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

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This Version: January 2, 2023

Abstract

Optimal distinctiveness postulates that entrepreneurs need to position themselves as distinct 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 content creators are likely to change if prior performance was below aspirations–expectations founded both on own and competitors' past performance. This response, however, is non-homogeneous, suggesting that narrowly failing aspirations induces problemistic search that leads to increased change, while missing aspirations by a wide margin induces rigidity, self-enhancement, and less change. Content creators that clearly fail their aspirations therefore change very little in their next video's narrative, while those that narrowly fail respond by releasing a video whose narrative is more distinct from their last own release as well as 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

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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 need to 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 that emphasize "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 therefore the entrepreneurial decision to position oneself, as a one-time event. This is in line with a rather 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). This, however, neglects that change may also be the result of deliberate entrepreneurial action. A premier example for 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 especially important 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 successfully keep their audience engaged. With each new release, this also leaves them with the challenge to position themselves in the highly dynamic competitive environment, finding the right narrative to differentiate from scores of competitors in order to attract audiences to their channel (Johnson et al., 2022).

We propose that 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 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, often the effect of aspirations on change is not linear, as shortfalls below aspiration–performance gaps or attainment discrepancies (Lant, 1992)–frequently trigger more change, while performance equal to or above aspiration makes change less likely (Greve, 2003; Tarakci et al., 2018; Ref and Shapira, 2017). A proposed explanation for this is that performing below aspirations triggers "problemistic search" that initiates a learning process and the more clearly an organization misses aspirations, the more it supposedly engages in problemistic search (Posen et al., 2018). Yet, this perspective has been labelled overly positive, as organizations that miss their aspiration by a wide margin may also experience less change due to strategic rigidity (Greve, 1998) or an exaggeratedly positive interpretation of achieved performance and 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 overly positive interpretations of performance are well documented in entrepreneurial markets (Forbes, 2005; Politis, 2005), we deem aspirations a suited theoretical lens to analyze and understand change in entrepreneurial narratives and optimal distinctiveness–an aspect that has so far been neglected in the literature. Consequently, we ask the following two research questions: (1) Does missing or exceeding aspirations cause equal change in entrepreneurial narratives? (2) Do entrepreneurs become less or more distinct in them as a result?

To answer these questions empirically, we collected secondary data from the most successful English-speaking content creators on YouTube. YouTube is a premier example for a content creation-based online platform that provides an ecosystem for entrepreneurs to get in contact with potential viewers (Cutolo and Kenney, 2021; Mardon et al., 2018). Utilizing the YouTube API, we collected a wide array of variables on the videos, most importantly the automatically generated transcripts and viewer comments. We utilize 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 that are below aspirations are more likely 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 stronger 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 to the literature on strategy and organizational theory alike. 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. 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 finding themselves missing their aspirations and in need 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, to contextualize these relationships, and to identify the different 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 important 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 make legitimizing and differentiating claims about who and what they are and thereby help evaluating audiences make sense of 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 interesting and unique, as well as desirable and appropriate, is therefore a key factor in their early success (Navis and Glynn, 2011). Creating an effective narrative is especially important in contexts of strong 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 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 rather 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 as a result of changing attractiveness over time is thereby 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, so it becomes less important for a venture to gain legitimacy.

Likewise, the market matures over time and audiences' expectations evolve, so the benefits of being different for a venture diminish. Against this backdrop, entrepreneurs need to take action to strategically position their ventures when entering the market–yet, beyond describing the aforementioned effect, existing work provides little insights on how entrepreneurs should change.

This holds also true 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 his or her 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 for 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 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 in that entrepreneurial learning and improvement in general 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 in particular play a key role in future differentiation decisions such as the narrative design.

We focus our arguments on failing as deviating from aspirations–either by exceeding it or falling below it–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 more prevalent when entrepreneurs fail to meet their aspiration and less likely when they exceed them.

Falling short of aspiration signals a problem and entrepreneurs engage in 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 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 oneself as well as 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 seems very valid to assume that entrepreneurs that fail aspirations engage in problemistic search and that they both 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 build 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 discrepancy is perceived to be repairable–and decreases away from it–where discrepancy is perceived to threaten survival (Greve, 1998; Audia and Greve, 2006). Self-enhancement and threat rigidity seem to be of particular relevance in contexts where entrepreneurs are prone to biased self-reflection (Forbes, 2005) and usually also carry a higher personal risk that may make them wary to 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 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 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 result in adverse effects on 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 significantly change their distinctiveness appeal.

