0.235***				0.235***		0.385***				0.390***		0.474***				0.469***
		(0.018)				(0.018)		(0.033)				(0.034)		(0.047)				(0.046)
Community insider			0.001***			0.001***			0.002***			0.002***			-0.000			-0.000
			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)
Past narrative distinctiveness				1.448**		3.145***				8.365***		9.415***				-3.066**		-4.631***
				(0.574)		(0.654)				(0.979)		(1.117)				(1.270)		(1.353)
Live narrative distinctiveness					-1.220***	-2.189***					0.564	-2.385***					1.444**	2.828***
					(0.327)	(0.370)					(0.542)	(0.631)					(0.699)	(0.792)
Constant	0.027	0.131	-0.069	-1.182**	1.024**	-0.796	-1.074**	-1.212**	-1.399***	-8.225***	-1.540**	-7.548***	-2.011***	-1.935***	-2.002***	0.587	-3.178***	-0.303
	(0.296)	(0.285)	(0.297)	(0.541)	(0.399)	(0.537)	(0.543)	(0.522)	(0.541)	(0.973)	(0.688)	(0.930)	(0.588)	(0.586)	(0.588)	(1.272)	(0.852)	(1.204)
R^2	0.685	0.689	0.687	0.686	0.686	0.691												
AIC	37988.3	37820.1	37922.9	37984.0	37976.0	37723.2	183738.0	183364.3	183448.1	183570.8	183737.5	182918.8	133194.0	132709.4	133195.8	133178.0	133182.9	132667.7

Includes dummies for country, gender, season, and weekdays.
Robust standard errors reported in parentheses.
*Signif. codes: ***: 0.01, **: 0.05, *: 0.1.*
N=14,108.

Table 7: Regression analysis.

In line with our expectations, a significant positive direct effect of *staff pick* can be found on the *amount pledged* and *first-time* and *repeat backers*. This lends support to our Hypothesis 1. We also find a positive direct effect of *community insider* on the *amount pledged* and the number of *repeat backers* but not on the number of *first-time backers*. The coefficient for *community insider* in Model 14 is negative and not statistically significant (p<0.883). This lends initial support to Hypothesis 2. Models 10, 11, 16, and 17 test Hypothesis 3, which postulates the legitimating effect of *past narrative distinctiveness* and *live narrative distinctiveness* on a campaign's ability to enlist *repeat* or *first-time backers*. Model 10 shows a positive and highly significant direct effect for *past narrative distinctiveness* on a campaign's ability to enlist *repeat backers*. Model 16, in contrast, shows a negative and highly significant direct effect of *past narrative distinctiveness* on a campaign's ability to enlist *first-time backers*.

The coefficient of *live narrative distinctiveness* in Model 11 is positive but not statistically significant. Whereas the coefficient of *live narrative distinctiveness* in Model 17 is positive and highly significant. This supports Hypothesis 3, indicating that deviating from past campaign narratives has a positive legitimating effect on *repeat* and deviating from live campaign narratives has a positive legitimating effect on *first-time backers*.

Finally, we formally test if the legitimacy mechanisms are equally strong for *repeat* and *first-time backers*. Comparing the two coefficients builds on the fact that testing $\beta_1 = \beta_2$ is equivalent to testing $\beta_1 - \beta_2 = 0$. To statistically test this, one can use the Wald test for the equality of the coefficients:

$$z = \frac{\beta_{repeat} - \beta_{first}}{\sqrt{\sigma^2_{repeat} + \sigma^2_{first} - 2\sigma_{repeat,first}}} \tag{3}$$

where β_{repeat} and σ^2_{repeat} resemble the coefficient and standard error respectively from the repeat backer equation, β_{first} and σ^2_{first} the coefficient and standard error respectively from the first-time backer equation, and $\sigma_{repeat,first}$ the covariance between β_{repeat} and β_{first}. If z

Independent variables	Model 1 Repeat backers	Model 2 First-time backers	M1-M2
Staff pick (0=No, 1=Yes)	0.390***	0.469***	-0.078**
	(0.034)	(0.046)	(0.034)
Community insider	0.002***	-0.000	0.002***
	(0.000)	(0.000)	(0.000)
Past narrative distinctiveness	9.415***	-4.631***	14.046***
	(1.117)	(1.353)	(1.149)
Live narrative distinctiveness	-2.385***	2.828***	-5.213***
	(0.631)	(0.792)	(0.652)

*Robust standard errors reported in parentheses. Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Only variables of interest listed. Based on Models 12,18 in Table 7.*

Table 8: Cross-model testing of regression coefficients.

exceeds the critical value, then the null hypothesis of both coefficients being equal is rejected. As both coefficients and standard errors originate from different estimations, comparing their relative strength formally demands cross-model hypotheses testing, which faces the challenge of lacking the joined covariances $\sigma_{repeat,first}$ (Mize et al., 2019). To compute these covariances, we use the Stata post-estimation command *suest*.[5]

Estimating the linear combinations ($\beta_1 - \beta_2 = 0$) of these coefficients with the *lincom* command allowed us to compile Table 8 and analyze the extent to which the coefficients differ significantly. Although full models with all control variables were estimated, we only display the variables of interest for parsimonious reasons. To illustrate: The coefficient of *staff pick* in Model 1 of Table 8 is precisely the same as in Model 12 of Table 7. The column "M1-M2" shows the differences in the coefficients across the respective models M1 and M2 from Table 8 and indicates whether the difference is significant. In line with Hypothesis 1, the associative mechanism *staff pick* has a significantly stronger effect on *first-time* than *repeat backers*. The organizational mechanism *community insider* has an effect that is stronger for *repeat backers*, as put forward by Hypothesis 2. In line with Hypothesis 3, we also find that the effect of *past narrative distinctiveness* between *first-time* and *repeat backers* is significant. Caution is advised in interpreting the differences for the *live narrative distinctiveness* as one has to take into account that for *repeat backers*, the effect of the *live narrative distinctiveness* seems at least partially driven by the correlation with the *past narrative distinctiveness*, as

[5]See https://www.stata.com/manuals/rsuest.pdf for additional information.

its effect on *repeat backers* is not significant (see Model 11 in Table 7). Therefore, in this case of the *live narrative distinctiveness*, we repeated our calculations by estimating the linear combination of the direct effect coefficients taken from Models 11 and 17 in Table 7. We find a marginally significant effect that *live narrative distinctiveness* is stronger for *first-time* than for *repeat backers* ("$M1 - M2$" : $\beta = -0.880, se = 0.549, p = 0.109$).

4.5 Discussion

We set out to explore if what we know about establishing legitimacy with crowdfunding backers extends to a broader range of campaign topics and backer types. Replicating past research on how technology-based campaigns use identity, associative, and organizational mechanisms to establish legitimacy (Fisher et al., 2017; Taeuscher et al., 2021), we find that all three mechanisms have a similar, positive impact on the amount of funding raised, even in our very diverse cross-section of "on our radar" campaigns. However, key differences prevail in their relative importance and effectiveness for repeat and first-time backers. With the increasing establishment of crowdfunding (Clough et al., 2019; Le Pendeven et al., 2022) and the rising numbers of both first-time and repeat backers (Murray et al., 2020), we believe that a more fine-grained perspective on backers' evaluation of legitimacy is needed and essential. To provide this perspective, we systematize differences between repeat and first-time backers by focusing on both cognitive and normative aspects of legitimacy (Suchman, 1995) and argue along the extent to which backers' abilities to comprehend and evaluate the normative desirability of a campaign have been shaped by experiences, as well as interactions and enculturation as they progress along their membership in the crowdfunding community (Thornton and Ocasio, 1999).

Therefore, our first contribution is conceptualizing and highlighting the differences between first-time and repeat backers and how they matter in establishing legitimacy with them. Although both repeat and first-time backers are not entirely different audiences and share some commonalities in what they deem legitimate, some key differences prevail. First, repeat and first-time backers are receptive to associative mechanisms that showcase endorsement from influential community actors, such as the Kickstarter staff (Fisher et al., 2017). While this is a crucial tool to determine normative appropriateness for first-time and repeat backers alike, it is essential for first-time backers who cannot substitute it with their own experience, compared to repeat backers who may rely on their accumulated knowledge as they progress along their community tenure. As such, an endorsement is also always an indicator of high campaign quality (Soublière and Gehman, 2020); first-time backers favor the fact that some campaigns have been vetted by the Kickstarter staff even more strongly as it also helps them to comprehend campaigns cognitively.

While repeat and first-time backers are relatively close in their evaluation of endorsement by the Kickstarter staff, their receptiveness to the organizational mechanism of expected community behavior already shows some signs of divergence. When evaluating whether a campaign leadership genuinely aligns with the community's values and objectives, repeat backers who are community insiders themselves are well equipped to do so (Brewer, 1999). For them, the organizational mechanism is particularly normatively important. On the other hand, first-time backers are community outsiders. They, therefore, lack the normative and cognitive capabilities to estimate differences in the extent to which a campaign leadership acts in line with community values. Organizational mechanisms are thus rendered ineffective in addressing them.

The differences between repeat and first-time backers regarding the identity mechanism and the campaign narrative are most pronounced. Here, we highlight that repeat and first-time backers utilize different cognitive referents and reference levels when evaluating narratives and their desirable distinctiveness (Durand and Haans, 2022). Repeat backers have a more backward, more historically focused perspective and evaluate narratives compared to past campaigns, while first-time backers have a contemporary focus (Chan et al., 2021). As the evaluation of identity claims always includes the weighing of decision alternatives (Haans, 2019), we, therefore, show that first-time backers find these in live campaigns, where their "first" pledge of support could still have an impact, while the repeat backer approach is more "anchored" in historical precedent and probably their past behavior. With these findings, our study helps to bring together parts of prior literature on entrepreneurial resource mobilization (Fisher et al., 2017; Murray et al., 2020) by conceptualizing how repeat and first-time backers differ and how their values and beliefs have been shaped as they progressed along their membership in the crowdfunding community. Conceptualizing these differences and showing that what we know about repeat backers (Fisher et al., 2017) cannot one-to-one be transferred to first-time backers is our core contribution.

Our second contribution relates to comparing the legitimacy mechanisms of different desirable outcomes, such as attracting repeat versus first-time backers and acquiring funding. While most existing work focuses on the amount of funding pledged as the ultimate performance measure (Le Pendeven et al., 2022), our approach provides a more fine-grained perspective. The effectiveness of legitimacy mechanisms across outcomes differs, most notably for the identity mechanism and the narrative. Here, even opposite preferences emerge, and campaign leaders face a dilemma: While a narrative distinct from past campaigns helps attract repeat backers, it harms their efforts to attract first-time backers. This trade-off can be considered particularly consequential for serial campaign creators that intend to launch repeated campaigns (Soublière and Gehman, 2020) and therefore are keen on building their loyal community (Fisher, 2019). We would explain this result with the fact that first-time backers, as compared to novelty-seeking repeat backers, still rely on the legitimating effects of conformity to established norms and practice (Janisch and Vossen, 2022), as expressed via non-distinct narratives that adhere closely to those of past campaigns (Vossen and Ihl, 2020).

However, as the effect of past narrative distinctiveness is significantly stronger for attracting repeat than for repelling first-time backers, we would conclude that under most conditions, utilizing a narrative distinct from past campaigns seems advisable. Although distinctiveness from live campaigns does attract first-time backers and simultaneously does not repeal repeat backers, it unfortunately also lowers the amount of funding pledged, adding another facet to the dilemma of deciding on a suited campaign narrative that yields the desired funding (Martens et al., 2007). This adds to the significant relevance of the identity mechanism that demands careful managerial attention and consideration, as the trade-offs to be considered are likely very consequential.

This also leads to the focal point of our third contribution, which relates to the literature on cultural entrepreneurship and optimal distinctiveness, particularly in a crowdfunding setting. Our results offer relevant insights into the trade-off between legitimizing and differentiating entrepreneurs face when designing their cultural tools while seeking funding from crowdfunding audiences (Parhankangas and Renko, 2017; Nielsen and Binder, 2021). Narratives have traditionally been shown to need to strike a balance between conforming to appear legitimate and standing out to generate competitive advantages (Haans, 2019; Vossen and Ihl, 2020). Particularly in a crowdfunding setting, it has been shown that the distinctiveness of narratives not only brings competitive benefits but also creates legitimacy (Taeuscher et al., 2021). Our results contextualize these findings by offering a more fine-grained perspective on repeat and first-time backers, who differ in what they relate their distinctiveness evaluation to (Chan et al., 2021; Durand and Haans, 2022). Our results contribute to the growing literature on optimal distinctiveness that focuses on temporal dynamics of conformity and differentiation claims (Zhao and Glynn, 2022). Our results also showcase that backers' preference for distinctiveness over conformity manifests in somewhat transactional and technology-driven campaigns (Taeuscher et al., 2021) but also generalizes to more civic campaigns (Logue and Grimes, 2022) that score high on community relevance and value. Thus, crowdfunding audiences' novelty-expecting and -seeking behavior (Vossen and Ihl, 2020) seems to persist regardless of the campaign's topic.

Besides the aforementioned contributions to theory, this paper also has several important implications for management practice. This paper aids campaign leaders who intend to rely on crowdfunding to fund their idea. Our findings help to understand in which competitive situation it might be more appropriate and valuable to leverage the different means of acquiring legitimacy (Fisher et al., 2017). Notably, these insights go beyond technology-based campaigns and extend to cultural and civic ones. Campaign leaders are advised to spend much effort carefully designing a suitable narrative that can appeal to first-time and repeat backers (Vossen and Ihl, 2020), but also maximize the monetary commitment of first-time backers. Which strategy is best may depend on the individual case and especially on the extent to which campaign leaders favor repeat over first-time backers. The latter is essential for community-building (Fisher, 2019; Murray et al., 2020). If campaign leaders are eager to attract repeat backers, they should strive for an endorsement from the platform host and build a track record of engaging with platform users and campaigns before launching their campaign. Regardless of the individual strategy and the respective objectives, campaign leaders must be sensitive to the subtle and more pronounced differences in establishing legitimacy between repeat and first-time backers.

4.6 Limitations, outlook, and conclusion

This work has limitations that can serve as a starting point for future research studies. As with all empirical studies, limitations arise from the sampling strategy. While we deem the "on our radar" section an appropriate empirical field for testing the suitability of findings from technology-based campaigns for broader, more general campaign topics, it remains a cross-sectional subsample that only accounts for about three percent of all Kickstarter campaigns. While this sampling approach, to our mind, increases the generalizability of our results by showing the effects across all Kickstarter categories, researchers that are interested in specific campaign categories, such as art campaigns, may find it worthwhile to ensure that their sampling strategy puts a greater emphasis on these. As we use the entire sample of available "on our radar" campaigns, we feel sure our results are reliable for campaign creators seeking funding for topics close to the Kickstarter community. To further increase generalizability, particularly regarding the differences between repeat and first-time backers, it seems worthwhile to test our results on different platforms and in different "crowd-based" settings, such as equity crowdfunding (Block et al., 2018; Butticè et al., 2022). However, it could provide challenges operationalizing differences between first-time and repeat backers as only a few platforms utilize such a distinction.

Our list of legitimacy mechanisms is based on recent work (Fisher et al., 2017) but is not intended to be exhaustive. Other mechanisms could play an important role, and their interplay with the ones we focused on could be an exciting venue for further research. A limitation in operationalizing our community insider variable arises from the fact that only the total number of campaigns supported by campaign leadership is now publicly available, not the specific times when that support occurred. It would be interesting to replicate our results in a setting that allows us to control for dynamics in campaign founder support behavior. As our data is by nature cross-sectional, we may suffer from endogeneity that may, for example, arise from omitting essential variables. Although our results remain statistically very robust across different empirical models, and we tried to address this issue with a range of control variables used by prior studies, a future approach using panel data may be able to alleviate such concerns. Other concerns arise from causality issues. We rely strongly on the conceptual work on institutional logic and the different legitimacy mechanisms to address it (Fisher et al., 2017; Murray et al., 2020; Pahnke et al., 2015). However, because of the nature of our secondary data set, we can only measure these mechanisms and their effectiveness through suitable proxies. Future research could strengthen the causal link and create experimental evidence with explicit randomization and manipulation better suited to infer causality.

Moreover, a more fine-grained perspective on the origin of first-time backers could be a suitable venue for future research. While community-based resource mobilization sees first-time backers as a result of leveraging personal networks and existent ties (Murray et al., 2020), our data and interviews suggest that the number of first-time backers that campaigns attract is too high to be explained by this. More work is needed here to help explain the determinants of successful recruitment of first-time backers beyond the campaign-specific network, such as convincing so-called “lurkers” (Malinen, 2015).

Our setting does not allow us to factor in the cost and effort of using one or the other legitimacy signal, that is, how costly and work-intensive developing a suited identity narrative is compared to establishing a track record of proven platform community engagement. Although our operationalization is appropriate and consistent with the conceptual work, future research could give campaign leaders a better sense of what legitimacy signal might be economically responsible and meaningful.

We encourage future research on how backers diverge to understand and classify heterogeneity within the group of backers more deeply. This work shows how repeat and first-time backers differ, how this affects their legitimacy assessment of campaigns, and how campaign creators can best convince these different backer types of their legitimacy. In doing so, we have taken a first step toward understanding the complexity and mechanisms involved in legitimacy evaluation in community-based resource mobilization and entrepreneurial resource provision. We believe that our work has provided first insights for researchers and crowdfunding stakeholders that will help to establish the notion that, to garner legitimacy, crowdfunding campaigns should be “dancing to multiple tunes” of a heterogeneous backer audience.

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

Authorship	Weiss, Stephanie; Knöferle, Klemens; Vossen, Alexander.
Main theoretical concepts	Entrepreneurial narratives; optimal distinctiveness; sensory marketing.
Methodology and sample	Quantitative; large panel data set including 297 new ventures, 1,312 products, 292 weeks (2015-2020).
History of the study	Presented at the Academy of Management Annual Meeting (AOM) 2022.
Publication status	Planned submission for the Academy of Management Journal.
Contribution	In this study I was in charge of collecting all data, reviewing the literature, analyzing the data and writing the study.

Table 9: Information about study two.

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, and their richness—the amount of meaning conveyed. We find that both effects are strongly contextualized by the product category they are used in. A high semantic fit is beneficial in non-distinct product categories that share frequent relations with others in the meaning system. Still, this relative advantage diminishes with increasing product category distinctiveness. Semantic richness is evaluated favorably in distinct categories, 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 allows entrepreneurs to express differentiation and conformity and can also effectively 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

JEL Codes: C33, L1, L81, M13

5.1 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 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 transmitted 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 as 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 essential 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 instead 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 the 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 how 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 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 carries more semantic meaning because it contains multiple objects. It helps contextualize the product in terms of the intended target group, product features, possible use scenarios, and other vital 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 defines the competitive context and 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). A product category's distinctiveness further shapes these behavioral expectations–how uncommon a product category is to all other product categories in the same market (Lo et al., 2020; Taeuscher et al., 2022; Janisch and Vossen, 2022). Consequently, we ask two research questions: (1) How do visual storytelling's semantic fit and 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 five years of weekly sales data from 297 new ventures that offer 1,312 entrepreneurial products on Amazon Launchpad, a dedicated sub-section of Amazon's online B2C market for products by new ventures. We collected 9,072 unique product images to analyze visual storytelling and 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 positively affect product evaluation. This effect is contextualized by the product categories in which evaluation takes place. The positive effect of semantic fit is more pronounced in non-distinct product categories that overlap with other categories due to many shared properties. In contrast, 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. In contrast, the positive effect of semantic richness is accentuated. However, semantic fit and richness mutually reinforce each other, especially in distinct product categories.

