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Convincing Crowdvoting Campaigns

The persuasive characteristics of new venture crowdvoting campaigns

Abstract

Today, many entrepreneurs turn to online crowdsourcing platforms to acquire resources and support for their ventures. While the pursuit of financial capital through crowdfunding platforms has received much attention from researchers, the pursuit of non-financial support has grown significantly in importance among new ventures. In this context, entrepreneurs construct venture campaigns with the hopes of persuading supporters to endorse their ventures, with significant implications for future resource acquisition and venture growth. While the study of crowdfunding success has received much attention from researchers, how entrepreneurs go about persuading non-financial supporters to endorse their ventures in this newer context has largely been overlooked. In this study, we utilize the Elaboration Likelihood Model (ELM) and previous findings from crowdfunding to understand how entrepreneurs successfully persuade supporters on these crowdvoting platforms to endorse their ventures. By analyzing a sample of over 30,000 campaigns from the crowdvoting platform Product Hunt, we find that narrative length, source credibility, and visual cues of campaigns are all positively related to supporter endorsement. With this study, we take the first step in understanding the dynamics of this novel method of resource acquisition for new ventures and provide practical insights for entrepreneurs to consider when constructing their campaigns in these crowdvoting contexts.

Keywords: Persuasion, Elaboration Likelihood Model, Crowdsourcing, Crowdvoting, Crowdfunding, Endorsement

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Glossary

Venture	A new activity or project, usually in business, that involves risk or uncertainty (Cambridge University Press, n.d.-a)
Crowdsourcing	Participative online activity in which an individual, an institution, a non-profit organization, or a company sources resources, support or information from a group of individuals (Estellés & Gonzaléz-Ladron-de-Guevara, 2012; Howe, 2008)
Crowdvoting	A type of crowdsourcing where an individual, an institution, a non-profit organization, or a company sources resources, support or information from a group of individuals through votes (Estellés & Gonzaléz-Ladron-de-Guevara, 2012; Howe, 2008)
Crowdfunding	A type of crowdsourcing where an individual, an institution, a non-profit organization, or a company sources financial capital through a group of individuals (Estellés & Gonzaléz-Ladron-de-Guevara, 2012; Howe, 2008)
Campaign	A presentation of a venture in an online crowdsourcing platform, in which an entrepreneur seeks resources or support for their venture (Vachelard et al., 2016; Zhao et al., 2019)
Venture Description	The description of the project or company seeking resources or support via a campaign (Zhou et al., 2018; Cao, 2021)
Issue-Relevant Information	Quantifiable and fact-based information that is not influenced by biases, opinions, or emotions (Petty & Cacioppo, 1986; Petty & Cacioppo, 1983)
Peripheral Cue	An aspect exterior to the merits of an argument which can be utilized to supply a low-effort basis to form a judgment (Petty & Cacioppo, 1986; Teng & Khong, 2015)
Endorsement	The act of showing that you approve of or support something or someone (Cambridge University Press, n.d.-b). It can act as a means of communication where well-informed groups provide lesser-informed groups with a readily available cue from which they can convey useful information (Grossman & Helpman, 1999)

1. Introduction

1.1 Background

Upon deciding to pursue an entrepreneurial venture, entrepreneurs face a long uphill battle of continuous challenges. Ventures need access to resources in order to grow, something found particularly difficult to obtain for organizations young in age (Stinchcombe, 1965). The difficulties in acquiring resources are so extensive that the majority of new ventures survive less than just a few years (Watson & Everett, 1996; Franco & Haase, 2010; Headd, 2003).

The Liability of Newness captures the phenomenon of the constraints imposed on new ventures and their difficulting in acquiring resources to grow. Early-stage ventures lack the qualities that mature organizations have (Stinchcombe, 1965; Suchman, 1995), making them vulnerable in interactions with external stakeholders (Freeman & Hannan, 1983). These constraints are argued to be derived from both external and internal factors, such as a lack of access to networks, knowledge, and experience (Stinchcombe, 1965; Aldrich & Auster, 1986).

To overcome these struggles, many entrepreneurs and founders of early-stage ventures turn to online platforms and communities to acquire resources and support for their ventures (Macht & Weatherston, 2014; Gerber & Hui, 2014; Schou et al., 2022; Meurer et al., 2022). In recent years, crowdsourcing platforms have increasingly become a popular and viable way for entrepreneurs to acquire resources and support for their ventures. Crowdsourcing refers to the method of calling upon a crowd of individuals to support in the undertaking of a task (Estellés & Gonzaléz-Ladron-de-Guevara, 2012; Howe, 2008). The crowdsourcing of financial capital, termed crowdfunding, has become widely popular and received much attention from researchers (Howe, 2008; Zhao et al., 2019; AlShehry & Ferguson, 2015). These schemes entail the opportunity for entrepreneurs to showcase their ventures through campaigns to a large audience of users on the platform. Based on the information provided by entrepreneurs in the venture campaigns, “the crowd” of individuals can decide to provide financial capital to the ventures they find interest in and want to support (Kim et al., 2016).

The open-access, transparent, and often standardized campaign structure enables potential supporters to easily compare and choose the ventures they want to support, making campaigns a key channel for communicating with potential supporters (Mollick, 2014; Kim et al., 2016; Zhao et al., 2019). As a result, entrepreneurs need to carefully craft their campaigns in order to present their ventures in a persuasive way to potential supporters, as they will base their decision to support on the information provided in campaigns (Kim et al., 2016). It hence becomes of strategic importance for entrepreneurs to be able to present their ventures in a convincing way in pursuit of financial support.

Given the practical relevance and rich availability of information to discern from these platforms, studies on the characteristics of successful campaigns have become a fruitful avenue for research (e.g., Mollick, 2014; Courtney et al., 2017; Koch & Siering, 2019). Particularly, a large body of research has looked closely at the persuasive characteristics of successful campaigns in this competitive platform setting (e.g., Lee et al., 2019; Kim & Petrick, 2020; Allison et al., 2017).

A popularized theoretical perspective in this domain is the ELM, which has been utilized to determine how supporters process information and are persuaded to provide financial support. The theory posits that individuals process information according to the cognitive effort and involvement put into understanding the merit of a message (Petty & Cacioppo, 1986). Individuals high in involvement process information through the *central route*, trying to understand the true merits of a message via *issue-relevant information*, such as product details or objective arguments (Petty & Cacioppo, 1983; Petty & Cacioppo, 1986). In contrast, individuals low in involvement process information through the *peripheral route*, relying on *peripheral cues* such as the attractiveness of a source or visual cues instead (Petty & Cacioppo, 1986; Teng & Khong, 2015). The persuasiveness of a message is thus a function of the alignment between a receiver's processing route and a message's design.

How entrepreneurs present their ventures and construct their campaigns can greatly influence the persuasiveness of their messages. Hence, balancing the use of issue-relevant information and peripheral cues is of great importance in persuading potential supporters to support their ventures. Consequently, the ability to construct appealing crowdfunding campaigns becomes a critical skill in acquiring financial resources and growing their ventures.

1.2 Problematization

New ventures are in need of a variety of resources to grow and prosper. While crowdfunding platforms have been used extensively to acquire financial capital, entrepreneurs also participate in online platforms to receive other types of support. For example, it has been found that entrepreneurs also seek support related to aspects such as endorsement and exposure to potential customers, and an extended network (Cao, 2021; Wald et al., 2019; Di Pietro et al., 2018). Similarly, research has suggested that entrepreneurs seek feedback and input on their venture and its product or service(s) (Macht & Weatherston, 2014), as well as guidance and advice on action planning (Meurer et al., 2022; Schou et al., 2022; Meurer et al., 2022). These aspects broadly capture the type of support entrepreneurs seek from online crowdsourcing platforms.

While there is some evidence that crowdfunding platforms can provide entrepreneurs with some of this type of support as well (e.g., Gerber & Hui, 2013; Belleflamme et al., 2010), it is not the primary purpose of these platforms. Instead, there has evolved a new generation of crowdsourcing-like platforms and online communities more tailored to these non-financial supportive needs of entrepreneurs and ventures[1] (Cao et al., 2021; Meurer et al., 2022; Schou et al., 2022). These platforms commonly host a crowdvoting mechanism, where users support ventures through the casting of upvotes for various purposes (Cao et al., 2021; Araman &

[1]See for example: Product Hunt, Reddit: /r/Entrepreneur, Hacker News, AlternativeTo, G2

Caldeney, 2016; Hoornaert et al., 2017). We posit that the act of a supporter upvoting a venture can be viewed as an act of endorsement and non-financial support of that venture in the sense that the supporter implicitly communicates approval of its quality to others on the platform. Endorsement, the act of showing that you approve of or support something (Cambridge University Press, n.d.-b), has been described as a means of communication where well-informed groups provide lesser-informed groups with a readily available cue from which they can convey useful information (Grossman & Helpman, 1999). Research has shown that this crowdvoting method is utilized to acquire feedback and promotion, leading to an increased probability of raising funding while also being from more prominent investors for new ventures (Cao, 2021). Similarly, the method is applied as a means to improve pricing and product development decision-making (Marinesi & Girotra, 2013; Araman & Caldentey, 2016), entailing significant strategic implications.

Despite the practical value and evident influence on new venture growth that these crowdvoting platforms have for entrepreneurs, this context has largely been overlooked in academia. Most of the research on persuasion on online crowdsourcing platforms has been done on crowdfunding, providing entrepreneurs an extensive understanding of how to successfully persuade potential supporters to provide financial capital. Even though crowdfunding platforms are similar in many ways to these alternative crowdvoting platforms utilized by entrepreneurs, there is a distinct difference in the type of support sought and the financial implications related to the act of supporting a venture (Chen, 2021). Furthermore, as previous researchers call for caution to be taken before generalizing findings across platforms as users, decision-making processes, and drivers of success differ (Dushnitsky & Fitza, 2018; Short & Anglin, 2019), the existing literature provides little guidance in this new context.

Consequently, for entrepreneurs seeking non-financial support from these novel but influential crowdvoting platforms, the theoretical understanding of the persuasive mechanisms is scarce. The understanding of how non-financial supporters on crowdvoting platforms process information and are influenced in their decision-making is essentially non-existent. Hence, despite the considerable practical importance and influence, this type of support has on new venture growth, entrepreneurs are at a loss in how to construct their campaigns, making any attempt at support a shot in the dark.