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 a strong extroverted confidence (Roccapriore and Pollock, 2022).

Taken together, we believe that both problemistic search as well as rigidity and self-enhancement are consequential for changing entrepreneurial narratives and optimal distinctiveness strategy. If entrepreneurs miss their aspirations narrowly, they engage in problemistic search and are more likely to change as they deem their narrow miss "fixable." Therefore, new differentiation decisions will entail a narrative that differs more strongly from their last decision. However, failing by a wide margin induces rigidity and self-enhancement which both lead 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 change in distinctiveness in new differentiation decisions, as compared to 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 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 serve to 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). As a consequence, 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 that choose to conform to the category prototype reduces audiences' confusion about categorization (Negro et al., 2010) and can increase own 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, in crowded categories, conforming to the prototype has a negative effect because if every member aspires to be like the prototype of the category, the members of the category end up being too similar and each individual gets lost in the crowd (Barlow et al., 2019). Deviating from the prototype can therefore provide a competitive advantage, especially when audiences expect it, such as in the case of new ventures that need to have a certain "legitimate distinctiveness" (Navis and Glynn, 2011). Deviating too much from the prototype, however, can in turn 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 makes it more likely that entrepreneurs become more distinct from the prototype. A lack of performance, particularly in the case of content creators, is often founded on not being able to catch audience 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 stronger 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 in new differentiation decisions.*

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 exceptional representation of a category (Zhao et al., 2018) in terms of most well-known or highest performing member and use it as cognitive reference to compare it to another focal venture or product to gauge the latter's optimal distinctiveness. 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 exemplar creates both legitimacy and distinctiveness, which has a positive impact on venture performance (Barlow et al., 2019). The category exemplar establishes a basis of comparison for audiences, but 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 both 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 important to be also different from the category exemplar in order to be competitive (Younger and Fisher, 2020).

We believe that failing aspirations make entrepreneurs become less distinct from the exemplar. In general, the exemplar occupies a position that entrepreneurs strife for, as she is already "legitimately distinct" which is what audiences expect from entrepreneurs (Zhao et al., 2018). 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 stronger when entrepreneurs fail their aspirations by a wide margin, as in this case their need for additional audiences is the largest, and changing ones 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 that many entrepreneurs strife 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 to be 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 in new differentiation decisions.*

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 and 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 suc-

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

cess (most viewed channel, most subscribed channel, or highest Social Blade rating). The top 100 lists of channels are both 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. To make channel content comparable with our natural language processing approach (see below), we restrict this study to English-speaking channels. 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 for example 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]

In accordance with the established description for an entrepreneurial content creator (Roccapriore and Pollock, 2022), we applied several exclusion criteria. First, we excluded channels owned by persons who became famous through other activities or other social media platforms before starting a YouTube channel, e.g., musicians or comedians. Second, we excluded official channels of large firms, e.g., Apple, Google, Tesla, Ford, etc. Third, we excluded channels which focus on posting snippets from original TV shows. Fourth, we excluded channels that had less than one upload per year or released without 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

[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 for 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.

of the videos had an English transcript available and the comment section activated (again this relates to our natural language processing and 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 let to the exclusion of 793 channels. We also excluded 40 channels that are not associated with any channel category on Social Blade, as this missing piece of 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 of 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 that is 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 is verbally presented by the content creator into textual information. We utilized this textual information to

[3]The focus on five videos here is an arbitrary choice that was forced upon to cope with data collection restrictions of the API which only allows to collect 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 also the most salient benchmark for content creators in determining a success or not and are also the most obvious choice for the 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.

train a machine learning algorithm that helps us in identifying 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 that are adjacent to the same words share the same context and thus have a similar meaning (Le and Mikolov, 2014). As the name suggests, word2vec serves to translate words into unique numeric vectors. In order to mathematically compute and recognize the context of words, the so-called word embeddings, word2vec trains a neural network that learns the semantic and syntactic qualities of a word based on a large text corpus.