By adding a sensory perspective to the predominantly cognitively focused discussion on entrepreneurial storytelling, we bridge two major existing kinds of literature, namely in sensory marketing (Hulten et al., 2009; Krishna, 2012) and audience evaluation of strategic differentiation decisions (Navis and Glynn, 2011; Smith, 2011; Zhao and Glynn, 2022). Focusing on the context of new ventures in online B2C markets, we provide meaningful insights into when and why specific visual strategies favorably affect consumer audiences' evaluation. Cultural entrepreneurship research focuses on how entrepreneurs craft narratives that appeal to target audiences and support legitimizing new ventures (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 its semantic meaning help entrepreneurs compete in different categorical contexts.

Our work provides clear-cut implications for managers to incorporate visual storytelling in their appeals to consumer audiences. When designing product-promoting visuals, managers must not only consider their basic visual properties such as illuminance, shape, or color (Sample et al., 2020; Sgourev et al., 2022) but also 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 semantic fit and richness level for the categorical context, new ventures can ensure that there is "more than meets the eye" in their product images.

5.2 Theoretical background

5.2.1 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, and standing out to generate competitive benefits (Haans, 2019). Not only is this trade-off very context-sensitive (Haans, 2019), but it is also incredibly 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 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-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, have 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 essential factors for audience evaluation, we consider visuals from a storytelling perspective that focuses not so much on the design of a particular product but instead 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 primary 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 visual product 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 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 close to their expectations and more familiar because familiarity makes information easier to process, thereby saving 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 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 critical factor in whether audiences perceive distinctiveness positively or negatively (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 regarding visual semantic meanings can help new ventures signal 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 differs 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 uniquely 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 the 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 facilitates 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 distract consumers from the core product attributes due to the amount of information-carrying meaning (Kim et al., 2016).

These arguments show that semantic fit and richness can be valuable 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 discuss how semantic fit and richness affect audience evaluation and product performance across different product categories and develop our hypotheses.

5.2.2 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 their distinctiveness appeal (Deephouse, 1999; Zuckerman, 1999). Product categories facilitate audience comparison of products (Phillips and Zuckerman, 2001) by reducing audiences' consideration set as product categories group products with similar characteristics such as "cultural features, values, and potential use" (Vergne and Wry, 2014 p.68). Reduced consideration sets are particularly relevant as evaluating audiences have limited attentive and cognitive resources. Thus, the 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 to evaluate one product compared to others (Cattani et al., 2017). Thus, in 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 category distinctiveness, that is, their 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).

Using 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, making 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 category should thus adhere to consumers' expectations of conformity by using a visual narrative with a 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 explicitly 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 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 4: *High levels of semantic fit in visual storytelling increase product performance in non-distinct categories.*

Hypothesis 5: *Low levels of semantic fit in visual storytelling increase product performance in distinct categories.*

Consumers' demand for information may differ depending on whether a product is active in non-distinct or distinct product categories. 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 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 by 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. 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 through 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), 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 rich in semantic meaning. This leads to Hypotheses 3 and 4.

Hypothesis 6: *Low levels of semantic richness in visual storytelling increase product performance in non-distinct categories.*

Hypothesis 7: *High levels of semantic richness in visual storytelling increase product performance in distinct categories.*

	Semantic fit	Semantic richness
Non-distinct product category	High (H4)	Low (H6)
Distinct product category	Low (H5)	High (H7)

Table 10: Summary of hypotheses.

5.3 Empirical approach

5.3.1 Sample and data collection

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. Still, they are also subject to intense competition due to low barriers to entry, making it challenging to capture the attention of consumer audiences. To alleviate this problem for innovative new ventures (such as small and medium brands with unique selling points 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.[6] Thus, the Amazon Launchpad setting provides a unique perspective for studying new ventures that explicitly compete in existing product markets for consumers particularly interested in entrepreneurial products.

To identify our sample, we collected information on all products on the U.S. Amazon 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 develop high-quality visuals. To improve comparability, we only included products that were available at the time of data collection

[6]For more detailed information on Amazon Launchpad and its program terms, please refer to 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.

and also in all western Amazon Launchpad summaries (France, Germany, Italy, Spain, the United Kingdom, and Canada) between February 2015 and September 2020 (292 weeks). The reasoning 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, consequently, the resources for professional imagery. To uniquely identify a product and a new venture, we used the Amazon Standard Identification Number (ASIN) and venture information, such as the venture name, tax number, or trade register number. After eliminating resellers who exclusively sell products they do not produce themselves and ventures that could not be considered new ventures owing to their size or age, we were left with 1,561 products.

We used the commercial data analytics service Keepa.com to obtain panel data on price trends, sales performance, and product category information (Janisch and Vossen, 2022). Keepa.com tracks hundreds of millions of international Amazon products and allows subscribers to access this data through an API. 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 then removed products from the dataset for which these data were incomplete, leaving a total of 1,312 products. This entails products for which no sales data was available (10 products) or we had less than three daily observations (42 products). We removed all products for which Keepa.com did not provide category (195 products) or image information (43 products). Since our observation period is extensive, 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 these 292 weeks, our panel is unbalanced.

Next to data on prices and sales, Keepa.com also collects links to product images and product category tags about the respective products that play a crucial role in constructing variables for our analysis. Consumers can use product categories on Amazon Launchpad to find and compare products more efficiently. 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. Cycling lights and fitness watches share many features as they are both used for sports activities. Due to this feature overlap, these products can be found in the same basic category *Sports & Outdoors* as indicated by their affiliated top tags. Although cycling lights and fitness watches 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 groups them into first and second subordinate categories (Gehman and Grimes, 2017) (see Table 11).

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 11: 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. This distinction is too granular for investigating how the evaluative boundary conditions set out by the respective product categories shape the effectiveness of image semantic fit and semantic richness on product sales performance. We used a product's basic category provided by Keepa.com as a 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. Suppose products share the same basic category and the first and second subordinate categories. In that case, 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 category context's role in 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 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 that allows its users to detect labels, representing objects, scenes, actions, or concepts in images with artificial intelligence using deep learning.

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 4: Labels detected by Amazon Rekognition in sample image with confidence scores.

For each identified label, Amazon Rekognition provides a confidence score that indicates the accuracy of the label.[7] The illustrative example in Figure 4 shows a self-taken photograph's label results and confidence scores. For the depicted mountain scenery, Amazon Rekognition suggests labels such as tent (object), mountain range (scene), camping (action), and outdoors (concept). We set a threshold value to avoid false positives—incorrectly predicted labels—and false negatives—labels present in an image but not predicted. 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.[8]

5.3.2 Dependent variable

Our dependent variable is *Amazon sales rank*. To operationalize our dependent variable, we log-transformed and averaged the sales rank for each product and each week during observation (Chevalier and Mayzlin, 2006; Smith and Telang, 2009; van Oest et al., 2010). A product's market-specific sales rank does not represent sales performance in absolute terms. Compared to a product in a larger market, a product in a smaller market could achieve a high ranking even with relatively modest sales. To account for this, we control for competition within a market category. For interpreting the dependent variable, it is crucial to remember 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 the interpretation of our results more intuitive, we multiplied the sales rank by negative one.

5.3.3 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

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

[8] We opted for this value in line with Amazon's reasoning but would argue that a 55% certainty should be a lower bound, as anything below that would 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.

image links provided for a product by Keepa.com and analyzed them with Amazon Rekognition. For each image, we 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 resulting from human categorization data training. We assume that the amount of meaning an image conveys, 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 follows:

$$Image\ semantic\ richness_i = \frac{\sum_{x=1}^{X} L_{ix}}{X} \tag{4}$$

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

Image semantic richness measures the number of labels provided in visual storytelling. Still, it 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 the 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 adjacent to the same words share the same context and thus have a similar meaning (Le and Mikolov, 2014). As the name suggests, word2vec translates words into unique numeric vectors. To mathematically compute and recognize the context of words, the so-called word embeddings, word2vec trains a neural network that learns a word's semantic and syntactic qualities 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, assigning a unique vector to each word and document with variable text length. That is, doc2vec learns in what context a word appears and whether that context is specific to a particular document. Doc2vec can be used for different documents; the only requirement is that the documents 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, can 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 the 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 is used to calculate document similarities, we first had to convert the visual 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 to or above 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. We set the vector size for the word embeddings as training parameters to 300 dimensions. We specified that the meaning context of a label should be learned based on a local context window of three labels 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 a similar meaning close to each other. In contrast, different 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 5 shows ten sample input labels of our image training data and the three labels identified as most similar in meaning for each of these input labels. As seen in Figure 5, 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."[9]

[9]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. Compared 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 essential to consider that the similarities we measure relate to object labels in images, not words in textual documents. For example: While "whiskey" and "cocktail" are very similar to image labels, this only means they appear visually in the same context–think of a "hand," a "table," or a "bar." If we would analyze news articles and measure their similarity, they would likely be more different because "whiskey" could be reported more in the dark and gritty context of drunken violence.

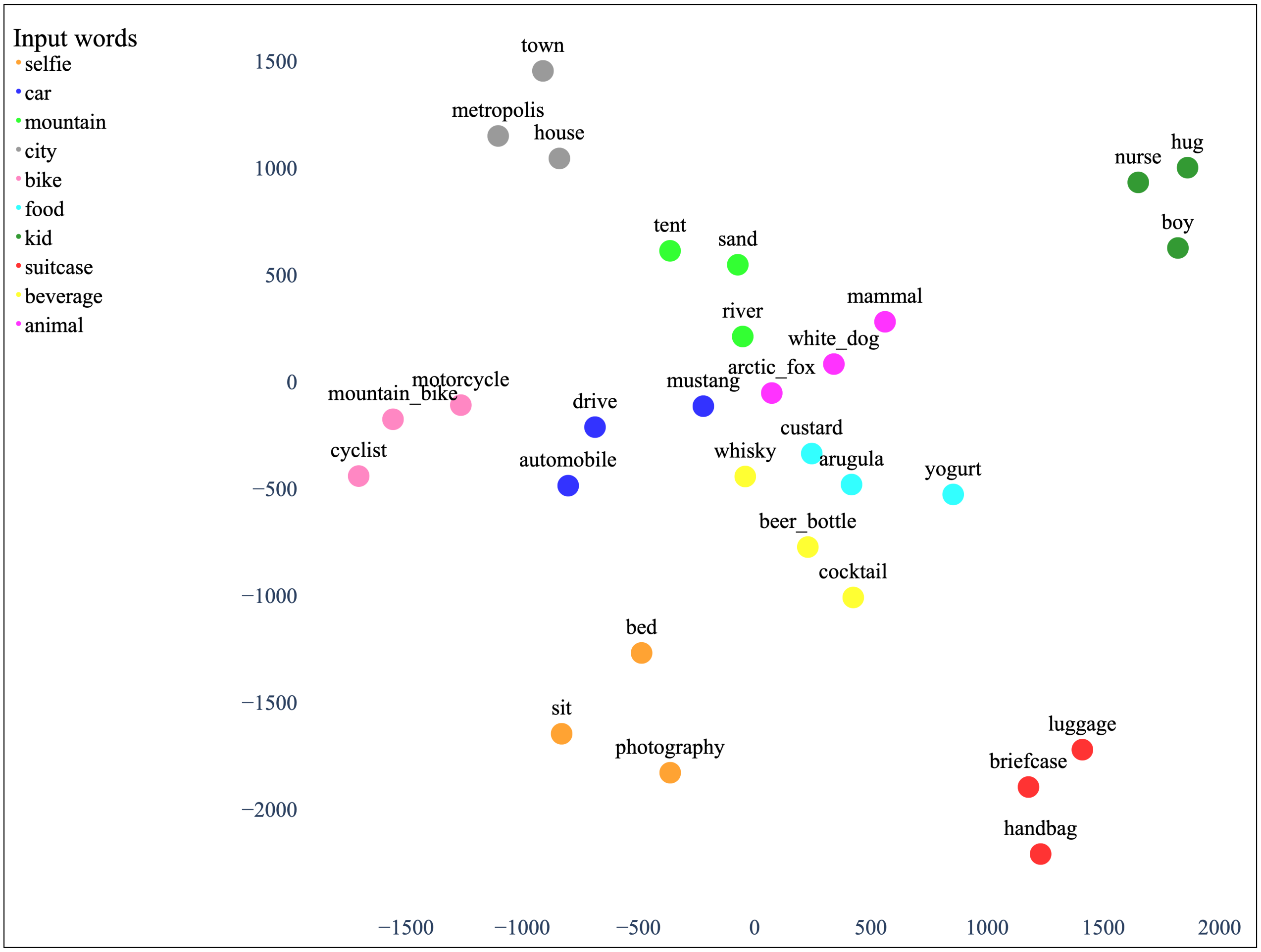

Figure 5: tSNE of image training data—ten sample labels and their three labels most similar in meaning.

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:

$$Image\ semantic\ fit_{ij} = \left[\frac{\sum_{w=1}^{W} f_{iw}\, f_{jw}}{\sqrt{(\sum_{w=1}^{W} f_{iw}^2)} \cdot \sqrt{(\sum_{w=1}^{W} f_{jw}^2)}} \right] \tag{5}$$

At the same time "cocktail" could be mentioned more frequently in the fun and bright nightlife context. Despite these limitations, results show that the algorithm works quite well.

We averaged all the comparisons, added, and then averaged the semantic fit values of all individual images of a product i.[10]

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. We 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 with the same top tag (belonging 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 then 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). As a result, we determined the distances between each product j in the same basic product category and the focal product i as follows:

$$Product\ distance_{ij} = 1 - \left[\frac{\sum_{k=1}^{K} f_{ik}\, f_{jk}}{\sqrt{(\sum_{k=1}^{K}\ f_{ik}^2)} \cdot \sqrt{(\sum_{k=1}^{K}\ f_{jk}^2)}} \right] \tag{6}$$

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

$$Product\ category\ distinctiveness_i = \frac{\sum_{j=1, j \neq i}^{N} Product\ distance_{ij}}{N} \tag{7}$$

[10] Although prior research often conceptualizes the relationship between fit (or distinctiveness) and performance as curvilinear, we do not find such a shape. Our results align with 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).

where N is the total number of products in the corresponding basic product category and week.

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.

5.3.4 Control variables

To increase the 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 established customer bases, higher awareness of older products, and learning effects (Cohen and Levinthal, 1990). In addition, we control for *new venture competition* and *product competition* in a specific market category based on the shared basic 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) Skincare, (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 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:

$$Firm - level\ distance_{ij} = 1 - \left[\frac{\sum_{c=1}^{C} f_{ic} f_{jc}}{\sqrt{(\sum_{c=1}^{C} f_{ic}^2)} \cdot \sqrt{(\sum_{c=1}^{C} f_{jc}^2)}} \right] \tag{8}$$

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 follows:

$$Firm - level\ distinctiveness_i = \frac{\sum_{j=1, j \neq i}^{N} Firm - level\ distance_{ij}}{N} \tag{9}$$

where N is the total number of new ventures launched during that particular week. Please refer to Table 12 for a summary of all variables used within the analysis.

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 fit	Cosine similarity of all image labels affiliated with a product i in the respective week t and subordinate category c using doc2vec.
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.
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 product introduction 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 12: Variable descriptions.

5.4 Results

Table 13 shows all variables' descriptive statistics and correlations. Except for the variables of *product category distinctiveness* and *product competition,* as well as for *product competition* and *new venture competition*, we find primarily low or moderate correlations. Table 14 provides the results of our hypothesis tests. Due to the structure of our data, we used a nested random effects model. We estimate random effects models as the *semantic richness* variable is time-invariant and use the nested option since one new venture can have multiple products. Still, 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 analyzed all statistics using the free statistics software R and the *PLM* package (Croissant and Millo, 2008).

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

N=240,790.

Table 13: Descriptives and correlations.

	Dependent variable:									
	Amazon sales rank									
	1	2	3	4	5	6	7	8	9	10
Control variables										
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)
Independent variables										
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)
Interactions										
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

Heteroscedasticity- and autocorrelation-robust standard errors (Newey West) reported in parentheses.
*Signif. codes: ***: 0.01, **: 0.05, *: 0.1.*
N=240,790.

Table 14: Results of nested (new venture) random effects regression (PLM)—image models (label recognition threshold value of 55%).

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), *image semantic richness* (b= 0.087, p= 0.037), and *product category distinctiveness* (b= 3.329, p< 0.001).[11]

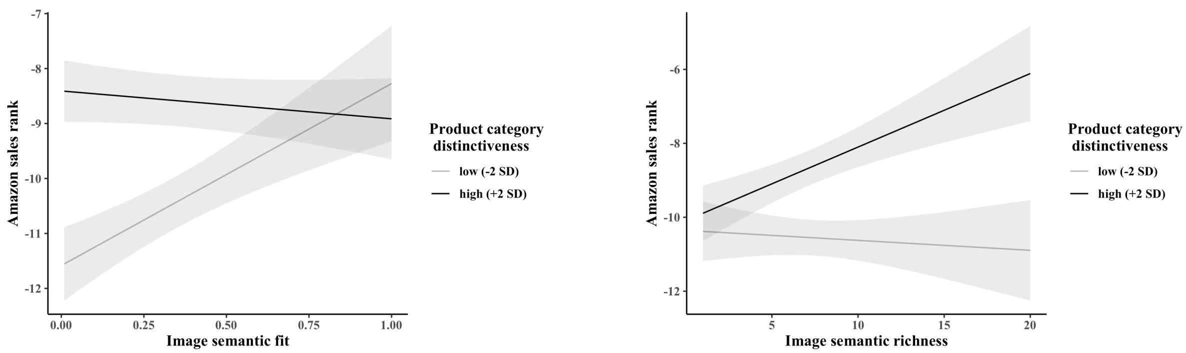

Figure 6: Effect of image *semantic fit* (image *semantic richness*) on product sales performance moderated by low (-2 SD) and high (+2 SD) *product category distinctiveness*. Based on model 6 (and 7) in Table 14.

To test our Hypothesis 4 that proposed a positive effect of high levels of *image semantic fit* in visual storytelling for products' performance in non-distinct categories and Hypothesis 5 that proposed a positive effect of low levels of *image semantic fit* in visual storytelling 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 6. 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 them. On the other hand, 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.