1.3 Purpose and Research Question

In light of the problematization, we thus aim to commence the exploration of the novel context of entrepreneurially-focused crowdvoting platforms utilized for non-financial support. By studying campaign characteristics and their persuasive success, we thus take the first step in understanding this novel method of resource acquisition for new ventures. Specifically, we intend to contribute to the literature by identifying how entrepreneurs construct their campaigns on these platforms to successfully persuade supporters to endorse their ventures.

We aim to advance the knowledge of the ELM by extending the theory to a new context not previously studied. In this, we hope to contribute to the literature on issue-relevant information and peripheral cues by exploring how these can be applied in a non-financial context. As a result of this, we hope to further develop an understanding of the central and peripheral route processing amongst entrepreneurial supporters in lack of financial implications.

Finally, we also set out to provide practical insight for entrepreneurs to consider when constructing their campaigns in these crowdvoting contexts, which we hope will aid them in their venture journeys.

Hence, the study aims to examine the following research question:

- How do entrepreneurs successfully persuade supporters on crowdvoting platforms to endorse their ventures through the use of issue-relevant information and peripheral cues?

1.4 Delimitations

In pursuit of clarity on the scope of our research, we will briefly discuss the delimitations of the study. This study aims at understanding how entrepreneurs persuade supporters on online crowdvoting platforms to endorse their ventures. This is done solely by studying how entrepreneurs construct their campaigns on said platforms. Any efforts to rally supporters outside of the platform, and specifically outside a campaign, are thus out of scope for the purpose of this study.

2. Theory

The following chapter consists of three main components. First, a review of the literature is conducted (2.1) outlining previous research in four parts; the type of resources and support entrepreneurs seek from online contexts, the act of crowdsourcing support from online platforms, the similarities between crowdfunding and crowdvoting platforms, and finally, how entrepreneurs persuade supporters on those platforms to support their ventures. Based on the literature review, a research gap is then described, whereupon the Elaboration Likelihood Model is introduced as the theoretical framework of this study (2.2). Finally, based on previous research and the theoretical framework, a number of hypotheses are generated for the study (2.3).

2.1 Literature Review

2.1.1 Resource Acquisition on Online Platforms

As resource acquisition is an expensive and time-consuming task for early-stage ventures (Winborg & Landström, 2001), many entrepreneurs turn to venture-focused online platforms and communities to get support and simplify the acquisition of resources (e.g., Meurer et al., 2022; Zhao et al., 2019). The concept of online platforms has been subject to extensive research and can, on a more general level, be described as an ecosystem and structure where stakeholders interact (Rochet & Tirole, 2003) to exchange resources and knowledge (Eaton et al., 2015; Gawer, 2009). These online settings are made up of individuals or organizations that come together around a shared meaning or activity, which in the case of entrepreneurship, often revolve around the sharing of knowledge and support (Kuhn et al., 2016; 2017; Faraj et al., 2011).

The entrepreneurial support and resources entrepreneurs seek from these online contexts vary greatly but can, for the purpose of this study, broadly be categorized into financial and non-financial support. While acquiring financial capital from supporters has received much attention in academia (e.g., Shneor & Vik, 2020; Zhao et al., 2019; Allison et al., 2017), the pursuit of non-financial support has also been found as a driver in the motivations for participating in these online platforms (Gerber & Hui, 2013; Schou et al., 2022; Mollick & Kuppuswamy, 2014). While non-financial support on online platforms is not a theoretically well-established concept, we define it as any non-monetary support provided by supporters on these online platforms.

According to the literature, this could entail the promotion and spreading of a venture to supporters' extended network, resulting in exposure and additional potential support from the network (Wald et al., 2019; Di Pietro et al., 2018). Feedback and input from supporters on a venture and its product or service(s) (Macht & Weatherston, 2014), as well as advice on action planning (Meurer et al., 2022), are further examples of support that entrepreneurs seek from online contexts, aspects which have been found to positively impact a venture's performance (Chrisman et al., 2005) and survival (Delmar & Shane, 2003; Song et al., 2021). Similarly, support in terms of help with problem-solving, reflection, and the sharing of tips and tricks are additional examples of non-financial support from these contexts. Moreover, there is also some research on the utility of these platforms, indicating that online communities can provide entrepreneurs with the support they seek more efficiently than in offline settings (Kuhn et al., 2016), making it an important area to understand practically and academically (Nambisan, 2017).

2.1.2 Crowdsourcing Resources and Support for New Ventures

A conceptual method that captures the attempts of entrepreneurs to rally supporters on these online platforms is crowdsourcing. Crowdsourcing has been defined by Estellés and Gonzaléz-Ladron-de-Guevara (2012) as "a type of participative online activity in which an individual, an institution, a non-profit organization, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task." According to Howe (2008), there are primarily four main methods of crowdsourcing; *crowd wisdom*, *crowd creation*, *crowdfunding*, and *crowdvoting*.

Firstly, crowd wisdom refers to the act of sourcing insights and knowledge from a crowd, often utilized to solve problems faced by organizations (Howe, 2008), for example, through idea generation from employees (Zhu et al., 2014; Bjelland & Chapman Wood, 2008). Secondly, crowd creation refers to the solicitation of ideas and creations from a crowd, such as Duolingo having users translate articles for the public (Garcia, 2013) or CrowdLearn letting a community create e-learning content (Tarasowa et al., 2015). Thirdly, crowdfunding refers to the acquisition of financial capital from a crowd. This method is commonly utilized in entrepreneurial contexts as means to interact with a crowd of potential supporters in pursuit of acquiring financial resources for their ventures (Howe, 2008). The final method of crowdsourcing is crowdvoting, which also is the focus of this study.

Crowdvoting refers to the act of using a community's judgment and leveraging it to organize, filter, and rank objects such as ideas, ventures, reviews, design options, and pricing levels (Howe, 2008; Cao, 2021; Marinesi & Girotra, 2013). Among ventures, this method has been found to be utilized largely in pursuit of non-financial support and information acquisition (Marinesi & Girotra, 2013; Araman & Caldentey, 2016). For example, studies have shown it to be applied to improve pricing and product development decisions by asking strategically chosen customers to vote on preferred alternatives (Marinesi & Girotra, 2013), as well as in determining the timing of new product releases (Araman & Caldentey, 2016). Furthermore, entrepreneurially-focused crowdvoting platforms, often consisting of a passionate and knowledgeable community of supportive enthusiasts (Cao et al., 2021, Meurer et al., 2022; Schou et al., 2022), have been found to be used as a means for exposure by enabling potential supporters to endorse ventures they like by casting votes (Cao et al., 2021).

Though academically lacking in its application to a crowdsourcing context, the concept of endorsement has been described as a means of communication where well-informed groups provide lesser-informed groups with a readily available cue from which they can convey useful information (Grossman & Helpman, 1999). Endorsement refers to the act of showing that you approve of or support something (Cambridge University Press, n.d.-b). We posit that the act of a supporter casting an upvote for a venture can be viewed as an act of endorsement and non-financial support for the venture in the sense that the supporter implicitly communicates approval of its quality to other stakeholders. Though likely primarily directed at other potential supporters and customers, research has found these cues to also be utilized by venture capital investors as a means to assess market demand for a venture's product or service (Cao, 2021). Furthermore, it has been found that ventures with a significant amount of endorsements and success on crowdvoting platforms experience substantial benefits in the form of more exposure, increased probability of securing future venture investments as well as attracting interest from investors of a higher prominence (Cao, 2021). Hence, achieving a large number of endorsements from supporters on these platforms appears to have significant strategic implications for venture growth.

However, even if these types of online platforms offer the opportunity for entrepreneurs to acquire resources and support for their venture, many fail to do so (Mollick, 2014). In pursuit of understanding the reason for this, we look closer at the adjacent crowdfunding research. Similar to that of crowdvoting, the structure of these crowdfunding platforms is described as open access, transparent, and often of a standardized structure where entrepreneurs display their ventures through informational campaigns. (Mollick, 2014; Spanos, 2018; Hunter, 2016; Zhao et al., 2019). Ventures campaigns and the information provided in these can thus easily be compared to each other, enabling supporters to make more informed decisions about what ventures to support. As supporters need to provide financial resources when deciding to support a venture in crowdfunding, they are limited in the number of ventures they are able to support (Chen, 2021). This, in conjunction with the platform characteristics, fosters a setting of intense competition for the attention and resources of potential supporters (Mollick, 2014; Lin et al., 2018; Bade & Walther, 2021). This is also showcased in crowdfunding studies, where as little as 40% of entrepreneurs succeed with their funding goals (Mollick, 2014; Chen, 2021).

While supporters are not constrained by their financial assets on crowdvoting platforms, they are however constrained by their limited capacity to process information (Bade & Walther, 2021). On an entrepreneurially-focused crowdvoting platform such as Product Hunt, for example, there are dozens of venture campaigns every day competing for the attention of potential supporters (Cao, 2021; Cao et al., 2021). Consequently, it may perhaps be supporters' limited processing ability rather than financial assets that foster the competitiveness on these platforms.

The successful pursuit of non-financial support and endorsements from crowdvoting platforms thus entails considerable implications for new venture growth. However, the open-access and transparent structure of these platforms, in conjunction with supporters' limited capacity of processing information, fosters a highly competitive environment for ventures seeking support. For entrepreneurs to be successful in their pursuit, they must effectively utilize campaigns to capture the attention of supporters and convince them to endorse their venture over the next. It hence becomes highly relevant to understand how supporters on these platforms are persuaded in their decision to non-financially support ventures with endorsements.

However, the novelty of crowdvoting as a means to acquire non-financial support for ventures, in conjunction with the scarceness of research applying a persuasion perspective in this domain, poses limitations to our understanding of the persuasive mechanisms on these platforms. Instead, we must look beyond crowdvoting and utilize research from adjacent crowdsourcing contexts to understand how supporters are persuaded in their decision-making. Crowdfunding research is an attractive alternative for this due to the extensive attention it has received in academia (e.g., Shneor & Vik, 2020; Allison et al., 2017; Kim et al., 2016) as well as the platform similarities further described below. In the following chapter, we will further advocate its relevance to this study by outlining the similarities between crowdvoting and non-financial support.

2.1.3 The Resemblance Between Crowdvoting and Crowdfunding

As aforementioned, crowdfunding platforms are open-access and transparent, often with a standardized structure to campaigns (Mollick, 2014; Zhao et al., 2019), similar to that of crowdvoting. Entrepreneurs present their ventures through campaigns consisting of both visual content and text mediums (Allison et al., 2017), just as commonly the case in entrepreneurially-focused crowdvoting platforms (e.g., Cao, 2021; Cao et al., 2021). Potential supporters then use the informational content and the claims that entrepreneurs make in their campaigns as a basis for their decision on whether to back their efforts or not (Kim et al., 2016).