Finally, computing the cosine similarity of two word vectors provides information about the semantic similarity of these words. Doc2vec is an extension of word2vec and assigns a unique vector not only to each word, but also to each document with variable text length. That is, doc2vec learns not only in what context a word appears, but also whether that context is specific to a particular document. Doc2vec can be used for different types of documents, the only requirement is that the documents must be in textual form. Thus, doc2vec can also be used for similarity computation of spoken language when converted to a textual form consisting of a string of words that reflect the contents discussed in a video.

Since textual information can be similar without using the exact same words, doc2vec, unlike other natural language processing methods, offers the possibility to 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 is able to 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. Doc2vec therefore provides us with a suitable method to measure the extent to which content creators change their narrative and positioning as compared to their own prior past releases or that of their peers.

Since doc2vec translates text of any length that uniquely identifies a document into a numeric vector representation, which in turn is used to calculate document similarities, we first had to retrieve the audio transcripts provided by YouTube's automatic transcript feature for the videos in our data set. We trained the algorithm with all audio transcripts we identified for our data set. As training parameters, we set the learning epochs to 40, the vector size for the word embeddings to 50 dimensions, and 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 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). We used negative sampling to improve predictions of a target word based on a given context by creating 10 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.

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 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 and allows us to visualize the 50 dimensions of the word embedding vector spaces for the video audio tran-

[4]There are no universally valid specifications for these parameters, as this decision should always be informed by the data used. For example, data that is 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, the selection of parameters always mandates testing, training models with different specifications, and comparing the similarity they attribute to word pairs and documents by means of face validity. As our corpus of documents is quite 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 in general not overly sensitive to changes in these parameters.

Figure 1: t-SNE of word2vec word embeddings—ten sample words and their three words most similar in meaning (words are stemmed)

scripts in a more intuitively interpretable two-dimensional space. Figure 1 shows ten sample input words of our training data set and the three words that are used in the most similar meaning context for each of these input words. As can be seen in Figure 1, the three words most similar in meaning to, e.g., the word "content" are "youtub," "video," and "entertain." Not only can we represent clusters of similar word meanings, but we can also see how far the meanings of 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 for us a vector for each document for which we can compute measures of distance. To operationalize the variable *narrative change*, we computed the cosine distance between the audio transcript of a content creator's focal video and his or her 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:

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

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 exemplar we considered the content creator that at the time of a focal video's release had accumulated the most commentators on his or her 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:

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

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 a video needs to be released prior to 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 of entrepreneurs.

3.3 Independent variables

To examine whether content creators change their narrative as a result of 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 own 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 both individually and collectively important (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 and 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 via the YouTube API, which provides access to the comments posted under a video where each comment also entails a unique ID of the user that has posted it. This allowed us to count the number of unique user IDs that have posted a comment to a certain video. This is also the reason why we discarded videos with disabled comments as stated in the sample description.

We used the number of unique commentators as performance measure as it possesses significant advantages over other measures of success such as views or likes, mostly 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 a video follows viewing it and 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 takes into account the fact 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 of 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 findings from the organizational learning and optimal distinctiveness literature 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 obvious 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 exemplar, entrepreneurs set challenging goals for their own 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 previous historical aspiration has a weight of 0.64.

To measure how a content creator performs relative to his or her aspirations, we subtracted the aspirations from a video's current performance. The extent to which a content creator deviates from his or her aspirations–either by falling short or exceeding it–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 larger effect than exceeding them (Bromiley, 1991; Greve, 1998). For this, we split each of our performance gap variables 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. In the same vein, aspiration performance < 0 equals zero for all observations in which the performance gap is greater than zero and equals the absolute performance gap otherwise.

3.4 Control variables

Many drivers other than aspiration performance may affect entrepreneurial content creators' channel success. Accordingly, we controlled for a range of video and channel attributes, as well as 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 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 a 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

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 prior to 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 most unique commentators in the respective video category at the time mr) that were released at least 30 days prior to 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 less 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 a 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 prior to video i.
No. of creators in video category	Number of content creators in the same video category at release of video i.
Algorithm change	Time event on 12th October in 2012, when YouTube changed its recommendation algorithm from a view-based to a watch time-based system.

