Reaching for the stars? Entrepreneurial aspirations and optimal distinctiveness on YouTube

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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 induce a problemistic search that leads to increased change. In contrast, missing aspirations by a wide margin cause 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
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1 Introduction

Deciding on how to position oneself in the market is a central part of 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, 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 change in its appeal over time (Goldenstein et al., 2019; Zhao et al., 2018) or change 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 need to constantly release new content 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, the more 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

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ask the following 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 lead 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 venture pursue via narratives. For the latter, we show how entrepreneurs stand out in their non-homogeneous response to missing aspirations and 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. Showcas-

ing 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.

2 Theoretical background

2.1 Optimal distinctiveness and strategic change

From the strategic management literature, we know that entrepreneurs need to position their ventures strategically 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 that 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 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, and finding a compelling narrative that portrays them as attractive, unique, desirable, and appropriate is, therefore, a critical factor in their early success (Navis and Glynn, 2011). Creating a compelling narrative is especially important in contexts of strong competition where new ventures are even more challenged to capture audiences' at-

tention (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 both in terms of 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 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 not solely orient themselves 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.

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

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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 them 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 conceptualized as 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, may be both on themselves and competitors. This is mirrored in the literature on optimal distinctiveness where decisions on positioning do not solely have to take into account the behavior of competitors (Haans, 2019), but also on within-organizational precedents (Bu et al., 2022) and characteristics (Janisch and Vossen, 2022; Goldenstein et al., 2019). As such, it looks pretty valid to assume that entrepreneurs who fail aspirations engage in a problemistic search and look 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).

Similar effects are also described in the literature on optimal distinctiveness, as deviating too much from audiences' expectations, and distinctiveness preferences can adversely affect product performance (Janisch and Vossen, 2022; Zhao and Glynn, 2022) and in alienating 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 a threat to their self-image, they are likely to engage in cognitive processes that contribute to self-enhancement by biasing information in a self-interested manner (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 1: *Narrowly missing aspirations results in more distinctiveness change than widely missing aspirations.*

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

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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 very notion of a category prototype requires an established category with clear boundaries (Zhao et al., 2018), and in categories that lack these, conforming to the category prototype can also be detrimental to 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 not being able 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 that entrepreneurs 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 2: *Missing aspirations increases distinctiveness from the category prototype.*

A category exemplar is defined as 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 representative of a category and 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). 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, which positively impacts 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 a change would be hindered by self-enhancement, as becoming more like the most successful actor could also be perceived as 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 3: *Missing aspirations decreases distinctiveness from the category exemplar.*

3 Empirical approach

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, on a crowded platform like YouTube, content creators are unlikely to know all of 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.

To identify the most successful English-speaking content creators, we used publicly available data from Social Blade[1] as a starting point. 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

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

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 introduced its "Thumbs" rating system (444 channels), we obtained a list of 1184 channels.[2]

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, e.g., Apple, Google, Tesla, Ford, etc. Third, we excluded channels that focus on posting snippets from original TV shows. Fourth, we excluded channels that had less than one upload per year or no monetary interest, e.g., non-profit organizations, as 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 the exclusion of 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

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[2]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.

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.[3] For less than 20 % of our data set, not all of the five most viewed videos of a channel 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.

3.2 Dependent variable

Our study uses three dependent variables that are *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). To compile such a narrative, we utilize 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 transcripts 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, which is 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

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[3]The focus on five videos here is an arbitrary choice to cope with data collection restrictions, which only allow the collection of transcripts and comments of about 10-20 videos a day. Given this constraint, we decided to observe the five most popular videos. We believe that the most successful videos are the most salient benchmark 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.

the semantic similarity of these words. Doc2vec is an extension of word2vec and assigns 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 actually 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 from each other 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 a very similar meaning 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.[4] To avoid over-representation of

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[4]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),

seldom and very frequent words for learning the context of a word, we set 10 occurrences as the minimum threshold a word should 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– and assigning lower weights to the output nodes of these words as compared to the output node of words matching the given context.