[11]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).

To test our Hypothesis 6 that proposed a positive effect of low levels of *image semantic richness* in visual storytelling for products' performance in non-distinct categories and Hypothesis 7 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 6. Our results suggest that new ventures in distinct categories rich in semantic meaning in their visual storytelling perform better than those less rich. 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 an interaction between *semantic richness* and *fit* on sales performance and 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.

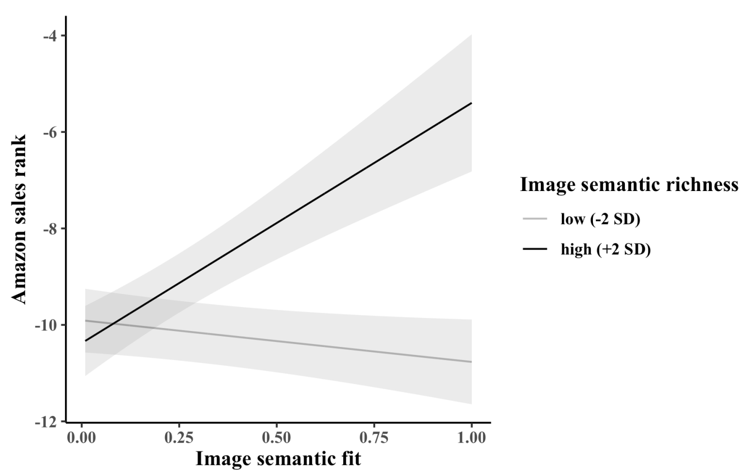

Figure 7: Effect of image *semantic fit* on product sales performance moderated by low (-2 SD) and high (+2 SD) *image semantic richness*. Based on model 8 in Table 14.

However, analyzing the respective plots visually showcases that the interaction effect

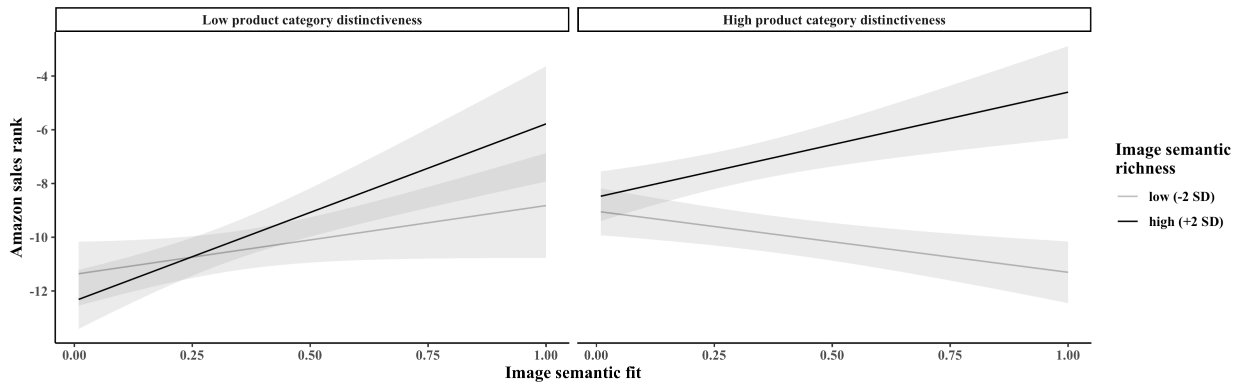

Figure 8: Effect of image *semantic fit* on product sales performance moderated by low (-2 SD) and high (+2 SD) image *semantic richness* and low (-2 SD) and high (+2 SD) *product category distinctiveness*. Based on model 9 in Table 14.

of *semantic fit* and *richness* is not meaningful for low levels of *semantic fit* in Figure 7. This induces that if new ventures rely on non-conforming visual labels, the number of labels used does not impact the *sales rank* differently. However, looking at Figure 8 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 a low *semantic richness* in most cases, especially in highly distinct product categories.

5.5 Discussion

This study aimed to understand 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 essential 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 influence their appeal to evaluating audiences actively. Thus, our work extends past studies' focus on using 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 new ventures can strategically use this visual component 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 favor visual storytelling that aligns with competitors and provides meaningful, additional context that helps sensemaking. As such, visual semantics not only offer new ventures suitable tools for 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 in its fit or distinctiveness and the degree to which 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 first showcases how state-of-the-art machine learning and image label recognition approaches may open up future research avenues in how storytelling may help balance the need for conformity and distinctiveness (Zhao and Glynn, 2022).

Our third contribution relates to the contextual role of product categories in 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 audience preferences (Janisch and Vossen, 2022; Lo et al., 2020; Taeuscher et al., 2022). This also showcases that interpreting the average direct 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 audiences prefer an effortless evaluation (Paolella and Durand, 2016; Smith, 2011). Using semantic fit is less effective in distinct product categories, where audiences and the cultural code provided favor distinctiveness (Taeuscher et al., 2022). In such a categorical context, the benefits of semantic richness unfold as its impact on evaluating audiences is stronger in distinct product categories. In contrast, it is rendered weaker in non-distinct ones.

Differences in product category distinctiveness also affect how semantic richness and fit interact. Visual storytelling with high semantic fit benefits significantly from semantic richness, gradually becoming more relevant in product categories with increasing distinctiveness. Thus, while the effects of semantic fit and richness are primarily independent 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 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 empirical and conceptual arguments on why semantic fit and semantic richness are effective means to measure the functional properties of visual storytelling and how the meanings conveyed influence audience evaluation. In this way, our study extends the current literature's focus on low-level visual features, such as color schemes and patterns (Sgourev et al., 2022). Our analysis also adds an essential 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) and design complexity (Kosslyn, 1975; Pieters et al., 2010) on audience evaluation. We further provide guidelines on measuring semantic meanings using state-of-the-art machine learning algorithms. Using 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 methods in the field of sensory marketing (Golder et al., 2022).

From a managerial point of view, our results have clear-cut implications for management practice on incorporating visual storytelling in their appeal to consumer audiences, an audience significant for entrepreneurial growth. When designing visual storytelling, managers should know the product categories they intend to use. That requires managers to understand consumer audiences' expectations in their target product category, regarding the type and richness of meaning they need to convey before designing visual storytelling. Especially in distinct product categories, managers may want to ensure they accompany their highly fitting visual narrative with strong semantic richness to avoid audience devaluation. Although the categories set out the evaluative boundary conditions for evaluating their visual narrative (Janisch and Vossen, 2022) and serve as meaning systems to tap into (Vossen and Ihl, 2020), managers should not underestimate the agency they have when designing their visual storytelling. If they carefully use the fit and richness of the semantics they entail, it may help them achieve optimal distinctiveness and be perceived as meaningfully different.

5.6 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 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 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 rank may improve due to a decline in competitors' performance (Chevalier and Mayzlin, 2006; Smith and Telang, 2009).

We applied novel machine learning-based algorithms to make visual storytelling measurable and thus map visual processing by consumers. Follow-up studies could determine whether experimental evidence can confirm this procedure. For this purpose, subjects could be asked to confirm which labels they can recognize in an image or video using 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 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 data 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 primary tool to convey information. Another limitation of this work is that we 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 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 what extent evaluative boundary conditions shape their effectiveness 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 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.

6 Reaching for the *stars*: Entrepreneurial aspirations and optimal distinctiveness on YouTube

Authorship	Weiss, Stephanie; Vossen, Alexander.
Main theoretical concepts	Entrepreneurial narratives; optimal distinctiveness; organizational learning.
Methodology and sample	Quantitative; panel data including 348 YouTube creators, 1,392 YouTube videos.
History of the study	Submitted for presentation to the Academy of Management Annual Meeting (AOM) 2023. Accepted for presentation at the European Academy of Management (EURAM) 2023.
Publication status	Work in progress.
Contribution	In this study I was in charge of collecting all data, reviewing the literature, analyzing the data and writing the study.

Table 15: Information about study three.

Abstract

Optimal distinctiveness postulates that entrepreneurs must position themselves as distinctively as legitimately possible. Extending this view on strategic positioning as a one-time decision, we examine how the most successful entrepreneurial content creators on YouTube repeatedly change their narrative in new video releases. Relying on organizational learning and performance feedback literature, we find that content creators are likely to change if prior performance was below aspirations–expectations founded on their own and competitors' past performance. This response, however, is non-homogeneous, suggesting that narrowly failing aspirations induces a problemistic search that leads to increased change. Missing aspirations by a wide margin causes rigidity, self-enhancement, and less change. Content creators that clearly fail in their aspirations change very little in their next video's narrative. In contrast, those that narrowly fail, respond by releasing a video whose narrative is more distinct from their last release and the market average but is simultaneously less distinct to the exemplar–the most successful content creator "star" in the category. Our work has important implications on how aspirations affect entrepreneurial strategy decisions and adds organizational learning to the contextual factors that shape optimal distinctiveness. Extending the role of competitors from actors to either conform to or differentiate from to a source of learning adds to our understanding of institutional pressures and competitive dynamics in entrepreneurial markets.

Keywords: Optimal distinctiveness, organizational learning, cultural entrepreneurship

JEL Codes: L26, L82, M13

6.1 Introduction

Deciding how to position oneself in the market is a central part of the entrepreneurial strategy (Durand and Haans, 2022; Zhao and Glynn, 2022). Recent research on optimal distinctiveness has proposed that entrepreneurs must find a position that lets them appear as distinct as legitimately possible (Zhao et al., 2017). To express their distinctiveness from competitors in their product category, entrepreneurs often rely on narratives, primarily textual information emphasizing "who and what they are" (Glynn and Navis, 2013; Navis and Glynn, 2011). Past research has shown that narratives can take on many forms, such as product descriptions (Barlow et al., 2019; Taeuscher et al., 2022) and proposals (Vossen and Ihl, 2020), websites (Haans, 2019), or funding campaign texts (Taeuscher et al., 2021). Yet, all these studies observe creating a narrative and the entrepreneurial decision to position oneself as a one-time event. This is in line with a relatively static perspective on optimal distinctiveness in general that perceives changes in distinctiveness primarily as a result of either changes in its appeal over time (Goldenstein et al., 2019; Zhao et al., 2018) or in the competitive context (Janisch and Vossen, 2022). However, this neglects that change may also result from deliberate entrepreneurial action. A premier example of this could be the launch of additional products that prompt the need for new differentiation claims (Bu et al., 2022; Fernhaber and Patel, 2012; Parker et al., 2017). How do these claims differ from the ones entrepreneurs made in the past?

One ever-growing industry where this question is fundamental is online platforms for content creation, where entrepreneurial content creators create and distribute self-generated digital content via platforms such as YouTube, TikTok, Facebook, Instagram, and others (Roccapriore and Pollock, 2022; Johnson et al., 2022). In this way, entrepreneurial content creators "create businesses by interacting with consumers on social media platforms rather than in person, encouraging them to consume the social media content they generate, and purchase or use products and services they provide or endorse" (Roccapriore and Pollock, 2022 p.6). In 2022 alone, this market for so-called influencer marketing has doubled to

16.4 billion USD (Statista, 2022). Due to the low entry barriers (Dushnitsky and Stroube, 2021) and the resulting variety of free content offered (Cunningham et al., 2016), creators must release new content constantly to keep their audience engaged. Each new release also challenges them to position themselves in the highly dynamic competitive environment and to find the correct narrative to differentiate from competitors to attract audiences to their channel (Johnson et al., 2022).

We propose examining why and how entrepreneurial narratives and positioning change mandates a closer examination of the continuous feedback and learning process entrepreneurs experience (Peterson and Wu, 2021). Building on the literature on organizational learning and strategic change (Cyert and March, 1963), we argue that whether or not change occurs relates to entrepreneurial aspirations–actual performance relative to expectations based on own past performance and that of relevant competitors (Baum et al., 2005; Dong, 2021; Greve, 1998). However, the effect of aspirations on change is often not linear, as shortfalls below aspiration–performance gaps or attainment discrepancies (Lant, 1992)–frequently trigger more change. In contrast, performance equal to or above aspiration makes change less likely (Greve, 2003; Tarakci et al., 2018; Ref and Shapira, 2017). A proposed explanation is that performing below aspirations triggers a "problemistic search" that initiates a learning process. The more an organization misses aspirations, it supposedly engages in problemistic search (Posen et al., 2018). Yet, this perspective has been labeled overly optimistic, as organizations that miss their aspiration by a wide margin may also experience less change due to strategic rigidity (Greve, 1998) or feelings of self-enhancement by the responsible decision-makers (Jordan and Audia, 2012; Zhang and Baumeister, 2006). As both steep and unconventional learning, as well as self-enhancement, are well documented in entrepreneurial markets (Forbes, 2005; Politis, 2005), we deem aspirations a suited theoretical lens to analyze and understand the change in entrepreneurial narratives and optimal distinctiveness–an aspect that has so far been neglected in the literature. Consequently, we ask two research questions: (1) Does missing or exceeding aspirations cause an equal change in entrepreneurial narratives? (2) Do entrepreneurs become less or more distinct in them?

To answer these questions empirically, we collected secondary data from the most successful English-speaking content creators on YouTube. YouTube is a premier example of a content creation-based online platform that provides an ecosystem for entrepreneurs to contact potential viewers (Cutolo and Kenney, 2021; Mardon et al., 2018). We collected various variables on the videos, most notably the automatically generated transcripts and viewer comments. We use the former and natural language processing to compose our measures of distinctiveness and change and the latter as our measure for performance and aspirations.

We find that content creators below aspirations are likelier to change their narratives. In what research has coined a non-homogeneous response, this change is most meaningful around the level of aspiration and declines away from it (Greve, 1998). This effect is significantly more substantial for failing than exceeding aspirations. Thus, narrowly failing aspirations induces problemistic search (Posen et al., 2018), while failing aspirations by a wide margin leads to rigidity and self-enhancement behavior that triggers less change (Jordan and Audia, 2012). Analyzing the consequences of this change, we find entrepreneurs become more distinct from the overall market but more similar to the exemplar–the most prominent content creator "star" in the respective category (Barlow et al., 2019; Zhao et al., 2018).

By bridging the important fields of organizational learning and optimal distinctiveness, our work offers insights into the literature on strategy and organizational theory. To the former, we add entrepreneurial learning and past performance as new contextual factors that shape the effectiveness of new ventures' optimal distinctiveness and the strategic positioning new ventures pursue via narratives. For the latter, we show how entrepreneurs stand out in their non-homogeneous response to missing aspirations. We further highlight a new perspective on categorical dynamics and the role of prototypes and exemplars not only as competitors to differentiate from or conform to but as sources of learning. Showcasing how full-time content creators learn and change also provides valuable practical insights for millions of small-scale entrepreneurs that aim at creating content for online social media platforms. Following their example, future content creators should be "reaching for the stars" when they find themselves missing their aspirations and needing to revise their content.

6.2 Theoretical background

6.2.1 Optimal distinctiveness and strategic change

The strategic management literature shows that entrepreneurs must strategically position their ventures to successfully enter the market and secure funding (Williamson et al., 2021; Barlow et al., 2019). A relevant decision in strategic positioning is the pursuit of distinctiveness as shown by the optimal distinctiveness literature (Deephouse, 1999). The advantages entrepreneurs can derive from being different, namely avoiding competitive pressures, are in tension with adverse effects on their legitimacy (Zuckerman, 2016; Zhao et al., 2017). Hence, scholars seek to investigate how different levels of distinctiveness influence the performance of ventures, contextualize these relationships, and identify the various strategic tools at their disposal to position themselves with an optimal level of distinctiveness that yields the highest performance (Durand and Haans, 2022; Zhao and Glynn, 2022).

One crucial strategic tool that entrepreneurs use to convey their optimal distinctiveness is their entrepreneurial narrative (Taeuscher et al., 2021, 2022; Vossen and Ihl, 2020). Through such a narrative, entrepreneurs can legitimize and differentiate claims about who and what they are and thereby help audiences evaluate them (Martens et al., 2007; Lounsbury and Glynn, 2001). Often, entrepreneurial ventures early in their life cycle consist of little more than these claims. Therefore, finding a compelling narrative that portrays them as attractive, unique, desirable, and appropriate is a critical factor in their early success (Navis and Glynn, 2011). Creating a compelling narrative is especially important in contexts of intense competition where new ventures are even more challenged to capture audiences' attention (Taeuscher et al., 2022). Previous research has shown that entrepreneurs can use different forms of narratives to convey their legitimizing and differentiating claims, such as product descriptions (Barlow et al., 2019; Taeuscher et al., 2022) and proposals (Vossen and Ihl, 2020), websites (Haans, 2019), or pitch texts (Taeuscher et al., 2021). These have been analyzed regarding differences across content (Allison et al., 2013, 2015) and linguistic styles (Parhankangas and Renko, 2017) to establish whether certain types of narratives resonate effectively with key audiences. However, the basic tenor in this stream of literature is that the composition of a narrative, and thus the entrepreneurial decision to position itself, is a one-time event that is decided on at either financing rounds or market launch (Martens et al., 2007).

This relatively static perspective on narrative change is in line with that of optimal distinctiveness, where what we know about distinctiveness change centers on either a change of its appeal over time (Chan et al., 2021; Goldenstein et al., 2019; Zhao et al., 2018, 2017) or on a change in the competitive environment where own distinctiveness is attenuated/alleviated by competitors that enter the own market or product category (Bu et al., 2022; Goldenstein et al., 2019; Janisch and Vossen, 2022). Distinctiveness due to changing attractiveness over time is explained by the fact that expectations of a venture's legitimacy or distinctiveness depend on its establishment. Since a new venture does not yet have a track record, it must first legitimize itself in the eyes of evaluating audiences by conforming to the norms of its market category (Lounsbury and Glynn, 2001). Otherwise, it will be penalized as illegitimate and disregarded in purchasing decisions (Zuckerman, 2016).

At the same time, a new venture must differentiate itself to remain competitive (Fisher et al., 2016). However, once a venture has established itself in the market, evaluating audiences often take it for granted, making it less critical for a venture to gain legitimacy. Likewise, the market matures over time (Zhao et al., 2018), and audiences' expectations evolve, so the benefits of being different for a venture diminish. Against this backdrop, entrepreneurs need to take action to position their ventures when entering the market strategically–yet, beyond describing the effect mentioned above, existing work provides little insight into how entrepreneurs should change once they are inside such markets.

This also holds for the competitive context, the second frequently mentioned aspect to explain changes in distinctiveness. Previous studies concur that finding an optimally distinct strategic positioning requires considering different competitive contexts (Haans, 2019) and comparing it to multiple reference levels along the evolutionary stage of the market and category (Zhao et al., 2018). Notwithstanding the importance of these studies, missing from all of them is the consideration that entrepreneurs are not solely passively observing the dynamics that surround their narratives and distinctiveness claims but also have agency in changing it by intentional, entrepreneurial (re)action.