Table 1: Variable descriptions

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 prior to a focal video. We also control for *algorithm change*, a time 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 and clustered the standard errors on both content creator and video category. 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 their levels of significance that we used to test our hypotheses.

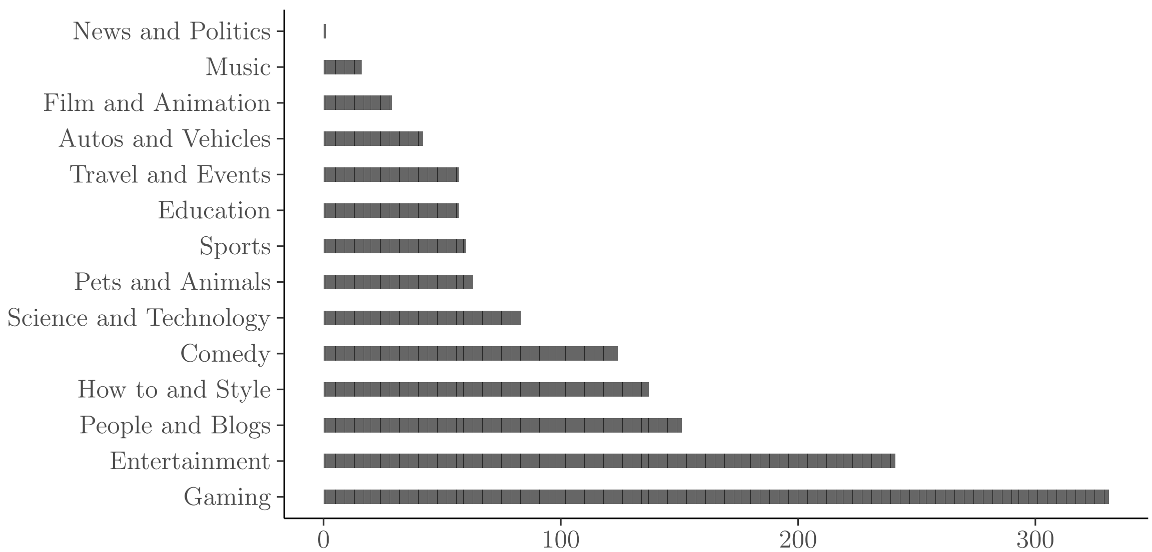

Figure 2: Number of videos per video category

The regression results of Model 1 lend support to our Hypothesis 1, which postulates that content creators who perform below aspiration become more distinct to 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 lends support to 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

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

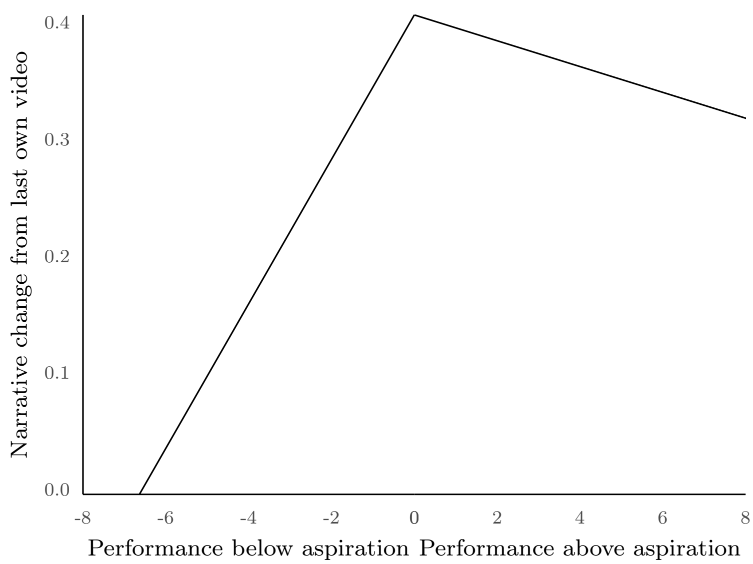

Figure 3: Predictions of narrative change from last own video (Model (1) in Table 3). Measured as 1-cosine similarity of video transcript *t* with transcript *t-1*

from each other ($\chi^2 = 16.958^{***}$). Model 3 lends support to our Hypothesis 3, which states that when content creators perform below aspiration, they will become less distinct to 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 3 graphically displays the results of Model 1 in Table 3. We find a non-homogeneous

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

response pattern with a stronger tendency for entrepreneurial content creators to drastically change their distinctiveness when they perform below aspiration. Entrepreneurial content creators are more likely to change their distinctiveness with respect to their own last video when they perform close to aspiration than when they obviously fail.