Entrepreneurs' motivation for participation in crowdfunding platforms has been found to be not only financially motivated but also in pursuit of non-financial support and resources (e.g., Gerber & Hui, 2013; Wald et al., 2019). Gerber and Hui (2013) interviewed 83 creators of crowdfunding campaigns and found that beyond financial support, entrepreneurs also actively sought to gain approval for their projects, expand awareness of their venture, connect with others, and learn. Similarly, Mollick and Kuppuswamy (2014) found that among successful campaigns, the primary reason for participation was to gather information on product demand, get exposure, as well as "To connect directly with a community of fans or supporters." Other examples from the literature on these are access to networks (Di Pietro et al., 2018), feedback on their products and services (Belleflamme et al., 2010), exposure and attention (Wald et al., 2019; Belleflamme et al., 2010), as well as advice, insight, and creativity (Onnée & Renault, 2016). It thus becomes clear that entrepreneurs actively participate in crowdfunding schemes in pursuit of non-financial support and resources as well, similar to those crowdvoting platforms provide.

The motivations behind the supporters' engagement on crowdfunding platforms can also be applicable to crowdvoting platforms. Harms (2007) surveyed supporters about their motivations to engage in crowdfunding and identified factors such as self-expression, enjoyment, and the ability to provide functional benefits with a tangible output for projects.

Similarly, Ordanini et al. (2011) found that beyond just seeking a monetary return from their investments, supporters enjoyed being publicly recognized for their support and were motivated by a feeling of being in part responsible for the success of others and a desire for social participation. The ideas of community, helping others, supporting causes, and a sense of involvement have also been identified as motivations for participation by supporters beyond just the collection of rewards or financial returns (Gerber & Hui, 2013). Hence, while the pursuit of tangible returns is likely the most distinct difference between these types of platforms, the motivations for participation also extend far beyond this for supporters.

To conclude, there are many reasons why research done on crowdfunding platforms should be applicable on platforms where entrepreneurs seek non-financial support. The design of these platforms offers many similarities in the sense of campaigning and competing for support. Moreover, a large part of crowdfunding platforms relates to non-financial support. From the literature, it becomes clear that beyond financial motives, both entrepreneurs and supporters also seek to connect with others, establishing social communities consisting of individuals with similar interests and passions (Gerber & Hui, 2013). Entrepreneurs utilize crowdfunding to gather info and assess market demand for their products, as well as connect with enthusiastic supporters (Mollick & Kuppuswamy, 2014). Similarly, supporters utilize crowdfunding to express themselves and be part of supporting entrepreneurial efforts, and as a result, they also enjoy being publicly recognized for their support (Ordanini et al., 2011).

Given the evident platform and context similarities between crowdfunding and crowdvoting, the following section will outline findings from the extensively researched domain of crowdfunding success to inform our understanding of supporter persuasion.

2.1.4 Persuasion in Crowdfunding

In the context of crowdfunding success, the study of communication and persuasion has received much attention from researchers (e.g., Kim & Petrick, 2020; Lee et al., 2019; Allison et al., 2017). This perspective has explored how entrepreneurs construct their campaigns and, in turn, how supporters perceive these campaigns. The persuasion literature has generally focused on three components making up campaigns that supporters consider in their decision to support. These are the narratives entrepreneurs use as part of their venture descriptions in campaigns (Bi et al., 2017; Moradi & Badrinarayanan, 2021), the visual content included in their campaigns (Li et al., 2016; Wang et al., 2021) as well as the objective characteristics of the source presenting the venture (Allison et al., 2017; Wang & Yang, 2019). Venture descriptions refer to the primary communication channel where entrepreneurs in-text present relevant information to potential supporters, whereas visual content refers to the informational images and videos associated with the campaign. In the remaining part of this section, we will bring to light some of the findings from the literature on crowdfunding success through a persuasion lens. Specifically, we will be looking at findings related to *venture descriptions*, *visual content*, and *characteristics of the source* and the influence these have on persuading supporters in crowdfunding contexts.

Venture Descriptions

Numerous studies have explored the relationship between the narrative length of venture descriptions and persuasive success in crowdfunding (e.g., Zhou et al., 2018; Moradi & Badrinarayanan, 2021). For example, Bi et al. (2017) studied a Chinese crowdfunding site and identified that longer venture descriptions were associated with a better funding performance. The authors argue that the narrative length is a signal of venture quality and that a more detailed description will increase supporters' willingness to invest. Moradi and Badrinarayanan (2021) also identified that narrative length positively influences the funding success of crowdfunding projects by particularly looking at entrepreneurial aftermarket enterprises. Similarly to Bi et al. (2017), the authors also suggest that narrative length influence supporters' perception of a venture's quality. The authors argue that longer venture descriptions indicate the effort and preparedness of the entrepreneur and further increases the understanding of the project, thus reducing uncertainty in the decision-making process of supporters.

Additionally, some research has found evidence that the extent to which narrative length influences supporters is dependent on the context in which it is applied. Shneor et al. (2021) studied the role of trust in online marketplaces and how it differed between high- and low-trust societies. They identified that the number of words used in a campaign description has a positive association with funding success in low-trust societies, such as Indonesia, Mexico, and Poland, but not in high-trust societies such as Finland.

Not only the length of venture descriptions have been found to influence the persuasive efficiency of campaigns, but also the informational content of these descriptions. Lee et al. (2019) examined message substances in civic crowdfunding and found evidence that the use of quantitative language improves funding performance, while mentions of potential risk factors had a negative association with funding success. Quantitative language refers to the number and money-related words, while risk factors refer to risk-related words (Lee et al., 2019). Similarly, Larrimore et al. (2011) examined language on peer-to-peer lending platforms and found that requests with longer, concrete descriptions, including quantitative words, were more likely to receive funding. This is in line with the findings of Koh et al. (2020), that found that objective and concrete project descriptions led to greater funding success. The authors argued these aspects could reduce the risk related to the uncertainty underlying the crowdfunding process and thus yield better outcomes. Moreover, uncertainty reduction and crowdfunding success have also been linked to the use of cognitive language, referring to reason-based and intellectual elaborations of a given subject (Cohn et al., 2004; Moradi & Badrinarayanan, 2021). In this case, it has been found that cognitive language can reduce uncertainty and enhance trust, increasing the likelihood of crowdfunding success (Moradi & Badrinarayanan, 2021).

Some research has also explored the relationship between narrative tone and persuasive success in crowdfunding (Lee et al., 2019; Parhankangas & Renko, 2017). The interest in affective language in crowdfunding research has been derived from previous literature showing that it can influence individuals' judgment forming and decision-making (Gibbons et al., 1991; Petty et al., 1993). Positive linguistic cues have been shown to be beneficial in entrepreneurial communication by creating a likable story and enhancing positive emotions in potential supporters (Martens et al., 2007). Lee et al. (2019) identified that the use of perceptual language, referring to an emphasis on hearing and seeing receivers, as well as positive affective language, were both positively related to civic crowdfunding success. Similarly, Allison et al. (2017) studied the use of positive tonality in crowdfunding and found directional, albeit weak, support for the case that it influences crowdfunding success.

Visual Content

The use of visual content in campaigns has also been associated with persuasive success in crowdfunding (e.g., Bi et al., 2017; Wang & Yang, 2019). The use of videos has been shown to be impactful in several studies (Bi et al., 2017; Wang et al., 2021; Li et al., 2016; Mollick, 2014). For example, Li et al. (2016) showed that the presence of a video in campaigns improved funding performance and argued that its persuasive influence could be explained by the reduction of information asymmetry and enhanced positive attitudes. Bi et al. (2017) also found a positive association between the use of videos and funding success and posited that its persuasive effect came from supporters' perception of the venture as being of higher quality. The positive effect of videos also increased when adding more videos as it mitigates concerns about venture quality (Wang et al., 2021). Beyond videos, there is also some evidence of images having a persuasive effect on supporters in crowdfunding. Wang and Yang (2019) studied the persuasive influence of campaigns' visual design, entailing both the use of images and videos and found this to influence supporters' funding intentions.

Characteristics of the Source

The characteristics of the source have also been shown to have a persuasive influence on supporters' funding intentions in crowdfunding (e.g., Allison et al., 2017; Wang & Yang, 2019). In crowdfunding research and particularly within the persuasion perspective, this concept has been termed source credibility, often relating to objective information such as the entrepreneur's education, experience, resources, and skills (Allison et al., 2017; Wang et al., 2021; Wang & Yang, 2019).

Wang et al. (2021) studied entrepreneurs' crowdfunding-specific experience and found that entrepreneurs with a greater crowdfunding track record were more successful in their funding. They argued this was because experienced founders were more highly skilled and had a higher social capital within the platform, which previous research has found to be influential in funding success (Buttice et al., 2017). Similarly, Allison et al. (2017) found that the education of a message source mattered in a crowdfunding context when supporters had the ability and motivation to evaluate an investment carefully.

The above-highlighted literature exhibits various aspects influencing persuasive success on crowdfunding platforms. Financial supporters are hence influenced in their decision to support a venture by a multitude of factors as part of crowdfunding campaigns. As becomes evident from the findings above, there remains little doubt that the way in which entrepreneurs present their ventures to potential supporters has a great influence on their success in achieving support.

As the crowdfunding context exhibits many similarities to the entrepreneurial crowdvoting context, one could presume findings from the crowdfunding literature to be applicable in informing entrepreneurs on how to construct their campaigns in this adjacent context. However, despite the evident platform similarities, previous research has found it to be tricky to generalize findings across online platforms. For example, Dushnitsky and Fitza (2018) argued that observing patterns on one online platform does not necessarily advance our understanding of other online platforms. The authors examined three types of crowdfunding platforms; donation-, reward-, and lending-based, and found that factors associated with success in one platform could not be replicated on other crowdfunding platforms (Dushnitsky & Fitza, 2018). The authors argued this was a result of platforms trying to differentiate from the competition, and as a result having the users and factors driving funding success vary greatly. Similarly, Short and Anglin (2019) specifically set out to explore the issue of generalizability by exploring rhetorics successful in one crowdfunding setting in another. In an attempt to replicate the findings from a previous study, their results uncover a limitation to the degree of generalizability across platforms, as their replication results "reveal relatively little consistency across contexts."

These studies illustrate that findings associated with success on one crowdfunding platform may be troublesome to generalize to the next. Extrapolated to this study's context, one can anticipate further complications in applying findings from crowdfunding to this similar but different crowdvoting setting without consideration. Exploring campaign characteristics and the persuasiveness of these in a crowdvoting setting hence emerges as a fruitful avenue for research.