This (re)action is particularly relevant when entrepreneurs must make new decisions about their strategic positioning (Fisher et al., 2016). Recent studies emphasize the recursive nature of strategic positioning (Soublière and Gehman, 2020) and suggest that the perception of an entrepreneur's strategic position "flows back" to their other endeavors over time (Lounsbury and Glynn, 2001 p.548). Such a spillover perspective, however, underemphasizes the active role entrepreneurs play in shaping their distinctiveness strategy. A premier example of this could be the launch of additional products (Bu et al., 2022; Fernhaber and Patel, 2012; Parker et al., 2017). We propose that in such a situation, entrepreneurs orient themselves not solely on competitors and time-variant audience perceptions (Haans, 2019; Janisch and Vossen, 2022; Goldenstein et al., 2019) but also on their past performance and the lessons they learned from the feedback they received.

6.2.1.1 Antecedents of change: Performance feedback and aspirations

Organizational learning states that organizations and individuals change their strategic behavior dynamically in response to their experiences and performance feedback (Cyert and March, 1963). A key antecedent of change is continuously setting *aspirations*–"the smallest [performance] outcome that would be deemed satisfactory" (Schneider, 1992 p.1053)–against which own performance is compared. While such aspirations and the reaction to performance feedback have been extensively studied in settings of established organizations (Greve, 2003;

Audia and Greve, 2006; Greve, 2011), research on how they change entrepreneurial behavior remains scarce (Politis, 2005; Chen et al., 2018; Peterson and Wu, 2021). This is surprising because entrepreneurial learning and improvement rely heavily on experiential concepts to explain how entrepreneurs improve their decisions and future actions (Politis, 2005). We propose that experiences entrepreneurs made from failing aspirations play a crucial role in future differentiation decisions such as narrative design.

Deviation from aspirations–either by exceeding or falling below them–usually has a non-linear effect on the likelihood of strategic change (Greve, 1998). When performance is above aspiration, entrepreneurs see less need to change and are often more risk-averse about it, as their success encourages them to pursue their current actions (Bromiley, 1991; Cyert and March, 1963). Following this line of argument, a change in their distinctiveness strategy should be less likely when entrepreneurs exceed their aspirations.

Falling short of aspiration signals a problem, and entrepreneurs engage in a so-called "problemistic search" to identify suitable actions as a solution. Problemistic search is the "process of search to discover a solution to the problem, resulting in a behavioral change intended to restore performance to the aspired level" (Posen et al., 2018 p.208). The locus of problemistic search, where entrepreneurs "look" for a solution, might be both on themselves and competitors. This is mirrored in the literature on optimal distinctiveness, where entrepreneurs must consider not only competitor behavior (Haans, 2019) but also within-organizational precedents (Bu et al., 2022) and characteristics (Janisch and Vossen, 2022; Goldenstein et al., 2019) when making strategic positioning decisions. As such, it seems reasonable to assume that entrepreneurs who fail aspirations engage in a problemistic search, looking at themselves and competitors for possible solutions.

Behavioral strategy responses also differ based on the magnitude by which aspirations are failed (Greve, 1998). Triggering problemistic search is often built on the premise of accurate self-evaluation (Greve, 1998), an assumption that is at odds with evidence on threat rigidity or self-enhancement (Ocasio, 1993; Jordan and Audia, 2012). According to these theories, organizations might change less or even refrain from changing altogether in situations of apparent failure (Audia and Brion, 2007). This results in a non-homogeneous response that makes change most likely near the aspiration–where the discrepancy is perceived to be repairable–and decreases away from it–where the disparity is perceived to threaten survival (Greve, 1998; Audia and Greve, 2006). Self-enhancement and threat rigidity seem relevant in contexts where entrepreneurs are prone to little self-reflection (Forbes, 2005) and usually also carry a higher personal risk that may make them wary of significant change (Gans et al., 2019).

Following the rigidity and self-enhancement arguments, entrepreneurs are therefore less likely to engage in problemistic search and change in the face of apparent failure (Greve, 1998; Audia and Greve, 2006; Jordan and Audia, 2012). Low performance puts an entrepreneur financially at risk (Gavetti et al., 2012), and when entrepreneurs see a threat to their survival, they may become rigid (Audia and Greve, 2006). Also, the stress and anxiety caused by a perceived threat to survival may lower entrepreneurs' ability to distinguish and process information. This results in a shift from a problemistic search to leaning on well-learned actions (Greve, 2011; Gavetti et al., 2012). Such behavior is exacerbated in smaller organizations, by extension, individual entrepreneurs who are more vulnerable due to their lack of resources (Greve, 2011). The literature on optimal distinctiveness describes similar effects. Deviating too much from audiences' expectations, and distinctiveness preferences can adversely affect product performance (Janisch and Vossen, 2022; Zhao and Glynn, 2022) and alienate core audiences (Vossen and Ihl, 2020). Consequently, rigidity and the fear of losing the revenues of these core audiences that are critical to survival may also hamper the extent to which entrepreneurs are willing to change their distinctiveness appeal significantly.

Yet, rigidity does not provide the sole explanation for why entrepreneurs may not engage in change but also the theory of self-enhancement. When entrepreneurs perceive the threat to their endeavor's survival as threatening their self-image, they will likely engage in cognitive processes that contribute to self-enhancement by biasing information self-interestedly

(Jordan and Audia, 2012). This entails re-actively adjusting their aspirations, downplaying their problems, and thus protecting or enhancing their self-esteem (Audia and Brion, 2007). This activation of a self-enhancement mode is particularly likely in settings where an entrepreneur is at the center of the entrepreneurial endeavor and feels personally responsible for the performance, such as in contexts of content creation and similar tasks where entrepreneurs rely on self-expression and strong extroverted confidence (Roccapriore and Pollock, 2022).

Taken together, we believe that problemistic search, rigidity, and self-enhancement are consequential for changing entrepreneurial narratives and optimal distinctiveness strategy. If entrepreneurs miss their aspirations narrowly, they engage in a problemistic search. They are more likely to change as they deem their narrow miss "fixable." Therefore, new differentiation decisions will entail a narrative that differs more intensely from their last decision. However, failing by a wide margin induces rigidity and self-enhancement, leading to less change. This will result in only marginal changes in the narratives of new differentiation decisions. We, therefore, formulate the following hypothesis:

Hypothesis 8: *Narrowly missing aspirations results in more distinctiveness change than widely missing aspirations.*

6.2.1.2 Consequences of change: Relative positioning to the category prototype and exemplar

We propose that missing aspirations not only influences the likelihood that entrepreneurs engage in problemistic search that leads to change or self-enhancement that does not, but also changes their relative distinctiveness appeal. A narrative intended to convey conformity and differentiation claims necessarily needs to focus on other actors in the same market or category (Barlow et al., 2019) that serve as *benchmarks for gauging optimal distinctiveness* (Zhao and Glynn, 2022)–such as category prototypes (Durand and Paolella, 2013) and category exemplars (Younger and Fisher, 2020).

A category prototype is frequently seen as the industry average (Vergne and Wry, 2014; Deephouse, 1999), the most-average member of a category (Haans, 2019), or as a fictional average in terms of relevant attributes and features for a given category (Vergne and Wry, 2014). Category prototypes define the boundaries of categories by grouping central or representative attributes or features of a given category in the eyes of a given audience (Vergne and Wry, 2014; Durand and Paolella, 2013). Consequently, most studies on optimal distinctiveness measure the extent to which the efforts to conform or differentiate, such as the narrative, differ from the category prototype (Zhao and Glynn, 2022).

Conforming to the category prototype has both positive and negative effects. Entrepreneurs who conform to the category prototype reduce audiences' confusion about categorization (Negro et al., 2010) and can increase their legitimacy. However, the notion of a category prototype requires an established category with clear boundaries (Zhao et al., 2018). In categories that lack these, conforming to the category prototype can also harm performance (Barlow et al., 2019). Also, conforming to the prototype in crowded categories has a negative effect because if every member aspires to be like the prototype of the category, the category members end up being too similar, and each individual gets lost in the crowd (Barlow et al., 2019). Deviating from the prototype can provide a competitive advantage, especially when audiences expect it, such as in the case of new ventures that need a certain "legitimate distinctiveness" (Navis and Glynn, 2011). However, deviating too much from the prototype can make it difficult for audiences to evaluate a venture or product due to the lack of a comparative baseline (Durand and Kremp, 2016). Audiences, in this case, struggling to understand a venture or product may even question it and evaluate it as illegitimate (Hsu, 2006; Negro et al., 2010), which may lead to negative performance consequences for ventures (Pontikes, 2012).

We believe that failing aspirations make entrepreneurs more likely to become more distinct from the prototype. A lack of performance, particularly for content creators, is often founded on being unable to catch the audience's attention rather than lacking legitimacy

(Johnson et al., 2022). This, in line with the legitimate distinctiveness audiences expect, renders it more likely for entrepreneurs to become more distinct from the category prototype, hoping that it will help them to stand out from competitors more clearly and catch the attention of new audiences (Navis and Glynn, 2011). We expect this effect to be more substantial in the range of problemistic search, as entrepreneurs that only narrowly fail their aspirations may believe that their core audience is already loyal enough to tolerate a positioning pivot to attract more audience members. Therefore, we hypothesize:

Hypothesis 9: *Missing aspirations increases distinctiveness from the category prototype.*

A category exemplar is the most salient category member or a clear market leader within a category (Barlow et al., 2019). Regardless of a category's maturity, audiences can detect a category's exemplar as an exceptional category representative, as the most well-known or highest-performing member they use as a cognitive reference (Zhao et al., 2018). While category prototypes are often implicitly recognized through some salient and prominent features, category exemplars, in contrast, also provide suitable benchmarks to gauge a focal venture's or product's optimal distinctiveness when a category prototype has not yet been established or when categories are highly dynamic or crowded (Zhao et al., 2018).

Conforming to a category exemplar may create a legitimacy spillover effect (Durand and Kremp, 2016), as category exemplars are often viewed as members worth aspiring to (Durand and Paolella, 2013). Being similar to a category exemplar renders a focal venture or product a plausible candidate in audiences' consideration set (Younger and Fisher, 2020). Conforming to the category exemplar not only creates legitimacy but also distinctiveness, positively impacting venture performance (Barlow et al., 2019). The category exemplar establishes a basis of comparison for audiences. Still, it already represents a flagship member of the category who stands out from the bulk of the category and is thus seen as a legitimate and distinctive member of the category.

We believe that failing aspirations make entrepreneurs less distinct from the exemplar.

In general, the exemplar occupies a position that entrepreneurs strive for, as she is already "legitimately distinct" which is what audiences expect from entrepreneurs (Navis and Glynn, 2011). Especially in markets such as content creation, where imitation is relatively easy and does not require extensive resources, it is feasible for entrepreneurs to become more comparable to the exemplar. Such an approach may also be an attempt to lure some of her audiences, which may be a great strategy when creating content that is non-exclusive in terms of consumption.

Also, it can be expected that this effect is more substantial when entrepreneurs fail their aspirations by a wide margin, as in this case, their need for other audiences is the largest, and changing one position towards the exemplar is a safe bet that involves little risk (Barlow et al., 2019). In addition, the exemplar is the most prominent actor in the category, a status many entrepreneurs strive to achieve. Hence, it is unlikely that self-enhancement would hinder a change, as becoming more like the most successful actor could also be perceived as a means to raise self-assurance (Jordan and Audia, 2012). We consequently believe that entrepreneurs become less distinct from the category exemplar, hoping that it will help them to create audience spillovers. We deem this effect stronger when they fail their aspirations by a wide margin and feel like the change needs to be a "safe bet" with demonstrated success. Therefore, we hypothesize:

Hypothesis 10: *Missing aspirations decreases distinctiveness from the category exemplar.*

6.3 Empirical approach

6.3.1 Sample and data collection

We test our hypotheses by analyzing videos from the most successful entrepreneurial content creators on YouTube. We believe there are several compelling reasons why those are an optimal empirical setting to examine aspirations and their effect on distinctiveness and narrative change. First, while there are many content creators in the market, only very few–namely the most successful–succeed in making a living from their activities on YouTube, which makes it reasonable to assume that all the content creators in our sample are full-time entrepreneurs. Second, successful content creators are also more likely to remain in the market for the long term, and their new decisions render it easier for us to observe change. Third, content creators on a crowded platform like YouTube are unlikely to know all their competitors but are most likely to compare themselves to similar competitors–other successful content creators. These compelling arguments resulted in our decision to focus on the most successful English-language content creators, examine how they react to failing aspirations, and adjust their strategic behavior accordingly.

We used publicly available data from Social Blade as a starting point to identify the most successful English-speaking content creators.[12] Social Blade is a YouTube analytics service that provides current top 100 lists of YouTube channels based on various measures of success (most viewed channel, most subscribed channel, or highest Social Blade rating). The top 100 channels are available for all 17 channel categories of YouTube and as grouped by country. First, we sampled the top 100 channels from all 17 channel types listed on Social Blade on June 14, 2021. We restrict this study to English-speaking channels to make channel content comparable with our natural language processing approach (see below). Second, we also included the top 100 channels from the four major English-speaking countries: Australia, Canada, the United Kingdom, and the United States, to mitigate the crowding out effect in the top 100 channel type lists by non-English speaking channels with large national audiences such as from India. We repeated this process three times and sorted in terms of most views, most subscribers, and highest Social Blade rating, for both the channel type-based top lists and the country-based top lists to obtain all the top 100 channels, respectively. After dropping duplicates–those that were both listed on the top 100 lists per channel type and country (31)–and including only channels that were created after March 2010 when YouTube

[12] More information available at https://socialblade.com.

introduced its "Thumbs" rating system (444 channels), we obtained a list of 1184 channels.[13]

Building on the established description for an entrepreneurial content creator (Roccapriore and Pollock, 2022), we applied several exclusion criteria to identify actual content creators among these 1184 channels. First, we excluded channels owned by people who became famous through other activities or social media platforms, such as musicians or comedians, before starting a YouTube channel. Second, we excluded the official channels of large firms, for instance, Apple, Google, Tesla, Ford, etc. Third, we excluded channels that focus on posting snippets from original TV shows. Fourth, we excluded channels with less than one upload per year or no monetary interest, for instance, non-profit organizations. We consider channels with such low upload frequency not to be full-time entrepreneurs. Fifth, we only included channels of which at least most of the videos had an English transcript available and the comment section activated (again, this relates to our natural language processing and the dependent variable used below). This led to excluding all channels in the kids category since YouTube, by default, disables comments on almost all videos featuring children to prevent predatory comments (Fox, 2019). These criteria led to the exclusion of 793 channels. We also excluded 40 channels not associated with any channel category on Social Blade, as this missing information prevents us from identifying their social reference groups for the aspirations. As a result, we ended up with a list of 348 actual content creators for which we collected all videos they had uploaded so far up to July 26, 2021. We created a subset of the most successful public videos by including the five videos with the most views on each channel.[14] For less than 20% of our data set, not all the five most viewed videos of a channel

[13] With the introduction of the "Thumbs" rating system, YouTube substantially changed how platform users can engage with video contents and enabled direct feedback. As such feedback impacts a video's performance metrics which may, in turn, play a role in YouTube's algorithm on how content is found, we decided to set this time event as cut off for our sample. This also ensures that we focus on a more recent sample.

[14] The focus on five videos here is an arbitrary choice to cope with data collection restrictions, which only allow the daily collection of transcripts and comments of about 10-20 videos. Given this constraint, we decided to observe the five most popular videos. We believe that the most successful videos are the most salient benchmarks for content creators in determining success and are also the most obvious choice for social aspiration, as content creators are likely to focus on their competitors' most successful videos instead of all their videos. We discuss further limitations resulting from this sampling approach in the limitation section.

fulfilled all our exclusion criteria mentioned above (having comments enabled, for example); in these cases, we included the next possible top-viewed video that met all requirements.

6.3.2 Dependent variable

Our study uses three dependent variables: *Narrative change*, *distinctiveness to the prototype*, and *distinctiveness to the exemplar*. Traditionally in the optimal distinctiveness literature, distinctiveness is often measured as the extent to which a venture's narrative deviates from those of others (Haans, 2019; Vossen and Ihl, 2020; Taeuscher et al., 2021, 2022). We compile such a narrative using the audio transcript provided by YouTube's automatic transcript feature. The audio transcript uses YouTube's state-of-the-art speech recognition algorithm that automatically transcribes the content that the content creator verbally presents into textual information. We utilized this textual information to train a machine learning algorithm that helps us identify similarities and differences between the transcripts, called doc2vec (Vossen and Ihl, 2020). Doc2vec builds on "word2vec" and follows the so-called distributional hypothesis: Words adjacent to the exact words share the same context and thus have a similar meaning (Le and Mikolov, 2014). As the name suggests, word2vec translates words into unique numeric vectors. To mathematically compute and recognize the context of words, the so-called word embeddings, word2vec trains a neural network that learns a word's semantic and syntactic qualities 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, assigning a unique vector to each word and document with variable text length. That is, doc2vec learns in what context a word appears and whether that context is specific to a particular document. Doc2vec can be used for different documents; the only requirement is that the documents be in textual form. Thus, doc2vec can also be used for similarity computation of spoken language when converted to a textual format consisting of a string of words that reflect the contents discussed in a video (Kaminski and Hopp, 2020).

Since textual information can be similar without using the exact words, doc2vec, unlike other natural language processing methods, can measure similarities between words that have never appeared in the same document. A very simplified example: One content creator may refer to his followers as my "fans," another as my "subscribers," and a third as my "viewers." While all words are distinct and would be recognized as such by more traditional algorithms, word2vec can capture the similarities by focusing on co-occurring words in the context. Imagine all three content creators open their videos with the phrase "Welcome to this week's video (*fans/subscribers/viewers*)! Happy to see you all again." As only the fans/subscribers/viewers word is different, word2vec would know that these three words have similar meanings, as the surrounding five words on each side (the context) are identical. Therefore, doc2vec provides a suitable method to measure the extent to which content creators change their narrative and positioning compared to their prior past releases or that of their peers.

We trained the algorithm with all audio transcripts we identified for our data set. As training parameters, we set the learning epochs to 40 and the vector size for the word embeddings to 50 dimensions. We specified that the meaning context of a word should be learned based on a local context window of 15 words.[15] To avoid over-representation of seldom and very frequent words for learning the context of a word, we set 10 occurrences as the minimum threshold for a word to appear in the corpus and 3000 occurrences as the maximum threshold (34 words were eliminated as a result of this). We used negative sampling to improve predictions of a target word based on a given context by creating ten negative examples–output nodes for ten "wrong" words that do not match the given context–

[15]There are no universally valid specifications for these parameters, as this decision should always be informed by the data used. For example, data trained on billions of newspaper articles may still be ill-suited for content creator transcripts because the language used in such videos may hardly be similar to the elaborate speech in newspapers. Therefore, selecting parameters always mandates testing, training models with different specifications, and comparing the similarity they attribute to word pairs and documents using face validity. As our corpus of documents is relatively small (at least compared to other text corpora), computing various measurements was not very time-intensive and allowed us to test several parameter constellations. The chosen parameter values are those that have proven to perform best. Our results are generally not overly sensitive to changes in these parameters.

and assigning lower weights to the output nodes of these words as compared to the output node of words matching the given context.