Figure 1: 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

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.

Maaten and Hinton, 2008). T-SNE maps words with a similar meaning close to each other, while dissimilar 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 1 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 seen in Figure 1, the three words most similar in meaning to, e.g., 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, e.g., the meaning contexts associated with the input words "content" and "famili."

This complex procedure created a vector for each document for 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 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 same content creator's most recent (mr) video:

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

To operationalize the variable *distinctivenes 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:

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

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, at the time of a focal video's release, had accumulated the most commentators on their top-performing and most recent videos. We argue that the content creator that is 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:

$$Distinctiveness \ to \ exemplar_{it} = 1 - \left[\frac{\sum_{w=1}^{W} f_{wi_t} \, f_{we_{mr}}}{\sqrt{(\sum_{w=1}^{W} f_{wi_t}^2)} \cdot \sqrt{(\sum_{w=1}^{W} f_{we_{mr}}^2)}} \right] \qquad (3)$$

For the identification of 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 for a video needs to be released before a focal video. 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.

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 aspiration.

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 be used to 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 "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 aspiration 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:

$$HA_{ti} = a_2 * HA_{mr,i} + (1 - a_2) * P_{mr,i} \tag{4}$$

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:

$$SA_{ti} = (\sum P_{mr,e})/N \tag{5}$$

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:

$$A_{ti} = a_1 * SA_{ti} + (1 - a_1) * HA_{ti} \tag{6}$$

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 has a weight of 0.2, a content creator's previous performance has a weight of 0.16, and the last historical aspiration has a weight of 0.64.

To measure how a content creator performs relative to their aspirations, we subtracted the aspirations from a video's current performance. The extent to which a content creator deviates 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 in which 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 more significant than zero and equals the total performance gap

otherwise.

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 release	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 1: Variable descriptions

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 *length of video title* and *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 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 led to an increased popularity of gaming channels (Youtube, 2012). Please refer to Table 1 for an overview of the descriptions of all variables used in our analysis.

4   Results

We used a fixed-effects OLS regression with category and content creator fixed effects and clustered the standard errors on both. Figure 2 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 *Gaming* and *Entertainment*, which is more or less in line with the findings by Bärtl (2018). Table 2 contains the means, standard deviations, and correlations for the variables used in our regression analyses. Table 3 reports the regression coefficients and significance levels we used to test our hypotheses.

The regression results of Model 1 lend support to our Hypothesis 1, which postulates that 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
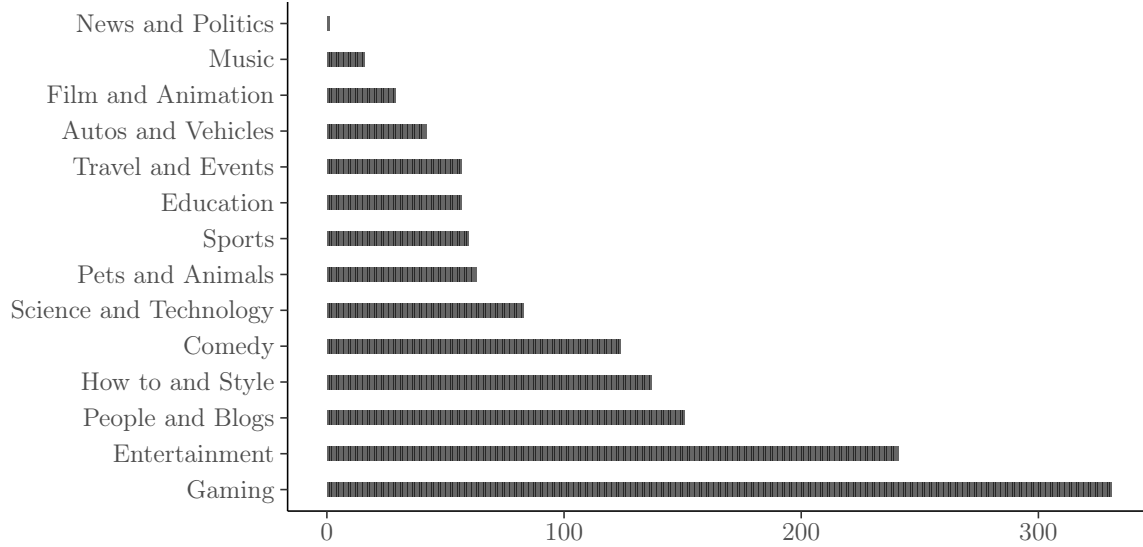
Figure 2: Number of videos per video category