2.1.5 Research Gap

The literature review shows that entrepreneurs turn to online platforms to acquire financial and non-financial resources and support for their ventures. The method of crowdsourcing support has grown in its application in the entrepreneurial context and is today a widespread method of acquiring support and growing new ventures.

While the crowdsourcing of financial resources, crowdfunding, has received much attention in academia, there is increasing evidence that entrepreneurs also actively utilize crowdsourcing for other forms of support on online platforms. One such platform type is entrepreneurially-focused crowdvoting platforms that are utilized to acquire non-financial support for ventures. This could entail aspects such as information acquisition from potential customers (Marinesi & Girotra, 2013; Araman & Caldentey, 2016) or endorsements from passionate and knowledgable communities of supportive enthusiasts (Cao, 2021).

We posit that the act of supporters upvoting a venture's campaign in this context can be viewed as an act of endorsement for that venture in the sense that the supporter implicitly communicates approval of its quality to other stakeholders. Ventures that greatly succeed in this regard have been found to enjoy significant levels of exposure for the venture, accessibility to future funding, and increased prominence among venture investors (Cao, 2021). However, despite the evident importance this type of non-financial support has on the growth of entrepreneurial ventures, very little research has yet to have been performed in this context.

Similar to crowdfunding, entrepreneurs in this context construct campaigns conveying information about their ventures in pursuit of convincing supporters of their cause. The ease of comparability of venture campaigns, in conjunction with the considerable implications of success in this context, fosters a highly competitive environment with many ventures competing for success. As seen in the crowdfunding literature (e.g., Allison et al., 2017; Bi et al., 2017), the ability to construct persuasive campaigns in this context likely has an influence on the success of one's calls.

As research on non-financial support in crowdvoting contexts is still in its infancy, we instead look to crowdfunding to explore how supporters are persuaded in their decision to support in this adjacent context. From this review, it becomes evident that the way in which entrepreneurs construct their campaigns significantly influences the persuasive success they have in achieving support for their ventures. As these contexts entail many similarities in structure and dynamics, one could effortlessly postulate that findings from crowdfunding are applicable to this adjacent crowdvoting context.

However, numerous authors in the field call for caution to be taken before making generalizations across platforms due to the significant differences between these contexts. The literature thus appears to present an interesting gap in how supporters are persuaded to non-financially support ventures in online crowdsourcing contexts. Therefore, we aim to bridge this gap by exploring how entrepreneurs persuade supporters to endorse their ventures on these online platforms.

2.2 Theoretical Framework

Below, the ELM will be introduced as the theoretical framework of this study. The theory was selected as it serves our purpose of uncovering how entrepreneurs persuade supporters on online platforms to endorse their ventures. Moreover, as it has been applied extensively for the same purpose in the financial crowdfunding context, this further argues in favor of its appropriateness to this study.

2.2.1 Elaboration Likelihood Model

The ELM is a framework for organizing, categorizing, and understanding the processes that explain the effectiveness of persuasive communication (Petty & Cacioppo, 1986). The model is based on a guiding principle that individuals are motivated to hold correct attitudes and that they will engage in behavior to ascertain whether those opinions are correct. However, even if individuals want to hold correct attitudes, the extent and type of elaboration they will engage in will differ depending on personal and contextual factors (Petty & Cacioppo, 1986). Petty and Cacioppo (1986) refer to elaboration as the cognitive effort put in to understand the issue-relevant arguments in messages. The extent of elaboration can be seen as a continuum going from not expending a thought about the issue-relevant arguments to fully elaborating on all included arguments of a message (Petty & Cacioppo, 1986). In situations when the elaboration is high, individuals would (1) reflect on experiences and memories that can be linked to the arguments, (2) evaluate and develop them based on these associations, (3) draw conclusions about the quality of the arguments, and (4) form an opinion or attitude about what the message wants to communicate (Petty & Cacioppo, 1986).

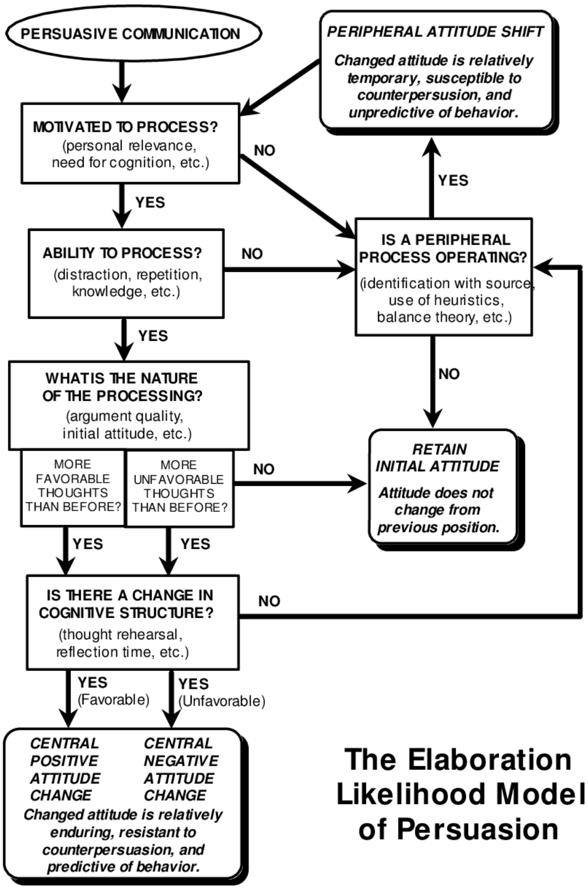
However, if the authors describe the extent of elaboration as a continuum, they argue that the theoretical processes can be specified into two routes to persuasion; the central route and the peripheral route (Petty & Cacioppo, 1986; Petty, Cacioppo, & Goldman, 1981). Depending on which route an individual processes information through, they will focus on and be appealed by different types of factors related to a message. See Figure 1 for an overview of the ELM (Petty et al., 2009).

The route a message is processed through is determined by an individual's motivation to engage in elaboration and the ability to understand the respective arguments. The degree of motivation to process the arguments can be determined by factors such as personal relevance, need for cognition (enjoyment of effortful cognitive work), and personal responsibility (Cacioppo & Petty, 1982). Moreover, the factors affecting the ability to process arguments can be related to prior knowledge, distractions, the number of times they consume the message, or the clarity of the message (Bhattacherjee & Sanford, 2006; Petty et al., 1995). When both the motivation and ability to process message arguments are high, people will process the arguments through the central route, and when any of them are low, they will be processed via the peripheral route (Petty & Cacioppo, 1986).

The central route is characterized by a high degree of elaboration where individuals carefully assess issue-related arguments in messages before making a behavioral or attitude change (Bhattacherjee & Sanford, 2006). The theory postulates that these individuals are appealed to through issue-relevant information, by focusing on the core contents of a message and the quality of its arguments (Petty & Cacioppo, 1983). For example, a phone reseller trying to persuade a customer to buy a phone by appealing in accordance with the central route would emphasize technical and functional elements such as, for example, the phone's camera features or battery capacity. If processing through the central route, the customer would thoughtfully consider the quality of the information and compare it to other alternatives when deciding what phone to purchase (Petty & Cacioppo, 1986). Furthermore, as individuals invest more cognitive effort when processing message arguments through the central route, resulting changes in attitude will last longer (Haugtvedt & Petty, 1989) and, to a larger extent, change peoples' behavior (Petty & Cacioppo, 1983).

On the contrary, when individuals are not as motivated or have the ability to elaborate extensively, they process information through the peripheral route and rely more on peripheral cues outside of the core message content (Petty & Cacioppo, 1986). The peripheral route requires less cognitive effort and individuals only consider obvious positive or negative cues related to a message. These peripheral cues include the attractiveness, likeability, and credibility of the information source and other heuristics than object arguments relevant to the issue (Chaiken, 1980; Bhattacherjee & Sanford, 2006). An example of appealing to individuals in accordance with the peripheral route could be having a celebrity endorse and promote a product in an advertisement. A potential customer processing through the peripheral route would then not focus much on the product's characteristics or message arguments; but rather on the fact that the celebrity is promoting the product and can, as a result, form a positive association with the product (Rahman, 2018). As judgments formed via the peripheral route entail less investment of cognitive effort, the following attitude changes have shown to be less firmly held compared to changes through the central route (Haugtvedt & Petty, 1989).

Figure 1: The Elaboration Likelihood Model (Petty et al., 2009).



2.3 Hypothesis Generation

As aforementioned, the ELM has been applied extensively in the crowdfunding literature in pursuit of understanding how entrepreneurs persuade financial supporters on crowdfunding platforms. Due to the evident platform similarities to that of entrepreneurially-focused crowdvoting platforms, we utilize the crowdfunding literature and the ELM to generate four hypotheses regarding persuasion in crowdvoting.

The purpose of this study is to identify how entrepreneurs successfully persuade supporters on online crowdvoting platforms to endorse their ventures through the use of issue-relevant information and peripheral cues. The ELM posits that issue-relevant information will be effective in persuading individuals if they process information through the central route as individuals put great effort into understanding the true merits of a message. On the contrary, peripheral cues will be effective if individuals process information through the peripheral route, as these are unwilling or unable to elaborate on all arguments and hence seek mental shortcuts to form judgments. To test the relationship between message strategies and persuasive success, we generate four hypotheses from the ELM and crowdfunding literature, two for each processing route and type of appeal.

The persuasive efficiency of issue-relevant information in achieving endorsement by potential supporters will be tested through the indicators of *narrative length* and *quantitative language*.

The persuasive efficiency of peripheral cues in achieving endorsement by potential supporters will be tested through the indicators of *source credibility* and *visual cues*.

The hypotheses are further described in detail below. Finally, at the end of this chapter, we also include an overview of our conceptual model in Figure 2.

2.3.1 Issue-Relevant Information

Narrative Length

The ELM describes that the central route is characterized by individuals trying to understand the true meaning of a message by elaborating on issue-relevant information (Petty & Cacioppo, 1983). Thus, when a message is processed through the central route, the number and quality of arguments should increase the persuasiveness of a message (Petty & Cacioppo, 1979; Petty, Cacioppo, & Heesacker, 1981). This has been shown in research as Petty and Cacioppo (1984) found that increasing the number of arguments in a message influences its persuasive impact.