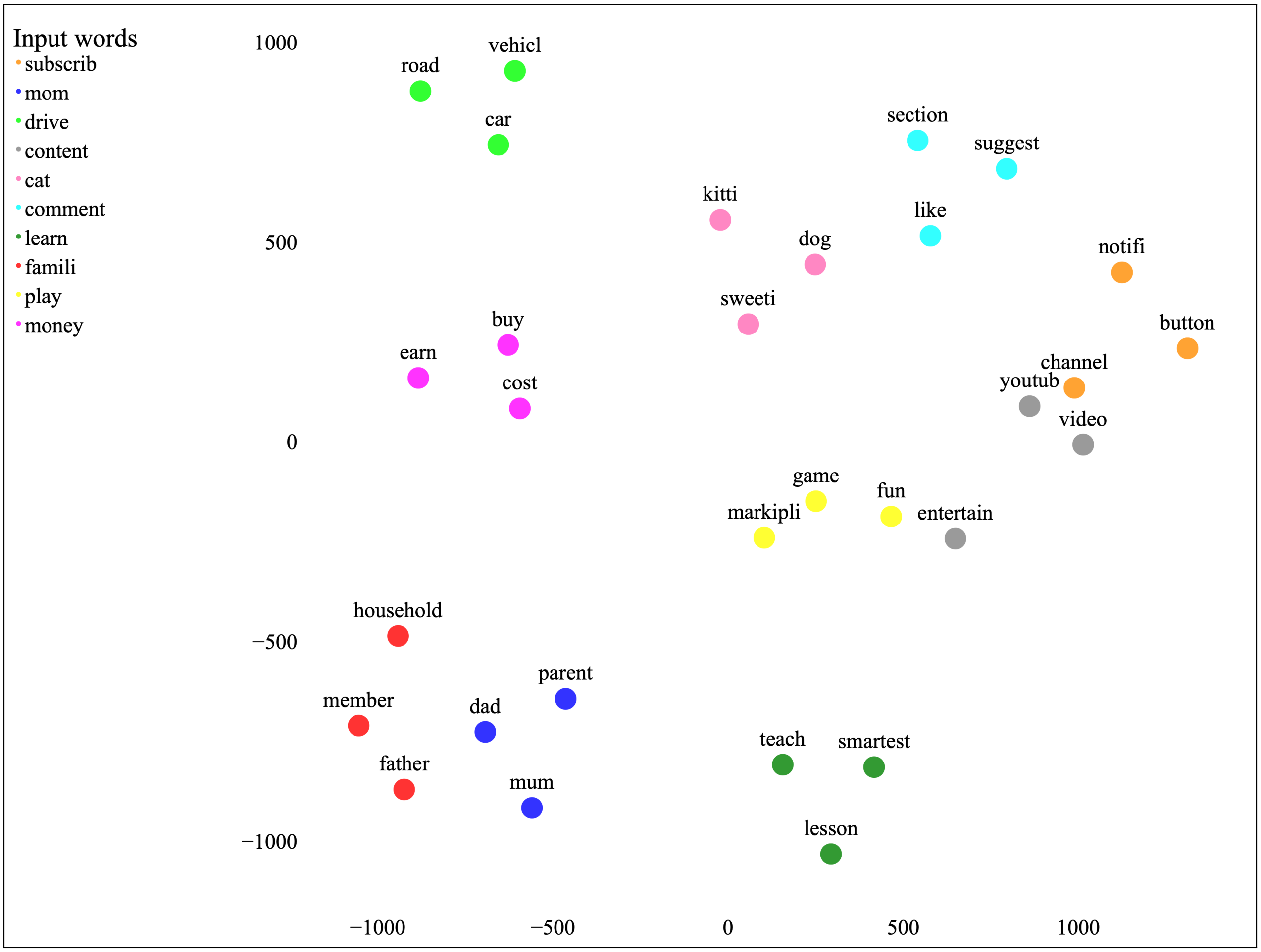

Figure 9: t-SNE of word2vec word embeddings—ten sample words and their three words most similar in meaning (words are stemmed).

To exemplify the logic underlying the word embedding vectors of the YouTube video audio transcripts, we used a t-distributed stochastic neighbor embedding (t-SNE) (van der Maaten and Hinton, 2008). T-SNE maps words with a similar meaning close to each other, while distinct words show a greater distance. This statistical method for visualizing high-dimensional data uses a non-linear dimensionality reduction technique. It allows us to visualize the 50 dimensions of the word embedding vector spaces for the video audio transcripts in a more intuitively interpretable two-dimensional space. Figure 9 shows ten sample input words of our training data set and the three words used in the most similar context for each input word. As exemplified in Figure 9, the three words most similar in meaning to the word "content" are "youtub," "video," and "entertain." We can represent clusters of similar word meanings and see how far these clusters diverge from each other. In the concrete example shown, this suggests that the meaning contexts associated with the input words "content" and "subscrib" are more similar since they are closer within the two-dimensional vector space than the meaning contexts associated with the input words "content" and "famili."

This complex procedure created a vector for each document, between which we can compute distance measures. To operationalize the variable *narrative change*, we computed the cosine distance between the audio transcript of a content creator's focal video and their most recent video at its release. More formally, we measured the cosine distance between all dimensions w of the embedding vector f of a content creator i's focal video at the time t and the embedding vector of the same content creator's most recent (mr) video:

$$Narrative\ change_{it} = 1 - \left[\frac{\sum_{w=1}^{W} f_{wi_t} f_{wi_{mr}}}{\sqrt{(\sum_{w=1}^{W} f_{wi_t}^2)} \cdot \sqrt{(\sum_{w=1}^{W} f_{wi_{mr}}^2)}} \right] \tag{10}$$

To operationalize the variable *distinctiveness to the prototype*, we computed the cosine distance between the audio transcript of a content creator's focal video and the audio transcript of a fictional prototype, representing an average embedding vector of all most recent videos released by other content creators in the same channel type at the time of the focal video's release. More formally, we measured the cosine distance between all dimensions w of the embedding vector f of a content creator i's focal video at the time t and the embedding vector of the most recent video of a fictional prototype p, which is an average of all the embedding vectors of all other most recent videos that were released in the same channel type as the focal video:

$$Distinctiveness\ to\ prototype_{it} = 1 - \left[\frac{\sum_{w=1}^{W} f_{wi_t} f_{wp_{mr}}}{\sqrt{(\sum_{w=1}^{W} f_{wi_t}^2)} \cdot \sqrt{(\sum_{w=1}^{W} f_{wp_{mr}}^2)}} \right] \tag{11}$$

Finally, we also computed the cosine distance between the audio transcript of a content creator's focal video and all most recent videos of the same channel type's exemplar at the time of a focal video's release. As an exemplar, we considered the content creator that had accumulated the most commentators on their top-performing and most recent videos at the time of a focal video's release. We argue that the content creator most successful in engaging users in active, participatory behavior on the platform can be deemed the most salient member of a channel type (Barlow et al., 2019). If a focal video was the first in its channel type in our data set or only other videos from the focal video's content creator had been released, this content creator represents the prototype or exemplar. Formally, we measured the cosine distance between all dimensions w of the embedding vector f of a focal video i at the time t and the embedding vectors of the most recent videos of an exemplar e and then averaged the cosine distances:

$$Distinctiveness\ to\ exemplar_{it} = 1 - \left[\frac{\sum_{w=1}^{W} f_{wi_t} f_{we_{mr}}}{\sqrt{(\sum_{w=1}^{W}\ f_{wi_t}^2)} \cdot \sqrt{(\sum_{w=1}^{W}\ f_{we_{mr}}^2)}}\right] \tag{12}$$

To identify the most recent own video, video of the fictional prototype, and videos of the exemplar at the time of a focal video, we set a time window of 30 days in which a video must be released before a focal video launches. We argue that after these 30 days, entrepreneurs can estimate the performance of their new videos and use this performance feedback as a source of learning. Therefore, the time window of 30 days also describes the learning period for entrepreneurs.

6.3.3 Independent variables

To examine whether content creators change their narrative due to missing or exceeding expectations, we build several measures of aspiration needed to test our hypotheses. As discussed earlier, content creators form aspirations based on two different performance levels–their historical one and that of a social reference group relevant to them. Studies of organizational learning have shown that the two levels of aspiration are individually and collectively significant (Bromiley and Harris, 2014; Dong, 2021; Shinkle, 2012). Following Greve (2003), we used a weighted average model–aggregated aspirations that integrate historical and social aspirations.

As a performance indicator, we consider the number of unique commentators a video received within the first 30 days of its release. We set the time window to 30 days for estimating a video's performance because previous research has shown that a video reaches a peak of attention in the first days after its release. Those numbers can predict long-term popularity and success (Borghol et al., 2012; Bärtl, 2018). We captured the number of individual commentators that posted under a video. Each comment also entails a unique ID of the user who posted it. This allowed us to count the unique user IDs that posted a comment to a specific video. We also discarded videos with disabled comments, as stated in the sample description.

We used the number of unique commentators as a performance measure as it possesses significant advantages over other measures of success, such as views or likes, mainly in that comments have a time stamp that allows us to track the success of a video in engaging commentators on a point-in-time basis. In contrast to viewing or liking, commenting on a video follows viewing it. It is often related to the "continued use of a site over a period of time [that] may cause users to build social connections leading to an increase in participatory and interactive behaviors" (Khan, 2017 p.239). Other than the number of comments, the number of commentators considers that users can comment on a video multiple times. For instance, if a commentator is in a lively exchange with other commentators of the video and thus comments on the same video multiple times, this would artificially increase the number of comments on a video.

Following prior research (Cyert and March, 1963; Greve, 2003), we computed a content creator's historical and social aspirations as follows. The historical aspiration gradually adjusts to the current performance of a content creator. It can thus be described as an exponentially weighted average of experienced performance (Lant, 1992; Greve, 1998). For the historical aspiration, we used the following formula:

$$HA_{ti} = a_2 * HA_{mr,i} + (1 - a_2) * P_{mr,i} \tag{13}$$

where a_2 are weights, $HA_{mr,i}$ represents the most recent historical aspiration of the focal venture i at time t, $P_{mr,i}$ is a venture's most recent performance at the time a focal video is released and a_2 indicates how much weight is placed on the historical aspiration in the previous period versus a venture's performance in the previous period.

For social aspiration, past research has often used the average performance of all other peers in the market. However, recent organizational learning and optimal distinctiveness literature findings suggest that social comparisons are more diverse (Labianca et al., 2009; Barlow et al., 2019). Therefore, there are several social reference groups with which entrepreneurial content creators can compare themselves. For our approach, the two apparent groups would be the prototype and the exemplar. As the content creator market is very crowded and identifying boundaries and relevant competitors is troublesome, we deemed it more likely that entrepreneurial content creators, rather than comparing themselves to all competitors, would take their cue from the most successful and salient member of a category–the exemplar (Barlow et al., 2019). By striving for the model, entrepreneurs set challenging goals for their performance (Labianca et al., 2009). We, therefore, calculate social aspiration as the current average performance of the exemplar as a social reference group. For social aspiration, we used the following formula:

$$SA_{ti} = (\sum P_{mr,e})/N \tag{14}$$

where, SA_{ti} represents the social aspiration of the focal venture i at the time t operationalized as the sum of the performances P of all most recent mr videos N launched by the exemplar e.

We used the historical aspiration and the social aspiration to compute a content creator's aspiration as follows:

$$A_{ti} = a_1 * SA_{ti} + (1 - a_1) * HA_{ti} \tag{15}$$

Following prior research (Greve, 2003; Bromiley and Harris, 2014), we tested our model with all weights from 0.1 to 0.9 in increments of 0.1 and settled for a_1 to 0.2 and a_2 to 0.8. This weighting implies that an exemplar's average performance weighs 0.2, a content creator's previous performance weighs 0.16, and the last historical aspiration weighs 0.64.

We subtracted the aspirations from a video's current performance to measure how a content creator performs relative to their aspirations. The extent to which content creators deviate from their aspirations–either by falling short or exceeding them–is referred to as a performance gap or attainment discrepancy. We lagged a content creator's performance gaps by one video to mitigate simultaneity problems (Baum et al., 2005). We used a spline function to measure whether failing to meet aspirations has a disproportionately more significant effect than exceeding them (Bromiley, 1991; Greve, 1998). For this, we split each performance gap variable into two variables. Aspiration performance > 0 equals zero for all observations where the performance gap is less than zero and equals the absolute performance gap otherwise. Similarly, aspiration performance < 0 equals zero for all observations in which the performance gap is greater than zero and equals the total performance gap otherwise.

6.3.4 Control variables

Many drivers other than aspirations may affect entrepreneurial content creators' channel success: Accordingly, we controlled for a range of video and channel attributes and platform characteristics. At the video level, we included variables to control for the *length of video title* and the *length of video description* because entrepreneurial content creators often use these tools to make claims about the content of their videos and to influence user navigation

Variable	Variable description
Dependent variables	
Narrative change	Cosine distance between the audio transcript of a content creator i's focal video released at the time t and the audio transcript of the same content creator's most recent mr video.
Video distinctiveness to prototype	Cosine distance between the audio transcript of a focal video i at the time t and the average embedding vector of all other video transcripts from videos in the same channel type released at least 30 days before the focal video.
Video distinctiveness to exemplar	Average cosine distance between the audio transcript of focal video i at the time t and all videos of the exemplar (the content creator that had the unique commentators in the respective video category at the time mr) that were released at least 30 days before the focal video.
Independent variables	
Last performance above aspiration	Spline variable indicating video attracted more unique commentators than expected by aspirations. Calculated by taking the achieved number of commentators and subtracting the number expected by aspiration. If the result is above zero, the value is set to that exact number; if less, it is set to 0.
Last performance below aspiration	Spline variable indicating video attracted fewer unique commentators than expected by aspirations. Calculated by taking the achieved number of commentators and subtracting the number expected by aspiration. If the result is below zero, the value is set to that exact number; if more, it is set to 0.
Control variables	
Length of video title	Total number of words in the title of video i.
Length of video description	Logged number of words used to describe the content of video i.
No. of video tags	Logged number of content tags a content creator assigns video i.
Video duration	Logged number of seconds video i lasts.
YouTube age	Logged number of days since YouTube was launched on 14th February in 2005 and the release of video i.
No. of prior uploads	Logged number of videos uploaded by content creator before video i.
No. of creators in video category	Number of content creators in the same video category at the release of video i.
Algorithm change	Time event on 12th October 2012, when YouTube changed its recommendation algorithm from a view-based to a watch time-based system.

Table 16: Variable descriptions.

within YouTube, which affects YouTube's relevance measures (Liikkanen and Salovaara, 2015). We also control for *video duration*, as the length of the video has been shown to affect video popularity (Welbourne and Grant, 2016). In addition, content-agnostic factors impact a video's popularity and success (Borghol et al., 2012). Therefore, we control for the *no. of video tags*. At the channel level, we included the variable *no. of prior uploads* to account for an entrepreneurial content creator's channel's maturity and learning effects (Welbourne and Grant, 2016). At the platform level, we control for *YouTube age* to account for platform-related inferences on channel success. As competition has been found to impact entrepreneurial content creator's channel success (Cunningham et al., 2016; Bärtl, 2018), we control for the *no. of creators in video category*, operationalized as the number of unique entrepreneurs who have generated content in the same video category before a focal video.

We also control for *algorithm change*, a timed event on 12th October in 2012, when YouTube changed its recommendation algorithm from a view-based to a watch time-based system to better account for engagement than just clicks, which has increased the popularity of gaming channels (Youtube, 2012). Please refer to Table 16 for an overview of the descriptions of all variables used in our analysis.

6.4 Results

We used a fixed effects OLS regression with category and content creator fixed effects and clustered the standard errors on both. Figure 10 displays the distribution of the videos in our sample across the different video categories. This distribution indicates that most of the videos from the most successful entrepreneurial content creators belong to the video categories of *Gaming* and *Entertainment*, which is more or less in line with the findings by Bärtl (2018). Table 17 contains the means, standard deviations, and correlations for the variables used in our regression analyses. Table 18 reports the regression coefficients and significance levels we used to test our hypotheses.

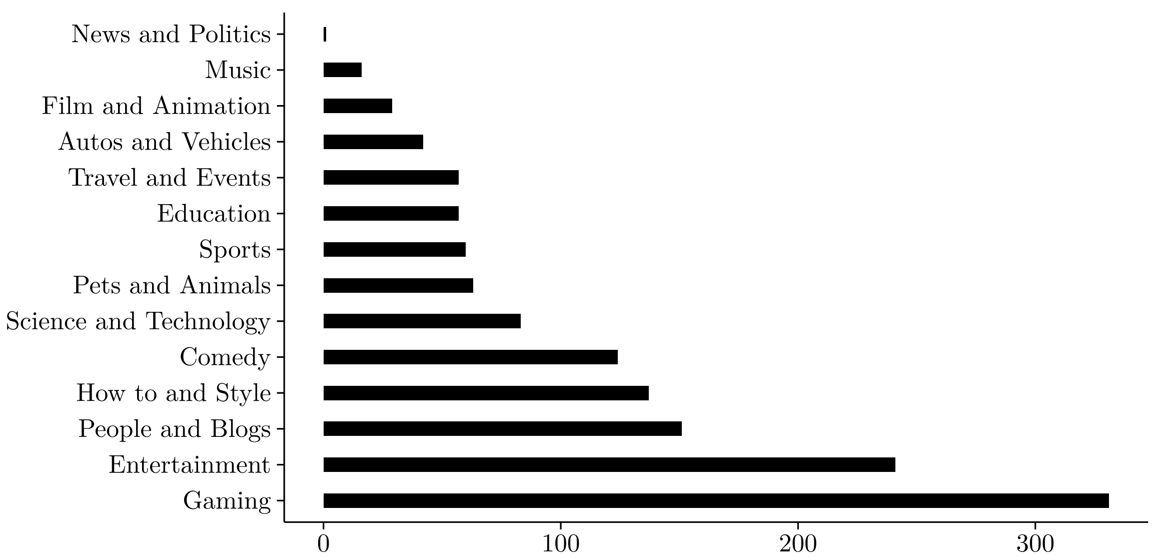

Figure 10: Number of videos per video category.