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
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										
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								
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. Age YouTube (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

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

Table 2: Descriptives and correlations

have different signs and are significantly different from each other ($\chi^2 = 40.313$***). Model 2 supports our Hypothesis 2, which states that when content creators perform below aspiration, they will become more distinct from the prototype ($\beta = 0.012$, 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

| Dependent Variables: | Narrative change | Video distinct./prot. | Video distinct./ex. |
Model:	(1)	(2)	(3)
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)
Age YouTube (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)
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*

Table 3: Fixed-effects OLS regression

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 3 graphically displays the results of Model 1 in Table 3. We find a non-homogeneous response pattern with a stronger tendency for entrepreneurial content creators to change their distinctiveness when performing below aspiration drastically. Entrepreneurial content creators are likelier to change their distinctiveness when they perform close to aspiration.
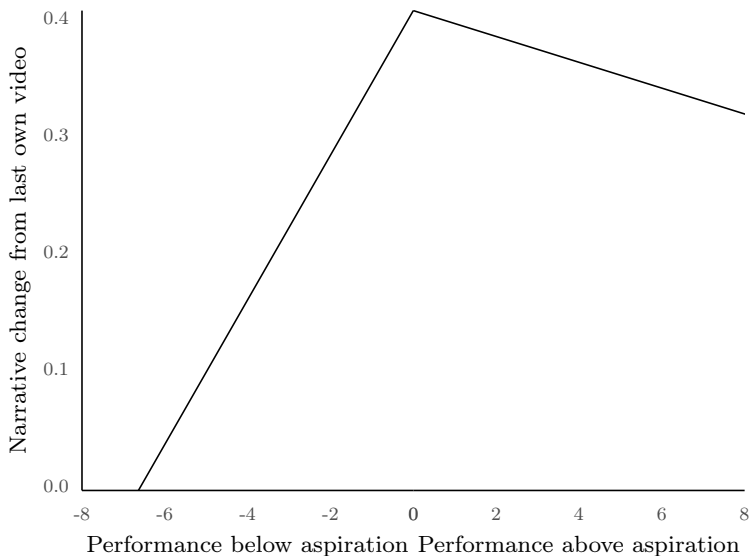
Figure 3: Predictions of narrative change from own last video (Model (1) in Table 3). Measured as 1-cosine similarity of video transcript *t* with transcript *t-1*

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 based on 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. It seems this concern was 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

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on performance.

We followed prior research (Greve, 2003) and employed a weighted average in aspiration–an aspiration that sets a performance trend (historical aspiration) in relation to a benchmark level (social aspiration)–affects entrepreneurial content creator's 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 to the exemplar ($\beta = -0.004$, p $<$ 0.001).

6 Discussion

Finding a way to achieve optimal distinctiveness has become a recent fixture in studies from strategic management, organizational theory, and entrepreneurship alike (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 aspirations are missed 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 still 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 on 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 the role of categories and the competitive and normative pressures in it (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 either 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 on revising their positioning strategy as they release new products (Parker et al., 2017) and build their portfolio (Fernhaber and Patel, 2012).

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 that are 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 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.

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