The elaborateness of text enables an added depth of information pertaining to details regarding an issue at hand, which has been found to influence decision-making (Mudambi & Schuff, 2010). Previous research on crowdfunding has utilized narrative length as issue-relevant information along the central route and found that more elaborate narratives increased the persuasiveness of campaigns (Bi et al., 2017; Zhou et al., 2018; Moradi & Badrinarayanan, 2021). More elaborative narratives enable entrepreneurs to include more arguments and details about their venture (Zhou et al., 2018; Bi et al., 2017), thus reducing uncertainty about its quality and simplifying decision-making (Mudambi & Schuff, 2010) for supporters.

Based on the ELM and the above-discussed findings from research, we expect that more elaborate narratives will enable entrepreneurs to include more venture details and arguments as part of their campaigns. Campaigns with longer venture descriptions should thus be more persuasive for supporters processing through the central route and thus receive more endorsement. Hence, we hypothesize the following:

H1: *The narrative length of venture descriptions in campaigns will have a positive relationship with supporter endorsement*

Quantitative language

The ELM postulates that if an individual processes information through the central route, they will engage in extensive elaboration to understand the benefits of an offering through the provided issue-relevant information (Petty & Cacioppo, 1986). Issue-relevant information is characterized by quantifiable and fact-based information that is not influenced by biases, opinions, or emotions and has been shown to influence customers' attitudes towards different products and services (Petty & Cacioppo, 1983).

The use of quantitative language has in previous crowdfunding research been utilized as a type of issue-relevant information, found to positively influence persuasiveness along the central route (Majumdar & Bose, 2018; Lee et al., 2019). In order for supporters to make informed decisions in this context, an understanding of the quality of the venture and the objective value of its offerings is an influential component of their assessment (Lee et al., 2019). Quantitative language has been suggested to help supporters understand detailed issues of the venture, such as aspects related to the financial viability of a venture, which can reduce uncertainty and risk (Larrimore et al., 2011) and act as a signal of effort and preparedness (Lee et al., 2019). Though potential supporters are not asked to provide financial support in this setting, we still expect that quantitative language will play a similar role as potential supporters try to understand the objective benefits and value of a venture's offering.

Based on the ELM and the above-discussed findings from research, we expect that quantitative language will provide supporters with more objective information and details pertaining to the venture. Campaigns with more quantitative language in their venture descriptions should thus be more persuasive for supporters processing through the central route and thus receive more endorsement. Hence, we hypothesize the following:

H2: *The presence of quantitative language in venture descriptions in campaigns will have a positive relationship with supporter endorsement*

2.3.2 Peripheral Cues

Source Credibility

In contrast to the central route, the ELM posits that information will be processed through the peripheral route when individuals are less motivated or able to elaborate on the issue-relevant information in a message (Petty & Cacioppo, 1986). In such situations, individuals are more easily persuaded by peripheral cues, such as the credibility of the source of a message (Chaiken, 1980; Petty, Cacioppo, & Goldman, 1981; Rhine & Severance, 1970). The source credibility acts as a cue in this situation, which can be utilized to form a quick judgment about something without investing much cognitive effort (Petty & Cacioppo, 1986). The two most impactful components of credibility in terms of persuasion have been argued to be trustworthiness and expertise (Hovland et al., 1953; Giffin, 1967; McGinnies & Ward, 1980). Trustworthiness refers to the perceived reliability, dependability, and honesty of the source (Erdogan, 1999), while expertise refers to the competence and knowledge of the source (McGinnies & Ward, 1980).

Previous research on crowdfunding has utilized source credibility as a peripheral cue along the peripheral route and found evidence of a positive relationship with funding success (Allison et al., 2017; Wang & Yang, 2019). Researchers studying credibility in this context have largely focused on entrepreneurs' success in previous entrepreneurial ventures, education, experience, resources, and skills (Wang et al., 2021; Wang & Yang, 2019; Allison et al., 2017). As entrepreneurs are perceived as more credible, supporters have a higher level of trust and belief that the entrepreneur will fulfill their proposed plans (Wang et al., 2021). Additionally, a source's credibility may also signal social capital on the platform that entrepreneurs can leverage to enhance the perceived quality of a venture and trust in its claims (Buttice et al., 2017).

Based on ELM and above discussed findings from research, we expect that the credibility of a source will act as a peripheral cue to supporters in their decision-making. Campaigns with a source of higher credibility should thus be more persuasive for supporters processing through the peripheral route and thus receive more endorsement. Hence, we hypothesize the following:

H3: *The credibility of a source in campaigns will have a positive relationship with supporter endorsement*

Visual Cues

The ELM refers to peripheral cues as heuristics and non-focal aspects of a message rather than its issue-relevant information. More specifically, rather than relying on the core rational arguments of a message, in the absence of argument processing, individuals will more easily be affected by simple cues acting as mental shortcuts requiring less involvement and cognitive load (Petty & Cacioppo, 1986).

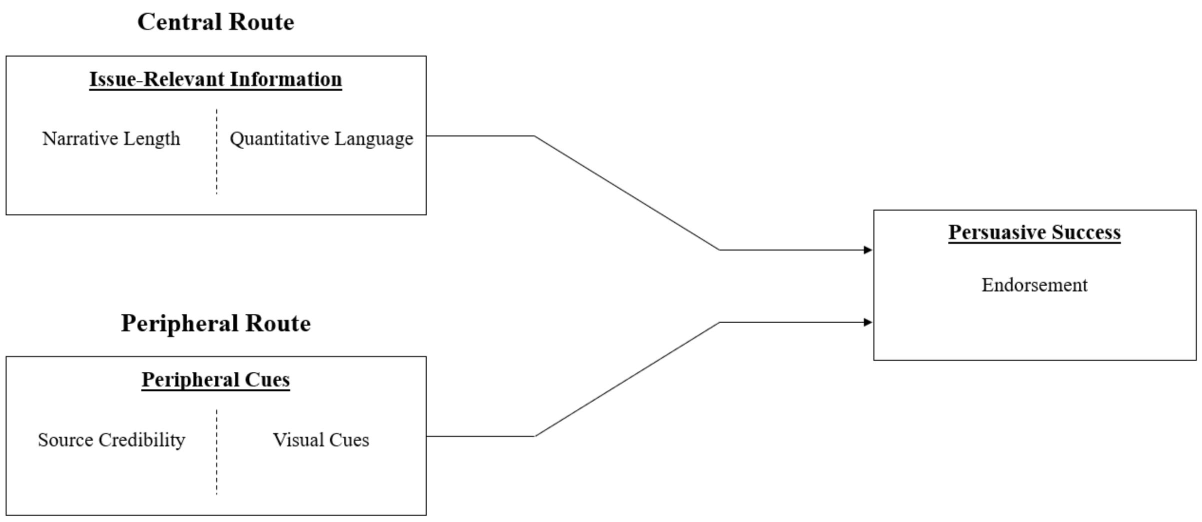
Many researchers have studied the effects of visual cues and their association with low involvement in information processing (e.g., MacInnis & Price, 1987; Edell & Staelin, 1983). Visual content has been shown to be processed faster and requires less cognitive effort than textual information (Pieters & Wedel, 2004), also being the initial point of attention for receivers when seeing a message (Riegelsberger et al., 2003).

In a crowdfunding context, the use of visual imagery has also been utilized as a peripheral cue along the peripheral route, with some evidence of its persuasive effect on supporters (Shneor et al., 2021; Lin & Boh, 2021; Majumdar & Bose, 2018). Researchers have suggested that the presence of visual imagery in campaigns is easy to identify, attracts attention (Majumdar & Bose, 2018), and is easier to process than detailed venture descriptions (Lin & Boh, 2021). Further, visual cues have also been said to induce a reassuring sense of information richness for supporters, implying transparency and willingness to share information of the entrepreneur (Lin & Boh, 2021).

Based on ELM and above discussed findings from research, we expect that visual cues will act as a peripheral cue to supporters. Campaigns emphasizing visual cues should thus be more persuasive for supporters processing through the peripheral route and thus receive more endorsement. Hence, we hypothesize the following:

H4: *The presence of visual cues in campaigns will have a positive relationship with supporter endorsement*

Figure 2: Conceptual Model.



3. Method

The following chapter describes the research methodology of the study. First, the methodological approach and fit to the research purpose are elaborated on (3.1). Next, the empirical setting of the study is introduced (3.2), followed by an outline of the data collection and processing procedure (3.3). Lastly, the analytical strategy is described by explaining the chosen variables and statistical model for the study (3.4).

3.1 Methodological Approach

The purpose of this study arises from a lack of research and understanding of the characteristics of persuasive venture campaigns in non-financial crowdvoting contexts. In order to fulfill the purpose of the study and answer the research question of how entrepreneurs persuade supporters to endorse their ventures through issue-relevant information and peripheral cues, a quantitative research strategy was adopted. Quantitative research is commonly applied by researchers to test theoretical arguments on an objective reality with its base in the positivist epistemological orientation (Bryman & Bell, 2011). From our selected theoretical framework and based on findings from the literature, we generate four hypotheses, which we aim to test in our empirical setting. As such, the study is of a deductive nature.

In line with Edmonson and McManus (2007), we deem a quantitative research methodology to be an appropriate fit for the theoretical maturity of this study as ELM and persuasion theory have been extensively applied in various contexts throughout the last 35 years. Hence, we consider a quantitative approach to provide the most contribution to theory by extending its application to a previously unexplored setting.

The decision to adopt a quantitative methodological approach was further made in pursuit of generating objective and replicable results and reducing the risk of bias in our findings. Furthermore, a quantitative approach enables the analysis of a large amount of empirical data and increases the generalizability of results, which further strengthens the argument of its suitability for this study (Bryman & Bell, 2011).

The data collection process was aimed at collecting quantifiable data on a large sample of many cases. From this, quantitative variables were constructed and statistically analyzed in pursuit of comparing performance and identifying relationships between these variables. Further, as data were collected at one point in time, the research design of this study can be said to be that of a cross-sectional design (Bryman & Bell, 2011).

The cross-sectional design is commonly adopted by researchers in pursuit of examining and identifying patterns of association, appropriate for answering the research question of this study. As with all research designs, the cross-sectional design entails certain implications and limitations which are important to consider. A shortfall of cross-sectional research design is commonly that of its internal validity as a result of its limitation in being able to draw causal inferences from findings (Bryman & Bell, 2011). We acknowledge this and do not intend to make predictive claims in our findings but rather explore relationships between different campaign strategies and the level of endorsement that ventures receive from supporters.