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 with respect to 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 in case when we assume a much shorter time window to measure initial success of a 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 that 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 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 additional, non-combinatory approaches to measuring aspiration are common (Bromiley and Harris, 2014), we considering 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 to their last video ($\beta = -0.020$, p $= 0.007$) and less distinct to 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 to 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 aspiration rather than when they exceed it. In our empirical context, this means that if a video attracts slightly fewer unique 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 would be significantly 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 looks like as entrepreneurs become more distinct from the category prototype but less from the category exemplar. We interpret that entrepreneurs who narrowly fail to meet their aspiration 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 self-enhancement of entrepreneurs (Audia and Brion, 2007; Ocasio, 1993). Although this renders change less prevalent, we, however, are still able to find one way change still occurs, namely in decreasing distinctiveness from the exemplar. We propose that this can be explained by the special role as a "star" exemplars play in categories (Barlow et al., 2019; Zhao et al., 2018). As all category members usually aspire to the exemplar, changing towards the exemplar seems not to 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 key driver of such change, how it specifically relates 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 on how this change actually looks like (Posen et al., 2018). By using multiple, more specific measures of change, we provide such a more fine-grained view that allows a clearer picture on how failing aspirations may induce specific and concrete entrepreneurial change. In our case, we find not only slightly, but detrimentally different ways in how change manifests with regard to 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 detrimental insights and our results advocate for more nuanced approaches to measuring the effect change has on 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 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 especially the contextual role of failing aspirations and engaging in problemistic search (Posen et al., 2018). 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 response is rather 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 be applicable 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. In terms of managerial implications, our findings first and foremost concern the millions of content creators that try to become a full-time entrepreneur on social media. Those may benefit from the examples set out by the full-time content creators in our sample and internalize the important lessons that learning from aspirations may provide them in refining their own positioning in new content releases. In this regard, our work also generalizes to many, mostly 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 how to revise their positioning strategy as they release new products (Parker et al., 2017) and build their own 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 performance in relation to historical and social aspirations by 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 for creating a social aspiration. In this paper, we discuss 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, which, simply put, allows like to be compared with like (Baum et al., 2005; Dong, 2021). Similarity in this sense is often related to comparable performance. However, we argue that similarity in the context of competing entrepreneurial content creators generating entertainment content 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 attempt to explore how the pursuit of channels with similar content influences entrepreneurial content creator in taking new distinctiveness decisions. For this purpose, a content creator could be compared either to all other content creators associated with the same channel tags or to those that share similar video tags. As some entrepreneurial content creators do not provide tags for their videos, the affected videos have to be excluded. Moreover, because these tags are biased by their creators and may not always optimally summarize the core content of a video, further studies could extract tags from video comments to identify entrepreneurial content creators who post similar content and use them as a new anchor to compute social aspirations (Ellouze, 2022). 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 performance and distinctiveness for these identified most similar social reference groups than for the less similar ones, since it is expected that content creator will be in stronger competition with the most similar ones and thus deem them more relevant for interpreting the own performance.

Our data set is also limited to the most successful entrepreneurial content creators on YouTube and it may also proof 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 aspiration 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 get a better sense of a content creator's strategic development in the long run.

The role of audience 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 own 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. Not only disentangling overlap between social networks, but also examining the number of first-time and repeat commentators could contribute to our understanding of how content creators should adapt their strategy of distinctiveness to not only grow their own niche audience, but also to keep them highly engaged. An interesting starting point for further research could also be how new content is influenced not only by learning from historical and social aspirations, but also by the intervention of commentators–the users of the platform–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 one that demands constant attention, adjustment, and refinement. We proposed literature on organizational learning as an intuitive, yet important theoretical lens for this perspective. We hope that our work serves as a meaningful and interesting starting point for more research that provides us with more insights on 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" in order to overcome this challenge.

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