The regression results of Model 1 lend support to our Hypothesis 1, which postulates that

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
Dependent variables														
1. Narrative change	0.42	0.31												
2. Video distinct./prototype	0.62	0.15	0.26											
3. Video distinct./exemplar	0.82	0.13	0.04	0.23										
Independent variables														
4. Last performance - asp. > 0	0.47	2.26	0.06	0.08	-0.01									
5. Last performance - asp. < 0	−1.05	1.70	0.14	0.05	-0.19	0.13								
Control variables														
6. Length of video title	8.08	3.39	-0.04	0.02	0.00	-0.04	-0.03							
7. Length of video description	122.89	136.14	-0.03	0.04	-0.06	0.01	0.17	0.24						
8. No. of video tags	20.07	12.17	0.08	0.12	-0.05	0.02	0.07	0.10	0.27					
9. Duration of video (sec.)	727.56	647.72	0.00	0.09	0.04	0.02	-0.11	0.08	0.08	0.10				
10. YouTube age (days)	4,885.60	789.84	-0.20	-0.21	0.26	0.01	-0.37	0.06	-0.02	-0.29	0.02			
11. No. of prior uploads	531.88	765.82	0.17	0.05	0.07	0.10	-0.13	0.02	-0.05	0.01	0.07	-0.07		
12. No. of creators in video cat.	35.71	26.61	-0.21	-0.11	0.24	0.00	-0.71	0.05	-0.15	-0.22	0.07	0.65	0.05	
13. Algorithm change	0.99	0.09	-0.01	-0.04	0.34	0.01	-0.06	0.05	0.04	0.02	0.06	0.28	0.04	0.12

The variables 4 and 5 are divided by 10,000.
N=1,392.

Table 17: Descriptives and correlations.

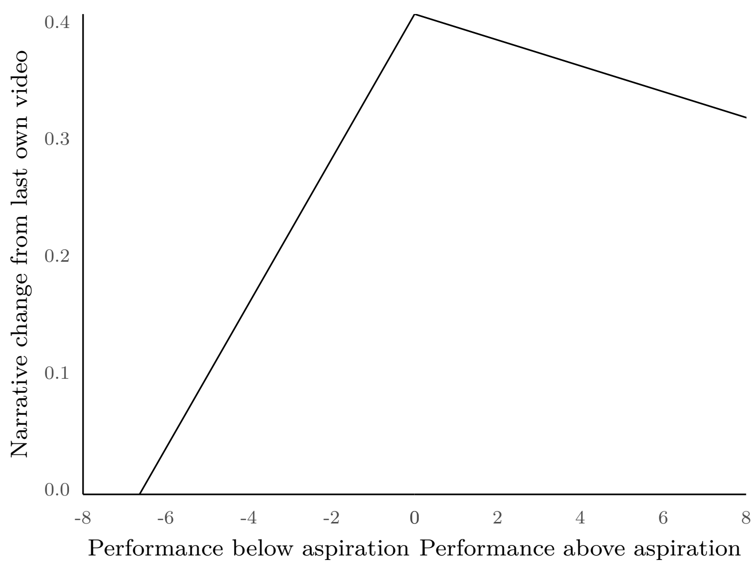

Figure 11: Predictions of narrative change from own last video (Model (1) in Table 18). Measured as 1-cosine similarity of video transcript *t* with transcript *t-1*.

content creators who perform below aspiration become more distinct from their last video (β = 0.062, $p < 0.001$). This response is also non-homogeneous as both aspiration coefficients have different signs and are significantly different from each other ($\chi^2 = 40.313^{***}$). Model 2

Dependent variables	Narrative change	Video distinct./prot.	Video distinct./ex.
Model	1	2	3
Control variables			
Length video title	-0.0013	0.0006	0.0000
	(0.0035)	(0.0014)	(0.0009)
Length video description (log)	0.0061	0.0039	-0.0047
	(0.0206)	(0.0066)	(0.0080)
No. of video tags (log)	-0.0050	0.0021	0.0039
	(0.0198)	(0.0086)	(0.0090)
Duration video (sec./log)	-0.0366**	-0.0021	-0.0108
	(0.0137)	(0.0077)	(0.0101)
YouTube age (days/log)	0.0001*	-0.0001***	0.0001**
	(0.0000)	(0.0000)	(0.0000)
No. of prior uploads (log)	0.0573**	0.0211***	0.0042
	(0.0248)	(0.0050)	(0.0101)
No. of creators in category	0.0026*	0.0021*	-0.0039**
	(0.0013)	(0.0011)	(0.0013)
Algorithm change (dummy)	-0.1093	-0.1434***	0.3449***
	(0.1107)	(0.0280)	(0.1044)
Independent variables			
Video distinct./prot.	0.0552		0.2315***
	(0.0591)		(0.0617)
Video distinct./ex.	0.0165	0.2784***	
	(0.0423)	(0.0640)	
Narrative change		0.0100	0.0025
		(0.0103)	(0.0061)
Last performance - aspiration > 0	-0.0050	-0.0004	0.0004
	(0.0038)	(0.0008)	(0.0011)
Last performance - aspiration < 0	0.0619***	0.0123***	-0.0181***
	(0.0114)	(0.0027)	(0.0032)
Fixed-effects			
Content creator	Yes	Yes	Yes
Video category	Yes	Yes	Yes
Fit statistics			
Adjusted R^2	0.36	0.51	0.41

Clustered (Content creator & Video category) standard-errors in parentheses.
*Signif. codes: ***: 0.01, **: 0.05, *: 0.1.*
N=1,392.

Table 18: Fixed effects OLS regression.

supports our Hypothesis 2, which states that when content creators perform below aspiration, they will become more distinct from the prototype (β = 0.012, p = 0.001). Again, the coefficients of both aspiration variables have different signs and are significantly different from each other ($\chi^2 = 16.958^{***}$). Model 3 supports our Hypothesis 3, which states that when content creators perform below aspiration, they will become less distinct from the exemplar ($\beta = -0.018$, p < 0.001). As with the other two, the coefficients of both aspiration variables have different signs and are significantly different from each other ($\chi^2 = 20.995^{***}$). Figure 11 graphically displays the results of Model 1 in Table 18. We find a non-homogeneous response pattern with a stronger tendency for entrepreneurial content creators to drastically change their distinctiveness when performing below aspiration. Entrepreneurial content creators are likelier to change their distinctiveness when they perform close to aspiration.

6.5 Robustness and post-hoc

We tested the robustness of our results in several ways. Most importantly, this concerns alternative measures of performance. We assumed that a 30-day period is an appropriate time window to evaluate the success of a video and based our assumption on the generated audience reach, representing the individual commentators who engaged with the video during that period. To test the sensitivity of our results concerning this assumption, we rerun our models with a time window of 7 days. The results of these additional analyses are all consistent with our main results. Thus, our results are also robust when we assume a much shorter time window to measure the initial success of video content. We also tested different measures than the number of unique commentators. We used the number of unique commentators to account for the fact that users may comment on a video multiple times and thus would increase the number of comments even if only a few commentators interacted with a video or–more crucially–with each other. This concern seems unfounded as our results remain consistent with the number of comments (not commentators) as a dependent variable. Thus, our additional tests provide arguments for a more general effect of aspirations on performance.

Following prior research (Greve, 2003), we employed a weighted average in aspiration–an aspiration which sets a performance trend (historical aspiration) in relation to a benchmark level (social aspiration)–affecting entrepreneurial content creators' new distinctiveness decisions. As also other non-combinatory approaches to measuring aspiration are common

(Bromiley and Harris, 2014), we consider historical and social aspirations as separate, independent influences that entrepreneurs can use for performance feedback. We, therefore, recoded our aspirations variable and split both below and above aspiration variables into their respective social and historical aspiration counterparts. Results show that when content creators perform above their historical aspiration, they become less distinct from their last video ($\beta = -0.020$, $p = 0.007$) and less distinct from the exemplar if they perform below their historical aspiration ($\beta = -0.071$, $p = 0.048$). We also find that if entrepreneurial content creators perform below their social aspiration, they become more distinct from their last video ($\beta = 0.016$, $p < 0.001$) as well as the prototype ($\beta = 0.003$, $p = 0.006$) and less distinct from the exemplar ($\beta = -0.004$, $p < 0.001$).

6.6 Discussion

Finding a way to achieve optimal distinctiveness has become a recent fixture in strategic management, organizational theory, and entrepreneurship studies (Durand and Haans, 2022; Zhao and Glynn, 2022). Our main goal was to contribute to this discussion by showing how entrepreneurs overcome the challenge of repeatedly designing new distinctiveness claims and what they learn from feedback on past ones (Jordan and Audia, 2012). As an empirical field, we used entrepreneurial content creators on YouTube who must constantly introduce new content and create new narratives in the videos they release for a living. For theoretical guidance, we relied on the literature on strategic change, performance feedback, and organizational learning, especially on the construct of aspirations (Gans et al., 2019; Greve, 2003).

We find that entrepreneurs have a non-homogeneous response to these aspirations, as a change in narratives and distinctiveness is most likely and significant around the level of aspiration and declines away from it (Greve, 1998). Moreover, the effects are more pronounced if entrepreneurs fail to meet their aspirations rather than when they exceed them. In our empirical context, this implies that if a video attracts *slightly* fewer commentators than aspired, content creators respond by releasing a new video whose narrative changes more significantly than it would if the number of unique commentators was *substantially* lower than aspired. In line with past studies that described such a non-homogeneous response pattern, we argue that the former can be explained by problemistic search (Posen et al., 2018) and the latter by entrepreneurs' rigidity and self-enhancement tendencies (Audia and Brion, 2007; Ocasio, 1993). Our results further highlight how such a change makes entrepreneurs more distinct from the category prototype but less from the category exemplar. Entrepreneurs who narrowly fail to meet their aspirations still feel comfortable enough to pivot further away from the market prototype, hoping to stand out more and thereby attract new audiences and close the performance gap.

If entrepreneurs miss aspirations by a wide margin, this usually induces rigidity and favors the self-enhancement of entrepreneurs (Audia and Brion, 2007; Ocasio, 1993). Although this renders change less prevalent, we can still find one-way change occurs: Decreasing distinctiveness from the exemplar. We propose that the unique role "star" exemplars play in categories can explain this (Barlow et al., 2019; Zhao et al., 2018). As all category members usually aspire to the exemplar, changing towards the exemplar does not evoke self-enhancement and the required entrepreneurial admission to own failure (Jordan and Audia, 2012). Despite the obvious importance, especially for entrepreneurs that need to make new differentiation decisions, little was known about the extent and type of change in the context of entrepreneurial narratives and optimal distinctiveness. Filling this blind spot by showcasing how slightly rather than widely missing aspirations is a crucial driver of such change, how it relates explicitly to distinctiveness from the prototype and exemplar, and offering theoretical explanations for it, is the key contribution of this paper.

Our second contribution relates to the literature on organizational learning (Gavetti et al., 2012). Most studies on organizational learning have a rather implicit approach to change, arguing that the mere fact of failing aspirations induces problemistic search that leads to change–often without a clear indication of how this change looks like (Posen et al., 2018). Using multiple specific change measures, we provide a more fine-grained view that clarifies how failing aspirations may induce specific and substantial entrepreneurial change. In our case, we find slightly but detrimentally different ways change manifests concerning the category exemplar and prototype (Barlow et al., 2019). It may very well be the case that more nuanced perspectives on how change influences organizational performance may provide further detrimental insights into the effect change has on different measures of organizational behavior and performance. Highlighting the role of the exemplar also shows that social aspirations do not necessarily have to focus on the average performance of all competitors but can also relate to the single most important one, especially when markets are very crowded and the identification of boundaries and actors are troublesome (Barlow et al., 2019).

Our third contribution relates to the literature on strategic positioning and institutional theory, especially on categories' roles and competitive and normative pressures (Taeuscher et al., 2022). Our results shed light on a new role of category prototypes and exemplars as sources of learning and improvement instead of mere competitors to conform to or differentiate from (Barlow et al., 2019; Haans, 2019). Notably, for optimal distinctiveness, this also provides new evidence that the decision to conform to or differentiate from prototypes and exemplars is by no means a one-time decision but one that entrepreneurs are constantly thinking about (Vaara and Monin, 2010)–especially when they feel that they are only trailing their aspirations by a small margin. Showcasing how learning and dynamic observations of performance influence pressures to conform or differentiate offers a novel and more fine-grained perspective on entrepreneurs' pursuit of optimal distinctiveness (Zhao et al., 2017). This entails the contextual role of failing aspirations and engaging in problemistic search (Posen et al., 2018) and as such, increasing distinctiveness is not solely a means of differentiation from fellow market actors but also a reply to failing aspirations and an attempt to become more prolific for evaluating audiences. The differences in this response between the prototype and exemplar showcase that if entrepreneurs learn from fellow market actors, their answer is somewhat more nuanced than universal (Zhao et al., 2018).

Our results also provide methodological as well as many practical implications. Our empirical approach highlights how machine learning and natural language processing can be used to analyze spoken language, which would be the most literal application of entrepreneurial storytelling (Navis and Glynn, 2011). Such an approach would likely apply to other storytelling scenarios, such as the transcripts of investment pitches or strategy meetings (Martens et al., 2007). By transparently highlighting the process of utilizing these methods, our work has important implications for quantitatively oriented researchers. Regarding managerial implications, our findings first and foremost concern the millions of content creators trying to become full-time social media entrepreneurs. Those may benefit from the examples set out by the full-time content creators in our sample and internalize the essential lessons that learning from aspirations may provide them in refining their positioning in new content releases. In this regard, our work also generalizes to many, primarily digital, industries and markets where many product releases are commonplace, such as the App market (Barlow et al., 2019; van Angeren et al., 2022). Here, our results may provide important lessons for new ventures in revising their positioning strategy as they release new products (Parker et al., 2017) and build their portfolio (Fernhaber and Patel, 2012).

6.7 Limitations, outlook, and conclusion

This study has some limitations that provide opportunities for future research. First, there are several approaches to operationalizing aspirations. This paper focuses on interpreting the performance of historical and social aspirations using a weighted average model. Future research could also consider a switch model (Baum et al., 2005; Dong, 2021) to examine how consistent performance feedback–performance below or above both historical and social aspirations–compares to inconsistent performance feedback–performance below one and above the other aspiration–in its effect on an entrepreneur's distinctiveness strategy in a social media context.

Another avenue for future research could be to investigate the influence of *similar* competitors' performance in creating a social aspiration. This paper discusses how comparisons to the prototype or exemplar influence new distinctiveness decisions for strategic positioning of entertainment content. However, the literature on organizational and entrepreneurial learning also suggests that social aspirations should be more influenced by competitors similar or comparable to a focal entrepreneur (Baum et al., 2005; Dong, 2021). The similarity, in this sense, is often related to comparable performance. However, we argue that similarity in the context of entrepreneurial content creators can also be interpreted in terms of targeting similar audiences, as evidenced by being active in the same channel type or video categories. Thus, future research could explore how pursuing channels with similar content influences entrepreneurial content creators in making new distinctiveness decisions. Future research could also follow the approach suggested by Baum et al. (2005) of comparing to all others in the market but giving more weight to more similar competitors.

Our data set is also limited to the most successful entrepreneurial content creators on YouTube, and it may also prove valuable to replicate our findings on alternative social media platforms. Future research could compare how aspirations affect the repeated strategic decisions of content creators compared to less successful content creators or aspirations across different social media platforms. Another limitation stems from our restriction to a content creator's five most successful videos. Future research could compare how aspirations develop over a larger time window, for instance, across multiple years, to understand better a content creator's strategic development in the long run.

The role of audiences in an entrepreneurial content creator's strategic positioning could also be studied in more detail. While we look at the number of commentators as an indicator of a video's popularity and success, it would be interesting to see if a channel builds its niche audience (Johnson et al., 2022), namely, how many commentators engage only with this focal channel, versus how much overlap in commentators it has with competing channels. Disentangling overlap between social networks and examining the number of first-time and repeat commentators could contribute to our understanding of how content creators should adapt their distinctiveness strategy to grow their niche audience and keep them highly engaged. An interesting starting point for further research could be how new content is influenced not only by learning from historical and social aspirations but also by the intervention of commentators–the platform users–who make suggestions for future videos in their comments.

Our goal was to offer a new perspective on how optimal distinctiveness is not a one-time strategy that should be followed meticulously once decided on but demands constant attention, adjustment, and refinement. We proposed literature on organizational learning as an intuitive yet meaningful theoretical lens for this perspective. We hope that our work serves as a significant and exciting starting point for more research that provides us with more insights into the antecedents, the process, as well as the consequences that learning and performance feedback have on the way that organizations, old and new alike, face the challenges of achieving optimal distinctiveness. Our work should be understood as a starting point towards that direction, showcasing how entrepreneurial content creators on YouTube are "reaching for the stars" to overcome this challenge.

7 Discussion and implications

7.1 General discussion of the results

The overall objective of this thesis was to understand how new ventures achieve to narrate optimal distinctiveness. To this end, this thesis examined the three assumed primary influencing roles of the preferences of different evaluating consumer audiences, the mode of a narrative, and the choice of reference levels on the evaluation of a new venture's narrative distinctiveness and, thus, its performance, using state-of-the-art machine learning-based natural language processing methods. This resulted in the following three research questions: (1) How does heterogeneity within audiences shape the effectiveness of distinctiveness claims in entrepreneurial narratives, (2) How do different narrative modes impact the effectiveness of distinctiveness claims on entrepreneurial performance, and (3) How does the choice of reference levels influence the evaluation of narrative distinctiveness? Three studies were conducted to answer these questions, each incorporating these three roles identified in the literature on optimal distinctiveness as critical to a new venture's success in narrating optimal distinctiveness. However, each of the three studies focused on a different consumer audience type, narrative mode, and reference level to better understand under what conditions what level of distinctiveness is considered optimal for new ventures. Table 19 summarizes this thesis's key findings and theoretical and managerial implications that the following subchapters discuss.