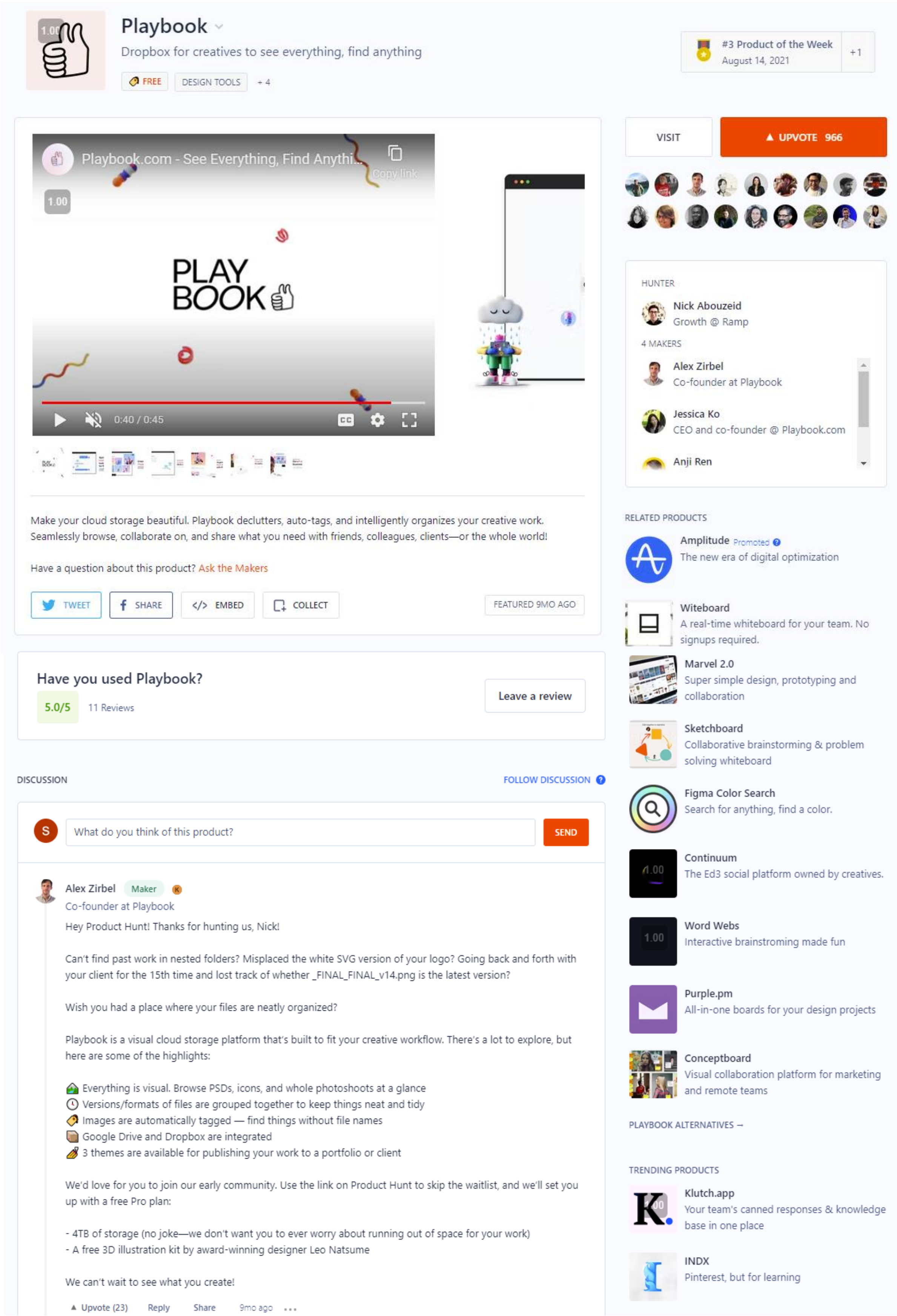
3.2 Empirical Setting

The empirical setting for the study is the website and online platform Product Hunt. Product Hunt was first founded in November 2013 as a small community for product launches and has since grown to become a global online platform made up of more than 2 million product enthusiasts (Cao, 2021). The platform is largely made up of entrepreneurs, software engineers, product managers, venture capitalists, and generally executives and technology leaders together, creating a community of tech enthusiasts eager to try new products (Cao et al., 2021; Cao, 2021).

Product Hunt is a platform where entrepreneurs can launch their ventures to a community of enthusiastic supporters and early adopters looking for new ventures and products. The ventures launched on Product Hunt vary greatly, but the most common type of products offered are apps, hardware, and software products, with the most common topics being “Tech”, “Productivity” and “Developer Tools” (Product Hunt, n.d.).

Entrepreneurs launch their ventures on the platform by submitting a campaign consisting of descriptive information about the venture, visual content such as images and videos, as well as a URL link to the venture’s website. It is also common practice for entrepreneurs to write a first comment in the comment section of the campaign to extend the introductory presentation of the venture. Figure 3 below is an example of how a campaign on Product Hunt looks with such a comment.

Figure 3: An Example of a Venture's Campaign on Product Hunt.



In order to understand the dynamics of the platform, there is some key Product Hunt-specific terminology that is important to cover. An entrepreneur or creator of a venture is defined as the "Maker" on the platform and can either be listed in the campaign, as shown in Figure 3, or not. Moreover, the individual that submitted the final campaign to the platform is defined as the "Hunter" of the venture. The hunter of a campaign can either be the maker of the venture or an external third-party individual that submits the venture's campaign for them, as is the case in Figure 3. Less established makers on the platform commonly use influential third-party individuals as hunters to submit their campaigns on their behalf, hoping to increase the chance of a successful campaign (Cao, 2021). These influential hunters often have a larger follower base on the platform, which enables these less established makers to reach a larger audience.

Users on the platform support entrepreneurs in their campaigns by casting upvotes on the ventures they like and want to support. Moreover, users can also support by engaging in the comment section of the campaign and providing feedback and input on ventures. Each user has a personal profile that showcases platform user activity, such as what ventures the user has upvoted and previous ventures hunted by the user. Followers of a user are also notified when a campaign is posted with the user listed as a maker or when the user itself submits a campaign. Starting at 12:00 Pacific Time, all of the ventures that are launched during a day are ranked in a list based on the cumulative number of upvotes that a venture has received during that day. Roughly 30% of all submissions are featured on the frontpage (Cao, 2021). The ranking list is showcased on the frontpage, where the top performers receive a significant amount of exposure both through the website as well as from being included in an official newsletter (Cao et al., 2021). A high ranking on the frontpage has also been found to have significant implications for the future success of ventures as they are more successful in securing future funding from more prominent venture investors (Cao, 2021).

Product Hunt is a suitable empirical setting for the purpose of the study as the number of upvotes a campaign receives by the members of the community can be seen as a measure of the endorsement given by the community. We posit that the act of a supporter upvoting a venture's campaign in this context can be viewed as an act of endorsement for that venture in the sense that the supporter implicitly communicates approval of its quality to other participants. An upvote by a supporter not only explicitly promotes the venture by improving its frontpage ranking and thus its exposure but also is showcased to others as a part of that supporter's profile.

3.3 Data Collection and Processing

3.3.1 Data Collection

The data used in the study were entirely collected from Product Hunt via their Application Programming Interface (API). The data was queried directly from the Product Hunt database via the V1 API with the use of Javascript. All data related to campaigns and users that have been generated since the platform's creation in 2013 is readily available through the API.

First, rather than using all campaigns created since 2013, we decided to limit the sample used in the study to a more recent set of campaigns as the platform, its users, and potentially drivers may have changed over time. By using recent campaigns, we expect data and findings to be stronger and more practically relevant than if we had included older observations. An example of this is that a large share of the campaigns created before 2018 were missing descriptions, a key component in our variable construction (see further 3.4.2 Independent Variables). As these campaigns would hence potentially bias the study's results, we decided to exclude all campaigns made earlier than 2018-01-01. Therefore, the selected sample consists of all featured campaigns made from 2018-01-01 to 2021-12-31. The unique campaign id's from these campaigns were collected via the "Posts / All" API call on 2022-02-22, and returned in 50-group iterations. This resulted in a list of 37,572 unique campaign ids, further used to collect the details and user information of these ids.

Next, the corresponding campaign details of all the unique campaign ids from the sampled campaigns were collected via the "Posts / Details" API call. This call returned three types of data. First, information on the content of the campaign, such as the campaign name, tagline, description, and images. Second, information on the performance of the campaign, primarily consisting of user-generated content such as upvotes, comments, and reviews. Third, contextual information such as basic information on the hunter's name and user id.

Lastly, the corresponding user details of all hunters of campaigns made during the period were collected via the "Users / Details" API call. The relevant data returned from this call consisted of detailed information on the hunter, such as the number of campaigns created and the number of followers.

Together, this provided a rich set of 37,572 campaigns to base the study on.

3.3.2 Data Processing

The processing of the collected data primarily consisted of cleaning and performing data checks using Python. The data cleaning process was done in a structured step-by-step manner to ensure the final data did not miss any key components. The first step of the data cleaning process was to merge the data sets from the API calls, including the comment data, the user data, and the media data. Following this, descriptive statistics were used to study the sample closer. During this process, 96 (192) duplicate records were found and removed from the data as a result of the API call and subsequent merging. A check was also performed to ensure all campaigns included in the sample had a name, tagline, and description. One campaign was identified as containing a misformatted date value which was corrected. Moreover, 47 campaigns were identified as being made by an official Product Hunt user account and were consequently removed from the sample. The remaining number of campaigns after these adjustments was 37,429. Finally, data consisting of text strings such as descriptions and comments were also cleaned by removing line breaks, HTML tags, links, and emojis.

The distribution of the data has implications for the statistical models used in quantitative studies. To determine whether the data followed a normal distribution, we formally tested this with a D'Agostino-Pearson test (D'Agostino & Pearson, 1973), showing that all variables were rejected as normally distributed ($p<0.05$) (see Appendix A). As formal normality tests suffer from sensitivity in large sample sizes, the distributions of the data were also visually assessed through the use of histograms and QQ-plots, in line with the recommendations of Ghasemi and Zahediasl (2012). The visualizations also indicated that variables did not follow a normal distribution but rather were right-skewed.

3.4 Analytical Strategy

3.4.1 Dependent Variable

The aim of this study is to identify how entrepreneurs successfully persuade supporters on crowdvoting platforms to endorse their ventures. Due to the novelty of research performed in this empirical setting, there is a lack of academically established operationalizations of endorsement readily available. Thus, we must construct our own operationalization of endorsement for this particular setting. Grossman and Helpman (1999) described endorsements as a means of communication where well-informed groups provide lesser-informed groups with a readily available cue from which they can convey useful information. We posit that the act of supporters upvoting a venture's campaign in this context can be viewed as an act of endorsement for that venture, in the sense that the supporter implicitly communicates approval of its quality to other stakeholders. A similar action to upvoting campaigns, liking posts on social media, has also been argued to be an act of endorsement, which further strengthens the argumentation (Mariani & Mohammed, 2014; Bernritter et al., 2016). Hence, we utilize upvotes as an indicator of endorsements and use this as the dependent variable.

As stated in 3.3.2 Data Processing, data were right-skewed and did not follow a normal distribution (see Appendix A). In the case of data being heavily skewed, variable transformation is one of the primary methods performed to make data conform more to normality in pursuit of increasing the validity of statistical analysis (Feng et al., 2014). The log transformation is one such transformation commonly used by researchers to make observed data conform more closely to normality, particularly when faced with right-skewed data (Feng et al., 2014). This has also frequently been done in crowdfunding research as a result of the nature of data from these platforms (e.g., Burtch et al., 2013; Zheng et al., 2014; Kim et al., 2016; Moradi & Badrinarayanan, 2021; Shneor et al., 2021). While log transformation has become an established practice in research, it is still a debated topic due to the associated implications of relying on this method, particularly in the case of ecological data (e.g., Feng et al., 2014; Keene, 1995; Ives, 2015).

Given the skewness of the data on upvotes, we have decided to log-transform the dependent variable with the common $\log(x+1)$, accommodating for zero-values in independent variables. In line with Feng et al. (2014), we have visually assessed the data and ensured that it followed a log-normal distribution previous to transforming it and consequently conformed more to normality upon transformation.

3.4.2 Independent Variables

The selected independent variables of the study can generally be categorized into two groups based on the type of data used. These are variables related to issue-relevant information included in venture descriptions and peripheral cues related to the campaigns. The issue-relevant information entails the linguistic properties of venture descriptions used by entrepreneurs on Product Hunt. On Product Hunt, there are three sections where entrepreneurs can use text to provide information about their ventures; the tagline, the description, and the comment section. As a result of the character limit of taglines and descriptions in campaigns, it is common practice for hunters and makers to write an introductory comment in the discussion section of a campaign, as illustrated in Figure 3 of 3.2 Empirical Setting. As this practice has largely become a standard within the platform and a fundamental component of venture campaigns, we include this introductory comment as part of the narrative descriptions of ventures. *Venture description* will henceforth thus be a concatenated construct of the *tagline*, *description*, and *introductory comment* as part of a venture's campaign.

To analyze the narrative of venture descriptions used in the study, we utilize the text analysis program Linguistic Inquiry and Word Count 2022 (LIWC-22)[2]. LIWC has been used in over 20,000 published articles in research areas such as management, finance, marketing, communication, persuasion, and leadership (Boyd et al., 2022).

The program analyzes the linguistic characteristics of text data by measuring the proportion of words in a text that are associated with certain psychological and linguistic dimensions (Tausczik & Pennebaker, 2010; Pennebaker et al., 2015; Boyd et al., 2022). LIWC uses a frequency word count approach in which a number of predetermined words related to certain psychological processes and linguistic dimensions make up dictionaries, enabling an analysis of over 100 dimensions of a text (McHaney et al., 2018; Tausczik & Pennebaker, 2010). Specifically, the program measures the relative frequency of words as part of a text, found in the categories of dictionaries related to the psychological processes and linguistic dimensions, thus returning a value between 0 and 100. Linguistic dimensions include measures such as function words, pronouns, determiners, adverbs, and conjunctions, whereas psychological processes include measures of dimensions such as cognition, affect, social processes, culture, motives, and perception (Boyd et al., 2022).

The validity of the word categories of previous versions of LIWC has been the subject of numerous studies assessing the validity of dimensions with convincing results of the program to be a valid method of measuring verbal expression (e.g., Kahn et al., 2007; Bantum & Owen, 2009). Moreover, due to its widespread application in the entrepreneurship literature (e.g.,

[2] https://www.liwc.app/

Pfarrer et al., 2010; Wolfe & Shepherd, 2015) and particularly its application to crowdfunding narratives (Parhankangas & Renko, 2017; Kim et al., 2016) and the persuasiveness of there (Lee et al., 2019; Moradi & Badrinarayanan, 2021) we find it to be a suitable for this study.

Below we will outline the operationalizations of constructs as per our hypotheses in detail by looking at the related literature. A full overview of variables and their explanation can be viewed towards the end of this chapter in Table 1.

Narrative Length

The narrative length has in previous studies on crowdfunding been utilized as issue-relevant information in venture descriptions and argued to persuade potential supporters through the central route (e.g., Allison et al., 2017; Zhou et al., 2018). In these studies, the construct has most frequently been operationalized as the number of words included in the venture description of a campaign (Allison et al., 2017; Zhou et al., 2018; Moradi & Badrinarayanan, 2021).

In line with this, we also operationalize the narrative length as the total number of words used in the venture descriptions and refer to the variable as *Word Count*. This variable is calculated through the LIWC-22 program. Furthermore, for similar reasons as mentioned in 3.4.1 Dependent Variable, the variable is log-transformed with log(x+1).

Quantitative Language

Quantitative language has in previous crowdfunding research been utilized to represent issue-relevant information in venture descriptions and found to increase the persuasive efficiency of campaigns for supporters processing through the central route (Larrimore et al., 2011; Lee et al., 2019). The variable has commonly been operationalized as the relative frequency of number and money-related words in venture descriptions as part of these studies (Larrimore et al., 2011; Lee et al., 2019).

While supporters are not asked to provide financial support on Product Hunt, thus potentially reducing the utility of money-related words, arguments of functional benefit and value of a venture's offerings are commonly highlighted to differentiate. Consequently, and in pursuit of comparability, we operationalize quantitative language in line with previous research as the relative frequency of number and money-related words of the total number of words used in venture descriptions (Lee et al., 2019). Number-related words include words such as *one, two, first, and once,* while money-related words entail words like *business, pay, price, and market* (Boyd et al., 2022). This variable, *Quantitative Language*, is also calculated using the LIWC-22 program, in line with previous literature (Larrimore et al., 2011; Lee et al., 2019). The variable is also log-transformed with log(x+1) for similar reasons as mentioned in 3.4.1 Dependent Variable.

Source Credibility

Given the social community-like setting with user profiles emphasizing community-related activity rather than the external experience, we postulate platform-specific credibility to be more influential to supporters than external credibility. We thus look beyond crowdfunding in our operationalization of this more social, platform-specific source credibility.

Source credibility has in previous research on online review platforms been studied as a peripheral cue and operationalized as the number of followers a user posting a review has on the platform (Cheng & Ho, 2015). Similarly, related research on social networking sites has shown that the number of followers of an individual can be a predictor of credibility (De Veirman et al., 2017), and the more followers a user has, the more credible source they are perceived as (Jin & Phua, 2014; Weismueller et al., 2020).

Using the same arguments and transferring them to our setting, we operationalize source credibility as the number of followers of the hunter of a campaign on Product Hunt and refer to the variable as *Hunter Follower Count*. Furthermore, the variable is log-transformed with log(x+1) for similar reasons as mentioned in 3.4.1 Dependent Variable.

Due to restrictions of the Product Hunt API, the data on the number of followers hunters have is based on the follower data at the date and time of data collection and not on the date of the respective campaign launch. We acknowledge that this is suboptimal as hunters' follower count may have changed since the time of posting the campaign. Additional robustness tests specifically addressing this issue were performed and are elaborated on in 4.3 Robustness Test.

Visual Cues

Visual cues have in previous research on crowdfunding been utilized as a peripheral cue and found to influence persuasion along the peripheral route (Majumdar & Bose, 2018; Shneor et al., 2021; Lin & Boh, 2021; Li et al., 2016). Researchers studying this concept have utilized both images (Majumdar & Bose, 2018; Shneor et al., 2021) and videos (Li et al., 2016; Lin & Boh, 2021) as part of their studies on how visual cues persuade supporters in crowdfunding.

Consequently, we operationalize visual cues being the combined number of images and videos included in a campaign and refer to the variable as *Media Object Count*. The variable is log-transformed with log(x+1) for similar reasons as mentioned in 3.4.1 Dependent Variable.

3.4.3 Control Variables

We use four control variables in our model to rule out possible alternative effects that may influence the number of upvotes a campaign receives. These are primarily based on previous literature on the adjacent crowdfunding context while incorporating considerations of the empirical setting as well. These are all included in Table 1 below.

First, we control for *Maker Listed*, being a dummy variable for whether at least one maker of a venture is listed in the campaign. Having makers listed as part of a campaign is an important aspect given the social community setting and is also a variable that has been part of previous literature on Product Hunt (Cao, 2021). Campaigns made by a third-party hunter without having the makers listed may be interpreted as more impersonal and detached than those with this included. Moreover, campaigns like these less often have an introductory comment made by the hunter or maker.

Next, we control for *Hunter Make Count*, representing the number of campaigns a hunter has been listed as a maker in campaigns, as previous studies on crowdfunding have shown that experience, education, and social capital positively influence campaign success (Allison et al., 2017; Wang et al., 2021; Cai et al., 2021). The distribution of the variable data was visually and statistically analyzed, which indicated it did not follow a normal distribution but rather was right-skewed (as discussed in 3.3.2 Data Processing). Hence, this was log(x+1)-transformed to make it conform more closely to a normal distribution while considering 0 values (see discussion in 3.4.1 Dependent Variable).

We also control for *Introductory Comment*, being a dummy variable for whether the hunter or maker of campaigns has made an introductory first comment. As elaborated on in 3.2 Empirical Setting and 3.4.2 Independent Variables, extending the description of campaigns with an introductory comment is common practice on Product Hunt. Writing an introductory comment resembles the advocating behavior of posting updates and comments shortly after launching a campaign which has shown to positively influence crowdfunding success as it can indicate preparedness and quality (Li et al., 2016; Wang et al., 2021; Mollick, 2014). Hence, it is not unlikely that campaigns with an introductory comment by the hunter or maker could influence the perception of the venture.

Lastly, we control for *Positive Tone*, being the share of positive affective words of the total number of words used in venture descriptions. This is in line with previous studies performed in a crowdfunding context (Lee et al., 2019), illustrating a degree of influence on success. The variable measures the relative frequency of positive affective words of the total number of words used in venture descriptions and is calculated with the use of LIWC-22. Similar to Hunter Make Count, the distribution of the Positive Tone variable was visually and statistically analyzed (as discussed in 3.3.2 Data Processing), which indicated it was heavily right-skewed and did not follow a normal distribution. As a result, this variable was also log(x+1)-transformed to make it conform more closely to a normal distribution while considering 0 values (see discussion in 3.4.1 Dependent Variable).