Because of consumer audiences' essential and understudied role as recipients and evaluators of entrepreneurial narratives, this thesis sought to understand how heterogeneity within consumer audiences affects the degree of narrative distinctiveness considered optimal. In general, consumer audiences are usually more reluctant to process detailed narratives about new ventures or products and favor gaining a quick impression (DelVecchio et al., 2019) to efficiently narrow down alternatives (Zuckerman, 2016). Therefore, consumer audiences value high levels of perceived legitimacy, which speed up their evaluation processes as the

Influential roles for narrating optimal distinctiveness	Evaluating audience (3.1.1)	Narrative mode (3.1.2)	Reference level (3.1.3)
Key finding	Consumer audiences differ in their distinctiveness preferences due to a differently entrenched institutional logic and enculturation of values and norms.	Not only the fit but also the richness of meaning in a narrative shapes mode-sensitive distinctiveness preferences.	A new venture's past self represents an important reference level for it to gauge narrative distinctiveness and learn from its distinctiveness trajectory.
Key theoretical implication to the literature on:			
-*optimal distinctiveness*	The optimum of narrative distinctiveness depends on the heterogeneous preferences within evaluating audiences.	Conveying claims of conformity and differentiation through visual and auditory modes offer entrepreneurs of new ventures non-textual modes to narrate optimal distinctiveness.	Multiple dynamic reference levels, including a new venture's distinctiveness trajectory, determine optimal distinctiveness in narratives.
-*entrepreneurial narratives*	A new venture's entrepreneurial narrative resonates differently with evaluators from the same audience group due to their heterogeneous distinctiveness preferences.	Different narrative modes offer entrepreneurs of new ventures various cultural tools to become skillful cultural actors. Machine learning methods allow measuring the meanings in these different narrative modes that make narratives from different market contexts comparable.	Optimally narrating distinctiveness remains an ongoing process for entrepreneurs of new ventures in which they profit from evaluating the effectiveness of their conveyed meanings through machine learning-based natural language processing.
-*institutional logic*	Not only investors but also consumer audiences differ in their institutional logic within the same audience group with consequences for what levels of distinctiveness they consider optimal and expect from a new venture in its narrative.		
-*sensory marketing*		Sight is a dominant sense when consumer audiences evaluate the distinctiveness of a new venture's entrepreneurial narrative. Also, consumer audiences process a narrative's distinctiveness on multiple dimensions by considering the fit and the richness of conveyed meanings.	
-*organizational learning*			New ventures aspiring and comparing the effectiveness of their narrated distinctiveness to the categorical prototype as a reference level for determining optimal distinctiveness follow a conservative, traditional strategy; using the exemplar instead represents an ambitious strategy.
Key managerial implication	Entrepreneurs of new ventures should consider the heterogeneous preferences within audiences to effectively align their entrepreneurial narratives with audiences' distinctiveness preferences.	Entrepreneurs of new ventures should consider how distinct the meanings they use in their entrepreneurial narratives are not only in terms of their fit but also their richness as compared to influential reference levels.	Entrepreneurs of new ventures should use competitors or their past selves as a comparative reference level to gauge optimal distinctiveness and as sources of problemistic search and learning to continuously remain or become optimal in narrating their distinctiveness.

Table 19: Summary of the key findings, theoretical, and managerial implications of this thesis.

normative appropriateness of a new venture relative to precedents in the same market triggers familiar cognitive evaluation schemes that allow consumer audiences to evaluate a new venture more quickly (Pontikes, 2012). However, high levels of distinctiveness also attract consumer audiences, making very distinct new ventures stand out from the crowd and leaving them with a more lasting impression (Pieters et al., 2002). Consumers value high levels of distinctiveness, primarily those acting as investors, who tolerate a higher level of distinctiveness and expect novelty (Taeuscher et al., 2021). In such consumer audiences, where this tolerance for distinctiveness and expectations of novelty are not evident, high distinctiveness may, in turn, be perceived negatively, increasing ambiguity and confusing consumer audiences about which cognitive evaluation scheme they could apply (Pontikes, 2012).

This thesis argued that the contrary effects that distinctiveness can have on consumer audiences might not necessarily be explained by market settings but by within-heterogeneity resulting from consumers' different roles. Therefore, this thesis investigated how a particular type of consumer audience evaluates distinctiveness in a new venture's narrative depending on its role as an investor (study 1), a buyer (study 2), or a user (study 3). High levels of distinctiveness legitimized a new venture in the eyes of consumer audiences taking an investor role, who expected novelty from a new venture, and had a positive effect on their evaluation. In this context, consumer investor audiences differed in their legitimizing perception of distinctiveness not only from other consumer audiences but also within their audience. In contrast, consumer audiences with a buyer role positively evaluated narratives whose meanings did not differ significantly from those of their competitors and which they perceived as normatively appropriate. However, the relative advantage of perceived conformity was most beneficial when a new venture competed in a mainstream market and decreased in a niche market. This thesis also finds that new ventures who narrowly fail to meet their aspired performance goal feel comfortable enough to pivot further away in their narrative from the market prototype, hoping to stand out more and thereby attract consumer audiences with a user role and close the performance gap.

In addition to the influence of audience evaluation on optimal distinctiveness and new venture performance, this thesis also considered the different modes–textual, visual, and auditory–that new ventures can use to narrate their distinctiveness. Prior literature on optimal distinctiveness and entrepreneurial narratives mentioned these three modes as the most frequently used by entrepreneurs to narrate their new venture's distinctiveness (Kaminski and Hopp, 2020). However, textual narratives represent the most researched mode by scholars who seek to understand how successfully entrepreneurs of new ventures narrate their distinctiveness (Martens et al., 2007) using established natural language processing methods such as dictionary-based analysis (Allison et al., 2013) or topic modeling (Hannigan et al., 2019). Visual and auditory modes have only recently attracted scholarly interest. These non-textual modes are becoming increasingly important for consumer audiences when evaluating a new venture due to the rising use of online formats for entrepreneurship, which rely heavily on images and videos (Cutolo and Kenney, 2021). To compute narrative distinctiveness based on the meanings conveyed and to understand what level of distinctiveness depending on the mode (textual, visual, or auditory) that entrepreneurs use to narrate their new venture's distinctiveness favorably impacts new venture success (Weick et al., 2005), this thesis used doc2vec. Doc2vec represents a state-of-the-art machine learning-based natural language processing method that, in combination with image and speech recognition, offers new possibilities for measuring narrative distinctiveness established through conveyed meanings across different modes (Kaminski and Hopp, 2020).

This thesis introduced the critical notion of richness for evaluation, not only fit. This thesis demonstrated that narrative distinctiveness not only manifests through the fit of meanings conveyed through a particular narrative mode–the extent to which their meaning differs from competitors within their category, but also the richness of meanings–the amount of meaning conveyed, for which a different optimum level of distinctiveness applies than for fit. Methodologically, this thesis explained how doc2vec helps to measure narrative meanings through learned word embeddings, translate a narrative into a unique narrative vector, and compute narrative distinctiveness by comparing these vectors using cosine similarity. As doc2vec is restricted to processing textual information, visual and auditory narratives were translated into a textual mode using image and speech recognition algorithms. The language model validity in doc2vec and, thus, its ability to measure meanings in narratives depends on the selected parameters used to train and learn word embeddings. Table 20 indicates that measuring meanings via word embeddings is mode-sensitive. Depending on the corpus size and whether doc2vec was used to measure meanings in a textual crowdfunding campaign (study 1), a visual product image (study 2), or an auditory video transcript (study 3), different training parameters led to better language model validities.

Study	Narrative mode	Corpus size	Min. word count	Max. word count	Total no. of words	No. of unique words	Local context window	Vector size	Architecture	Negative sampling	Training epochs
1	textual	15,319	5	-	9574458	39620	4	100	PV-DM	5	15
2	visual	9,035	2	-	67705	1543	3	300	PV-DM	5	40
3	auditory	1,755	10	3000	865178	6348	15	50	PV-DM	10	40

Table 20: Doc2vec parameter choice by study.

Finally, this thesis examined how the choice of reference levels influences the evaluation of narrative distinctiveness. Prior literature on optimal distinctiveness mostly assumed that both evaluating audiences or entrepreneurs themselves compare new ventures to competitors from the same overall market or category, such as the prototype (Haans, 2019) or the exemplar (Younger and Fisher, 2020). Thus, new ventures' narratives have often been contrasted against one of these reference levels at a single time within their life cycle to gauge narrative distinctiveness. Contrary to previous assumptions, more recent research assumes that determining narrative distinctiveness by restricting comparisons to a single reference level and looking at it from a static perspective does not adequately reflect the fact that new ventures are in dynamic, multiple competition with others and their past self and are often compared against multiple reference levels by both evaluating audiences and themselves (Fisher, 2020; Zhao and Glynn, 2022). When consumer audiences relate new ventures to multiple competitive reference levels, such as a category's prototype and exemplar, it has been shown that they disfavor similarity to the prototype because if every new venture is perceived as aspiring to be like the prototype, it gets lost in the crowd (Barlow et al., 2019). However, consumer audiences positively evaluate similarity to the exemplar, as this may create a legitimacy and distinctiveness spillover effect (Durand and Kremp, 2016) due to the status of the exemplar as the most salient member that is worth aspiring to (Durand and Paolella, 2013) and as an exceptional category representation (Zhao et al., 2018). Recently, evaluating a new venture's distinctiveness based on its past self has been introduced as another critical reference level, determining also how coherent a new venture is perceived (Bu et al., 2022; Janisch and Vossen, 2022).

This thesis provided insights into how market-based (study 1), category-based (study 2), or self-comparative (study 3) reference levels shape a new venture's narrative distinctiveness. It was shown that entrepreneurs who create a distinct textual narrative relative to other past narratives in the broader market context could maximize the number of repeat consumer investor audiences while differentiating it from current narratives positively impacted the number of attracted first-time consumer investor audiences. The findings also indicated the relevance for entrepreneurs of positioning their new venture relative to primary and subordinate categories when designing their visual narratives to be perceived by buyers as optimally distinct and generate better sales. What level of distinctiveness in its visual narratives was beneficial for a new venture depended on the overall distinctiveness of the different nested categories with which a new venture was associated. Moreover, this thesis has shown that in addition to the classic evaluation of optimal distinctiveness based on market- or category-based competitive reference levels, self-comparisons, in particular, play a crucial role for new ventures whose entrepreneurs evaluate their auditory narrative distinctiveness not only based on category-based reference levels but also based on their own past performance and distinctiveness trajectory. The dynamic nature of reference levels was highlighted, and their importance for entrepreneurs to not only evaluate their new venture's narrative distinctiveness but also to learn from the effectiveness of competitors' current narrative distinctiveness and their past performance and to use these insights to make multiple recursive decisions about when to adjust their strategic differentiation.

While each study considered in isolation how a particular evaluating audience, narrative mode, and reference level(s) shapes a new venture's optimal distinctiveness, the core findings of each study yield implications for the remaining studies and, thus, for the overall thesis. First, the critical insights about heterogeneous distinctiveness preferences within consumer audiences with an investor role, reflecting whether they are more likely to evaluate a new venture's distinctiveness based on past or current reference levels, have important implications for the heterogeneity within consumer audiences with the role of a buyer or user likewise. Heterogeneity within buyer audiences may manifest in how effective different visual narrative strategies are in helping first-time buyers who are buying from a new venture for the first time versus repeat buyers who have bought from new ventures multiple times. How distinct a new venture is in its visual narratives through the chosen richness and fit could impact buyer audiences differently, who may include visual narratives in their purchase decision process with different expectations. For example, it is conceivable that first-time buyers of a product from a new venture may have many uncertainties and concerns and may be untrained in understanding a new venture and sorting it into the competitive landscape (Radford and Bloch, 2011). Visual narratives that are particularly rich in meaning could help first-time buyers build a solid foundation of information by sufficiently portraying product features and use cases that empower first-time buyers to make a purchase decision (Adaval et al., 2018). Unlike first-time buyers, repeat buyers already bring experience with products from new ventures. If someone frequently buys products from new ventures, it is reasonable to assume that novelty is expected and, therefore, a higher level of distinctiveness is tolerated in visual narratives (Taeuscher et al., 2021; Vossen and Ihl, 2020). To attract repeat buyers, entrepreneurs may need to focus more on deviating from the category norm in the meanings of their visual narrative and on appearing novel (Labroo and Pocheptsova, 2016). The results for the heterogeneity within consumer investor audiences also imply that entrepreneurs might benefit from considering both past and current reference levels when determining a distinctiveness strategy for their visual narratives (Bu et al., 2022). Past interactions with others through Q&A or reviews may shape buyers' preferences for semantic fit and semantic richness. A similar enculturation process could be observed for consumer audiences with an investor role who follow a community logic. Accordingly, first-time and repeat consumer buyer audiences may differ in their abilities to cognitively comprehend and evaluate the normative desirability of a visual narrative in terms of its fit and richness, as these abilities have been shaped by past experiences and enculturation of the accepted norms and values. Therefore, different expectations on how much a new venture should deviate from past or current reference levels might also exist for consumer audiences with a buyer role that follow a market logic.

For consumer audiences with a user role, heterogeneity within audiences suggests that repeat users might be attracted to new ventures that are less distinct from themselves over time, that is, stay true to their previous activities and thus try to build their niche audience (Johnson et al., 2022), while first-time users might be more attracted to new ventures that are distinct from themselves. In addition, whether a user is a first-time or repeat user might not be the only factor contributing to the different preferences for distinctiveness within user audiences. User audiences' choice in entertainment markets to consume exclusively free content or become a more established part of a community by paying for additional offerings from their preferred content creators and increasing their participation activities (Bateman et al., 2011) might shape expectations for distinctiveness differently (van Angeren et al., 2022). Also, it is conceivable that, like consumer audiences with an investor role, repeat users primarily incorporate past reference levels when evaluating distinctiveness. In contrast, first-time users initially rely on current reference levels and only become familiar with more distant content as interest continues.

Second, how consumer audiences with a buyer role evaluate a new venture's distinctiveness based on the fit and richness of meanings in its visual narratives and its categorical context has relevant implications for how investor and user audiences evaluate new venture distinctiveness through a textual or auditory mode. For consumer investor audiences evaluating the distinctiveness of a new venture's narrative based on textual descriptions, this multidimensionality means that the perceived fit and the richness can determine a narrative's distinctiveness. Richness could be figuratively the word count in textual modes, which, unlike visual narratives, might be subject to norms due to limited word counts. However, richness could also be the number of topics mentioned in a textual narrative. The multidimensionality of measuring distinctiveness within a narrative mode also suggests that audiences have multimodal perceptions and process meaning this way. Some entrepreneurs take advantage of multimodality and use images in addition to textual narratives, as they are easier to process and remember (Chan and Park, 2015). The images serve to embed texts in an aesthetically pleasing way, to support texts simultaneously, or to explain the texts in more detail and facilitate sensemaking by consumer investor audiences. Entrepreneurs use visual narratives often to convey information about the team with images of the entrepreneurs, details about the product, prototype development, or stretch goals (Kaminski and Hopp, 2020). Categorical context can be expected to moderate what level of distinctiveness consumer investor audiences expect in terms of conveyed meaning fit and richness. For example, product-centric campaigns, such as technological campaigns (Taeuscher et al., 2021), in which consumer investor audiences receive the product as a reward, are more often associated with a higher financial contribution and, therefore, risk. The need of consumer investor audiences to reduce these information asymmetries is reflected, for example, in the relevance of prototype images, which should be close to the final product, as this positively influences the success of technology campaigns (Wessel et al., 2022).

The role of visual narratives in evaluating the narrative distinctiveness of a new venture based on the fit and richness of the meanings conveyed raises the question of how similar and detailed an auditory narrative should be in the meanings conveyed compared to those of competitors. Are preferences for semantic fit and richness of meaning similar when images "move" as in the case of videos or when audiences take more time to evaluate something and pay attention to a new venture, at least for the duration of a video? Given the relevance of categorical context highlighted for consumer buyer audiences' evaluation of the degree of fit and richness of meaning, it could also be that in entertainment contexts, where consumer user audiences evaluate new ventures based on their auditory narratives, that is, the content shared in videos, how distinct or rich that content should be depends on the categorical context. Accordingly, it is conceivable that explaining videos, for example, on niche topics such as do-it-yourself, repair, product reviews, or game instructions, should be more distinct to emphasize novelty but also richer in meaning to provide much instructive information and reduce audience evaluation complexity.

Third, how entrepreneurs learn from the aspirations they form based on competitive and self-comparative reference levels and what degree of narrative distinctiveness appeals to user audiences has critical implications for how investor and buyer audiences evaluate a new venture's distinctiveness when comparing its narrative to its past self as a reference level in addition to the overall market or its category. The role of aspirations was considered to incorporate the influence of learning effects (Baum et al., 2005; Bromiley and Harris, 2014; Kim et al., 2015). In the settings of this thesis, aspirations are easy to operationalize due to the transparent structures of the platforms considered. Thus, in crowdfunding settings, it is possible to measure how much money was raised, on Amazon Launchpad, how the sales rank of a product is, and on YouTube, how many unique commentators interacted with a video shortly after it was released. However, it remains unclear what role aspirations play in strategically adapting entrepreneurial narratives and behaviors of self-enhancement and rigidity, where these aspirations are less transparent.

Forming aspirations based on reference levels suggests that campaigns on crowdfunding platforms, such as Kickstarter, are in addition to a classic categorization that groups campaigns with shared attributes into both general primary categories and more specific secondary categories (Lo et al., 2020; Gehman and Grimes, 2017) also in dynamic competition with different reference levels resulting from categories such as "Upcoming Projects," "Just Launched," or "Nearly Funded." Consumer investor audiences can use these multiple, transparent reference levels to compare and gauge a new venture's narrative distinctiveness. A new venture's success may also depend not only on how distinct it is from competitive reference levels but, in the case of serial entrepreneurs, how it compares to its past self and has learned from prior successes or failures (Butticè et al., 2017). Narrowly failing aspirations in the past may lead to a strategic change in narrative distinctiveness (Greve, 1998), while missing aspirations by a wide margin may induce entrepreneurs to stick to what they stand for as they seek to reinforce themselves (Ocasio, 1993; Greve, 2011). At the same time, this self-reference also points to audience heterogeneity–it shows that serial entrepreneurs who remain true to themselves may try to conform to the values and norms of a particular group within an audience to build a loyal audience.

The importance of self-comparison for a new venture's strategic differentiation suggests that its visual narrative differentiation strategy could change if its previous presence is compared alongside competitors (Bu et al., 2022). Another important aspect that plays into this learning process concerning the development of a successful visual narrative differentiation strategy is how entrepreneurs learn, for example, from consumer feedback, either textual or in the form of consumer-generated product images and deal with it when certain product aspects were criticized as not being sufficiently presented or application scenarios remained unclear and led to negative product reviews from consumers. From a brand management perspective, it is also interesting to see how new ventures create their portfolio of visual narratives that appeal to both new and repeat buyers. In terms of images as a visual narrative, should the first image that is displayed for buyers be more or less distinct from the remaining images advertising the same product, and how should the image differentiation strategy for one product fit with that of another product from the same new venture (Janisch and Vossen, 2022)? How are prototypes for visual narratives created, and what do they look like?

7.2 Theoretical implications

The findings in this thesis about how the audience evaluating a narrative, the mode of a narrative, and the chosen reference level(s) affect the distinctiveness of a narrative have important theoretical implications. Each of the three studies in this thesis focuses more on one of these influential factors and, to this end, uses another core literature in addition to the literature on *optimal distinctiveness* or *entrepreneurial narratives*. Therefore, this thesis contributes in addition to the literature on *institutional logic*, *sensory marketing*, and *organizational learning* by focusing on audience evaluation, narrative mode, and reference levels, respectively.

Examining how consumer audiences differ in their distinctiveness preferences and how this affects the evaluation of new venture narratives adds to research on the consequences of audience heterogeneity for optimal distinctiveness. By contextualizing optimal distinctiveness from a consumer perspective, this thesis offers new insights into audience distinctiveness preferences beyond those previously gained primarily from looking at investor audiences (Smith, 2011). This thesis represents consumer audiences as heterogeneous groups that differ in their preferences for the level of distinctiveness they consider optimal. Consumer audiences evaluate new ventures through different lenses based on their roles as investors, buyers, and users (Bowers, 2015; Zhao, 2022). Considering the different roles of consumer audiences expands the prevailing view of audiences as heterogeneous groups with different needs for normative appropriateness (Fisher et al., 2017), expectations of novelty (Feurer et al., 2021; Taeuscher et al., 2021), and tolerances for distinctiveness (Pontikes, 2012) in the institutional logic literature to heterogeneity within audiences. So far, that audiences differ in their institutional logic within has only been shown for investor audiences (Fisher et al., 2017). Showing that heterogeneity also exists within consumer audiences likewise adds a new dimension to the assumptions that audiences differ in their evaluative frameworks (Zhao et al., 2017; Cattani et al., 2017; Gouvard and Durand, 2022), evaluative criteria, expectations, and categorical definitions (Durand and Paolella, 2013). Considering the heterogeneity of audiences within their group also has implications for the literature on entrepreneurial narratives that emphasizes the importance of a new venture's entrepreneurial narrative to resonate with its audience (Lounsbury and Glynn, 2001; Navis and Glynn, 2011).

Considering textual, visual, and auditory modes that entrepreneurs often use to narrate their new venture's distinctiveness extends the focus on textual narratives as key means for strategic differentiation in the literature on optimal distinctiveness and entrepreneurial narratives (Meyer et al., 2018). Furthermore, introducing doc2vec, a machine learning-based natural language processing method, shows new means to measure meaning in these three narrative modes and deepens our understanding of how different entrepreneurial narrative modes can convey optimal distinctiveness (Vossen and Ihl, 2020; Kaminski and Hopp, 2020). This thesis demonstrates that different narrative modes not only enable entrepreneurs to express distinctiveness and legitimacy but can also serve as an effective tool for managing categorical contexts with heterogeneous audiences and evaluative complexities (Taeuscher et al., 2022), which contributes to the discussions on audience diversity in the optimal distinctiveness literature. This thesis also contributes to the literature on entrepreneurial narratives and cultural entrepreneurship theory. It views narratives as cultural elements (Lounsbury et al., 2018) that take on different modes (Rindova et al., 2011) that entrepreneurs can use for strategically differentiating their new ventures. It emphasizes the constraining and enabling aspects of context as cultural environments that entrepreneurs must navigate to create an optimally distinct narrative to obtain needed and valued resources (Zhao and Glynn, 2022). By improving our understanding of visual narratives as means for strategic differentiation and considering their multidimensionality in terms of the fit and richness of conveyed meanings, this thesis adds to the visual turn in organizational studies (Boxenbaum et al., 2018) and to the critical role of sight as a dominant and impactful sense for consumer evaluation in sensory marketing (Krishna, 2012).

This thesis enhances our knowledge of how multiple coexisting reference levels impact narrative distinctiveness evaluations. The focus on category-inherent levels of reference, such as the prototype and exemplar, and levels of reference arising from the nested category structure complement discussions of a new venture's core competitors in the categorization literature. This thesis also extends the prevailing view on reference levels in the optimal distinctiveness literature as primarily prototype-based (Zuckerman, 1999; Miller et al., 2018;

Haans, 2019) or exemplar-based (Zhao et al., 2018; Younger and Fisher, 2020) and highlights the relevance of a simultaneous evaluation of multiple reference levels (Conger et al., 2018; Grimes, 2018; Barlow et al., 2019). Contrasting narrative distinctiveness against multiple coexisting reference levels has important implications for understanding the performance outcomes of new ventures (Zhao, 2022).

Besides the influence of *multiple* reference levels on optimal distinctiveness, this thesis contributes to the *dynamic* view of optimal distinctiveness (Zhao, 2022). New ventures are subject to various time-related influences due both to the dynamic development of reference levels (Chan et al., 2021) and to evolving legitimacy and differentiation pressures (Cattani et al., 2017) resulting, for example, from market maturity (Navis and Glynn, 2011; Zhao et al., 2018) and the organizational life cycle (Zhao et al., 2017; Goldenstein et al., 2019). To maintain optimal distinctiveness, new ventures must adapt to the dynamic evolution of their environment. By introducing the concept of aspirations from organizational learning theory into the literature on optimal distinctiveness, this thesis shows how competitive reference levels can serve as learning sources for new ventures to optimize their strategic differentiation over time. This extends the role of competitors as actors to either conform to or differentiate from to a source of learning (Greve, 1998, 2002; Dong, 2021) and adds to our understanding of institutional pressures and competitive dynamics in entrepreneurial markets. Also, considering the prototype and exemplar as influential reference levels adds to the discussion in the literature on organizational learning on different strategies available to form aspirations, such as following a conservative strategy by comparing to all industry peers like the prototype or an ambitious strategy by comparing to only top performers like the exemplar (Dong, 2021).

In addition to the importance of dynamically evolving competitive reference levels as a framework for optimal distinctiveness, this thesis highlights the relevance for new ventures to gauge their distinctiveness by comparing themselves to their past selves as an additional reference level. This complements the discussion of within-organization distinctiveness affecting audiences' evaluation as it impacts the perceived congruence of a new venture's portfolio (Chan et al., 2021; Janisch and Vossen, 2022). By relating a new venture to its past distinctiveness trajectory, this thesis also contributes to Durand and Haans (2022)'s call for "a better quantification of the actual efforts put forth by organizations in optimizing their assets and resources." Viewing optimal distinctiveness as a continuous process underscores the motivation of entrepreneurs to further optimize the strategic differentiation of their new venture by actively adjusting their strategic positioning (Durand and Haans, 2022). The insights into the active role that entrepreneurs, as experienced cultural operators, play in adapting the strategic differentiation strategy contribute to the optimal distinctiveness theory and likewise add to the literature on entrepreneurial narratives by also considering the construction of narrative distinctiveness as an ongoing process (Garud et al., 2014; Zhao and Glynn, 2022). Furthermore, measuring narrative distinctiveness in textual, visual, and auditory narratives by capturing their mediated meanings using doc2vec contributes to better comparability of narrative distinctiveness between reference levels.

7.3 Managerial implications

This thesis has several implications for new venture entrepreneurs that market their product(s) on online platforms and seek to narrate their distinctiveness optimally. Low barriers to entry on online platforms often lead to high competition (Rietveld and Eggers, 2018), amplifying the strategic challenges of differentiation in crowded markets for entrepreneurs of new ventures (Barlow et al., 2019). Especially in consumer markets, where short trend cycles are evident, suggesting that consumers are always looking for something new, and where attention spans are often short due to many offers, it is essential to stand out and appeal to consumers through an optimal level of narrated distinctiveness. However, there is little guidance on how new venture entrepreneurs should choose the level of distinctiveness of their narrative, depending on the type of consumer audience they are targeting, the mode they use, and in relation to different reference levels. It is unclear whether entrepreneurs can appeal equally to all consumers through an equal level of distinctiveness in their narratives. In addition, there is limited evidence on how entrepreneurs should design non-textual narratives, such as visual promotions and product images or visual and auditory clips, to best differentiate their new venture in the eyes of consumers who are often reluctant to read (DelVecchio et al., 2019). There is also a lack of guidance on how entrepreneurs should strategically develop their new venture relative to its distinctiveness trajectory (Durand and Haans, 2022).

Hence, this thesis considers how entrepreneurs can differentiate and, at the same time, sufficiently legitimize their new ventures in the eyes of different consumer audiences (Taeuscher et al., 2021; Janisch and Vossen, 2022) from market-, category-based, and their past self as reference levels (Zhao et al., 2017; Zhao and Glynn, 2022) through a textual, visual, or auditory product narrative (Kaminski and Hopp, 2020). Examining different entrepreneurial contexts characterized by different evaluating audiences with different preferences for distinctiveness, different primary modes for narratives, and relevance of different reference levels contributes to a better understanding of the contextual conditions under which entrepreneurs should choose which differentiation strategy.

This thesis advises entrepreneurs who aim to finance their entrepreneurial endeavors or conceptual ideas by attracting consumer investor audiences, such as in crowdfunding. The results are based on a cross-section of entrepreneurial endeavors from different categories and therefore address not only entrepreneurs of technological endeavors, which have been frequently studied in the past (Parhankangas and Renko, 2017; Kaminski and Hopp, 2020), but also entrepreneurs of cultural and civic endeavors. This work offers entrepreneurs clear guidelines on how to legitimize themselves in the eyes of first-time and repeat backers on a crowdfunding platform through their campaign in which they describe their entrepreneurial endeavors. To do this, entrepreneurs have various strategic tools (Fisher et al., 2017) that can be used individually, depending on whether the focus is on attracting first-time or repeat backers. The results show that a critical strategic tool is the narrative of a campaign description, and entrepreneurs should develop a narrative that appeals to both first-time and repeat backers. If entrepreneurs are concerned about primarily attracting repeat backers, they should create a textual narrative that differentiates their entrepreneurial endeavors from past campaigns. However, when relying more on first-time backers, entrepreneurs should focus on being distinct in their campaign's textual narrative from current campaigns. If entrepreneurs primarily want to attract repeat backers, they should create a textual narrative that differentiates their entrepreneurial endeavors from previous campaigns. However, if they want to focus on first-time backers, entrepreneurs should emphasize the distinctiveness of their campaign from current campaigns. Regardless of their strategy and goals, entrepreneurs should be aware of the subtle and apparent differences within consumer investor audiences in legitimizing first-time and repeat backers to succeed in "dancing to multiple tunes."

This thesis provides clear management implications for entrepreneurs who use textual narratives to portray the distinctiveness of their new ventures and those who operate in markets where it is essential to compete with visual narratives and where consumers base their purchasing decisions on product images. These entrepreneurs have had little insight from the optimal distinctiveness literature on designing visual narratives to appeal to consumer buyer audiences. When designing visuals such as images that promote products, entrepreneurs should consider not only essential visual characteristics such as illuminance, shape, or color (Sample et al., 2020; Sgourev et al., 2022) but also the impact of visual narratives on consumers' perceptual and meaning processing (Höllerer et al., 2018). In crafting these visual narratives, entrepreneurs should know their target product category particularly well, as well as the expectations of consumer buyer audiences regarding the fit and richness of meaning conveyed in visual narratives (Nielsen et al., 2018). Especially in distinct product categories, entrepreneurs should ensure that they also accompany a visual narrative fitting the expectations of their target product category with strong semantic richness to avoid devaluation by consumer buyer audiences. Although the categories shape consumer expectations and thus set the evaluative boundary conditions for evaluating a visual narrative (Janisch and Vossen, 2022), entrepreneurs should not underestimate their agency in shaping their visual narrative (Durand and Haans, 2022). By carefully matching the fit and richness of the semantics they bring to the categorical context, entrepreneurs can ensure that their product images contain "more than what meets the eye."

This thesis also offers important lessons for entrepreneurs who use auditory narratives to communicate their new ventures' distinctiveness to consumer user audiences, such as small-scale entrepreneurs who want to create content for online social media platforms to become full-time entrepreneurs. These lessons teach content creators how learning from aspirations can inform their strategic decisions and, thus, their pursuit of optimal distinctiveness, helping them refine their positioning in new content releases. Revising positioning strategy is relevant for content creators and other, primarily digital, entrepreneurs. Entrepreneurs in digital markets frequently launch new products (Parker et al., 2017; Fernhaber and Patel, 2012; Barlow et al., 2019) and can therefore benefit from this thesis's insights into the success factors, as well as the process and consequences of learning from performance feedback to overcome the challenges of achieving optimal distinctiveness as an ongoing process (Zhao and Glynn, 2022). In addressing these challenges, what emerges as relevant above all is that such entrepreneurs see other market participants not only as competitors to which they either adapt or differentiate themselves, but also to understand them as a locus of problemistic search and, thus, as a source of learning (Posen et al., 2018; Dong, 2021; Peterson and Wu, 2021). This source of learning, in addition to what entrepreneurs can learn from comparing themselves to their past selves, that is, their distinctiveness trajectory (Durand and Haans, 2022), is beneficial for content creators who have missed their aspirations and need to rethink their content. Here it becomes apparent that future content creators should "reach for the stars" to achieve optimal distinctiveness, that is, reaching for competitors already considered established and thus legitimate in the market but still stand out firmly from other market players (Barlow et al., 2019).

7.4 Limitations, future research, and conclusion

The three main limitations that emerge from this thesis provide avenues for future research. The first limitation arises from the methodological approach to operationalizing distinctiveness that unites all three studies. This thesis used the machine learning-based approach doc2vec to measure narrative distinctiveness. This type of natural language processing applies to different narrative modes, provided they are convertible to text. Thus, doc2vec allows computing the distinctiveness of crowdfunding campaign texts, Amazon Launchpad product images, and YouTube audio transcripts and studying their impact on new ventures' success or strategic decision-making. However, it also emerged that the different narrative modes and corpora sizes affect the suitability of doc2vec for measuring distinctiveness since a general setting of training model parameters does not lead to equally interpretable results.

Future research could compute the fit of a doc2vec model under different training parameter constellations for different narrative modes and contexts. In particular, when calculating the distinctiveness of images, the question of a suitable word window arose to capture the context of a word and, based on that, to learn the meaning of a word. Building on prior research (Kaminski and Hopp, 2020), this thesis invokes that the context word window should be chosen smaller in the meaning acquisition of images than in written texts or audio transcripts. Future research could further investigate the variability of the context word window for different narrative modes in different contexts to make a generalizable recommendation for the appropriate size of the context word window. The parameter fit of the doc2vec models used here needs to be investigated in more detail and across different corpora sizes, as these parameters are ultimately based on subjective judgment concerning the interpretability of the word and document embeddings. This thesis used distributed memory as a model architecture. Future research should also examine how using mixed model architectures, combining distributed bag of words and distributed memory, impacts model likelihood. Likewise, different algorithms for natural language processing, such as doc2vec, ELMO, BERT, GPT-3, and topic modeling, should be compared to uncover the unique algorithms' boundary conditions for specific applications.

The second limitation arises from the necessity of using doc2vec to convert non-textual into textual narratives using machine learning and the potential sources of error associated with this conversion process. This thesis considers three different narrative modes and market settings: Crowdfunding campaign texts from Kickstarter, product images from Amazon Launchpad, and audio transcripts of videos from YouTube. While the crowdfunding campaign texts, which represent self-authored texts by the entrepreneurs, could be directly converted into a numerical vector representation using doc2vec, the narratives of the product images from Amazon Launchpad and the YouTube videos first had to be transformed from a visual and auditory to a textual form, respectively.

Transforming product images into a textual narrative using machine learning-based image recognition runs the risk of being error-prone for misidentified or missing image elements. It was argued that a product image narrative could be represented as a sum of its labels of identified objects, scenes, and concepts (Dzyabura et al., 2021). Hence, the validity of image recognition influences whether the product image narrative is composed of the correct labels and, thus, the reliability of the subsequent distinctiveness computation using doc2vec. Further research should therefore test the image recognition approach used in this thesis under additional conditions, for example, with images from different contexts and quality features, to shed light on the boundary conditions of the methodology. Furthermore, the reliability of image recognition could be tested experimentally by matching machine image recognition results with human-identified objects, scenes, and concepts.

Also, converting spoken narratives in videos into a textual form using machine learning-based automatic speech recognition carries the risk that misrecognized or missing speech elements will result in erroneous representations. Audio transcripts of YouTube videos are not necessarily written by the creators themselves but often result from automatic speech recognition. Thus, they are subject to the influence of machine learning and the associated sources of error (Welbourne and Grant, 2016). Further qualitative and experimental research is needed to investigate automatic speech recognition's boundary conditions and validity. Of particular interest here could be whether and how strongly certain language features, such as colloquialisms or an accent, influence the validity of automatic speech recognition.

The third limitation arises from considering separately the influence of linguistically, visually, and auditorily communicated distinctiveness on new venture success. This uni-modal perspective neglects additional insights into how appealing to different senses simultaneously influences consumers' evaluation that a cross-modal perspective could provide. In the past, studies in the field of sensory marketing have often dealt with how consumers use several senses simultaneously to evaluate products (Krishna, 2012). In the research field of optimal distinctiveness and entrepreneurial narratives, however, such a cross-modal perspective has been neglected so far, and scholars primarily considered how ventures use a textual product or venture description (Haans, 2019; Vossen and Ihl, 2020; Taeuscher et al., 2022; Buhr et al., 2021), textual product attributes and category information (Zhao et al., 2018), and visual product designs (Chan et al., 2021; Bu et al., 2022) to differentiate from others. Future research should therefore investigate the interplay of different narrative modes, for example, how the description of a product and its visual images or how audio-visual elements in videos interact and influence the evaluation of audiences. From the literature on optimal distinctiveness, we know entrepreneurs can orchestrate multiple strategic dimensions to achieve optimal distinctiveness (Taeuscher and Rothe, 2021; Zhao et al., 2017). However, we still have a limited understanding of how orchestrating different narrative modes can help ventures achieve optimal distinctiveness. Future research here could provide new explanations of how the use of cross-modal narratives influences optimal distinctiveness.

Separately investigating different narrative modes has the limitation of not considering the interplay of information communicated through different narrative modes. Considering only the textual description of an entrepreneurial endeavor neglects the wealth of possible information insights from additional materials (Ormiston and Thompson, 2021), which may allow a complete picture of the entrepreneur, product, or venture. Crowdfunding research, for instance, could benefit from cross-modal investigations of the textual description of the project and the creator, visual displays of the creator and the product/service, and auditory impressions from a project's video pitch. This cross-modal approach could help to understand even better how entrepreneurs can best legitimize themselves with both first-time and repeat backers. Similarly, consideration of the semantic meaning of Amazon product images is limited to the influential role of static visuals on consumer sensemaking and evaluation. Future research could investigate how product videos and descriptions influence these sensemaking processes and affect consumer evaluation. Experimental studies could investigate how consumers behave on product pages in online markets to conclude how much attention they pay to which narrative mode and how the design of the different narrative modes influences the success of a product. Particularly in such settings where a visual mode is used in addition to a textual narrative mode, it would also be interesting to see how new ventures learn from different narrative modes. Examining how falling below or exceeding aspiration levels causes YouTubers to change their auditory narrative ignores the impact that video description, tagging for discoverability, and the video narrative's visual content have on a video's success. From this limitation, new starting points for future research emerge to understand better which factors influence the achievement of an aspiration level.

This thesis examined how new ventures, which must be distinct due to their entrepreneurial nature, can successfully convey an optimal level of distinctiveness that still sufficiently legitimizes them in the eyes of evaluating consumer audiences. For this purpose, this thesis demonstrated the central role of meanings conveyed through entrepreneurial narratives in achieving optimal distinctiveness and machine learning-based methods for measuring this distinctiveness. Only when entrepreneurs know how the evaluating audience, the narrative mode used, and the differentiation from multiple reference levels, including their past self, influence the perception of their entrepreneurial narratives and, thereby, also the strategic differentiation of their new venture, can entrepreneurs succeed in narrating optimal distinctiveness, and machine learning helps them to do so.

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