Table 1: Overview of Variables.

Variable	Explanation of Variable
Dependent Variable	
Upvotes (log)	The logarithm of the number of upvotes of a campaign + 1
Control Variables	
Maker Listed	A dummy with value 1 if maker is listed in a campaign, and 0 otherwise
Hunter Make Count (log)	The logarithm of the number of times the hunter has been listed as a maker of a campaign + 1
Introductory Comment	A dummy with value 1 if hunter or maker have posted an introductory first comment, and 0 otherwise
Positive Tone (log)	The logarithm of the relative frequency of positive affectual words to total words of a venture description + 1
Independent Variables	
Word Count (log)	The logarithm of the total number of words of the venture description + 1
Quantitative Language (log)	The logarithm of the relative frequency of number and money-related words to total words of a venture description + 1
Hunter Follower Count (log)	The logarithm of the number of followers of the hunter of a campaign + 1
Media Object Count (log)	The logarithm of the total number of images and videos included in a campaign +1

Note: The "relative frequency" holds a number between 0-100

3.4.4 Model Choice

To understand how entrepreneurs successfully persuade supporters to endorse their ventures in our empirical setting, a total of six primary regressions were performed. The selected statistical model for this study is the Ordinary Least Square (OLS), which is applied to all regressions of the study. The OLS is a method for estimating coefficients of linear regression equations explaining the relationship between a dependent variable and one or more independent quantitative variables (Hutcheson, 2011; Best & Wolf, 2013). As we seek to explore the relationship between certain campaign characteristics (independent variables) and upvotes (dependent variable) rather than make causal inferences, we deem the OLS a suitable model for this purpose. Furthermore, as the model has previously been used in research on crowdfunding success, the comparability of our results with previous findings increases by using the same model (e.g., Burtch et al., 2013; Shahab et al., 2019).

A point for discussion is the appropriateness of applying a least-squares linear model to data with a dependent count variable, as is the case here before the transformation. Though the application of least-squares linear models to transformed data has been found to yield robust results on par with alternative model specifications (Ives, 2015), count data being non-continuous and non-normal suggest generalized linear models to be attractive (Dunteman &

Ho, 2006). We acknowledge that the application of OLS is not always ideal in this case and should be carefully weighed against alternatives in these situations. The application of OLS to count data is, however, not unprecedented as it is commonly utilized in the management literature with similar data (e.g., Cabral & Li, 2015; Liu et al., 2014) and log transformations (Burtch et al., 2013, Vakili & McGahan, 2016). The decision to utilize OLS was further made in pursuit of comparability as we pursue similar statistical methods and operationalizations to that of previous studies. To ensure our results' robustness, we have also conducted alternative model specifications of generalized linear models applied before log-transforming the data, which is further elaborated on in 4.3 Robustness Tests and displayed in Appendix B.

Similar to other authors in the research area (e.g., Allison et al., 2017; Anglin et al., 2018), we use robust standard error estimates (HC3) in our models (Long & Ervin, 2000; Kaufman, 2013) to manage heteroskedasticity (see further discussion in 4.3 Robustness Tests). Additionally, a number of alternative model specifications were run with certain sample variations pertaining to limitations in the data to explore the robustness of our findings (see further in 4.3 Robustness Tests).

Moreover, based on the nature of the data available from these platforms, it is common practice to remove extreme values in the case of outliers (e.g., Mollick 2014; Bi et al., 2017). The decision to remove outliers should not be performed hastily without reason but can be attractive to ensure external validity in the case when few influential observations significantly distort the value of regression coefficients (Allen, 2004), likely as a result of faults or biases in the data or errors in the collection process (Mowbray et al., 2019). In this study, we performed univariate and multivariate outlier removal for all variables. Univariate outliers are set as values 1.5 times the interquartile range (Walfish, 2006; Field & Miles, 2010) and multivariate outliers using the Mahalanobis distance (Mahalanobis, 1936), reducing our sample by 5,403 observations to 32,026 observations. In Appendix C, we have added three examples of campaigns identified as outliers during this process and briefly discussed the problems with the data of these.

3.5 Reliability, Replicability and Validity

To critically evaluate and ensure a high-quality standard of our research, we will briefly discuss the reliability, validity, and replicability of the study. Reliability refers to the consistency, accuracy, and stability of the measures used, thus greatly influencing the replicability of the study (Bryman & Bell, 2011). As this study employs a quantitative analysis of objective data, reliability is generally not an issue of significance (Bryman & Bell, 2011). Moreover, we aim to maintain a high ethical standard in our research by thoroughly explaining how data were collected and processed, variables operationalized, and finally statistically analyzed throughout this chapter. As a result, we believe the replicability of the study to be high.

Validity refers to the accuracy in the measurement choice, meaning whether a measure truly captures what is set out to be captured (Bryman & Bell, 2011). We primarily acknowledge measurement validity here, as structural validity of statistical analysis is further covered in 4.3 Robustness Tests. For measurement validity, we base our operationalizations on the works of previous authors within the persuasion and crowdfunding domain, which have been trialed and tested. While this ensures comparability in the least, it also argues in favor of measurement validity (Bryman & Bell, 2011). However, due to the novelty of endorsement as a concept in this context, as well as certain setting-specific operationalizations on which research is scarce, we acknowledge that this may reduce the validity of measurements of the study.

4. Results and Analysis

The following chapter outlines the empirical findings of the study. First, the descriptive statistics of the data are presented, followed by the results from the statistical analysis (4.1). Next, the study's hypotheses are systematically presented and answered based on the results of the statistical analysis (4.2). Finally, the chapter ends with an assessment and discussion of the robustness of the results (4.3).

4.1 Descriptive Statistics

Tables 2 and 3 present the descriptive statistics for the selected sample. After performing the previously described outlier removal from the sample, the studied period between 2018-01-01 to 2021-12-31 includes a total of 32,026 campaigns. The average number of upvotes in the sample was 210.8, and the median was 114. The mean value of the number of followers a hunter has was 3,127, while the median was 118, suggesting a positively skewed distribution. Moreover, 84% of campaigns utilized the option to include an introductory comment. In terms of linguistic style, the average share of positive words was 4.69%, and the share of quantitative language was 3.15%. The average hunter make count of 5.67, which illustrates the existence of active hunters participating in the making of several campaigns, where some hunters are highly active, with the maximum number of times being listed as a maker being 62.

Table 3 illustrates the correlation coefficients between all the variables. The highest correlation, 0.626, is between the number of followers a hunter has and the number of ventures a hunter has been listed as a maker of. This indicates that active community participants frequently participating in the making of ventures tend to have a larger follower base.

Table 2: Descriptive Statistics (N=32,026).

	Mean	**SD**	**Min**	**Median**	**Max**
Upvotes	210.79	274.36	4	114	3,094
Maker Listed	0.93	0.25	0	1	1
Hunter Make Count	5.67	7.16	0	3	62
Introductory Comment	0.84	0.36	0	1	1
Positive Tone	4.69	2.49	0.29	4.27	17.95
Word Count	165.56	118.03	11	138	1,467
Quantitative Language	3.15	3.23	0	2.27	29.09
Hunter Follower Count	3,127.30	7,859.72	0	118	67,084
Media Object Count	4.79	2.15	1	4	15

Note: Before log-transformation

Table 3: Correlations (N=32,026).

		1	2	3	4	5	6	7	8
1	Upvotes (log)								
2	Maker Listed	**0.101**							
3	Hunter Make Count (log)	**0.313**	**0.105**						
4	Introductory Comment	0.001	**0.163**	**0.087**					
5	Positive Tone (log)	0.007	**-0.030**	**0.012**	**-0.045**				
6	Word Count (log)	**0.166**	**0.257**	**0.106**	**0.619**	**-0.158**			
7	Quantitative Language (log	**0.070**	**0.018**	**0.044**	**0.101**	**-0.122**	**0.196**		
8	Hunter Follower Count (log)	**0.466**	**-0.074**	**0.626**	0.009	**0.013**	**0.091**	**0.091**	
9	Media Object Count (log)	**0.118**	**0.019**	**0.025**	**0.046**	**0.019**	**0.190**	**0.081**	**0.091**

Note: all | ρ | above 0.012 are significant at 0.05 and in bold

The results of the OLS regression model are presented in Table 4, illustrating the relationship between the dependent variable and independent variables. Model 1 involves only control variables, whereas Models 2-6 include independent variables corresponding to the hypotheses. The results of Model 1 indicate that having a listed maker and using a hunter that has posted campaigns previously are both significant and positively associated with the number of upvotes. In contrast, having an introductory comment shows a significant negative relationship with the number of upvotes. Lastly, the presence of a positive tonality in venture descriptions does not show a significant relationship to upvotes in Model 1.

All the independent variables except for quantitative language show a positive significant relationship with the number of upvotes in Model 6. This means that there is a significant positive relationship between Word Count (log), Hunter Follower Count (log), Media Object Count (log), and the number of upvotes of campaigns. Word Count (log) shows the greatest beta coefficient in Model 2 (0.349) and in Model 6 (0.245), indicating that the number of words used in venture descriptions has the largest relative log unit impact of all independent variables.

The adjusted coefficient of determination, Adjusted R2, explains the extent to which the independent variables can estimate the variation in the dependent variable. Similar research on crowdfunding success has shown Adjusted R2 values between 0.1 - 0.22 (e.g., Kim et al., 2016; Allison et al., 2017), which are similar to our values ranging from 0.104 to 0.257. The largest adjusted R2 value comes from Model 6, indicating that the variance in the number of upvotes can be explained to 25.7 percent by the control and independent variables.

Table 4: Regression Coefficients of Campaign Characteristics on Upvotes.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(OLS)	**(OLS)**	**(OLS)**	**(OLS)**	**(OLS)**	**(OLS)**
	Dependent Variable: Upvotes (log)					
Control Variables						
Maker Listed	0.138***	0.070***	0.138***	0.258***	0.136***	0.202***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Hunter Make Count (log)	0.376***	0.364***	0.373***	0.004	0.373***	0.016*
	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)
Introductory Comment	-0.048***	-0.225***	-0.055***	-0.033***	-0.054***	-0.162***
	(0.007)	(0.008)	(0.007)	(0.006)	(0.007)	(0.008)
Positive Tone (log)	0.008	0.084***	0.026*	0.008	0.003	0.060***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)
Independent Variables						
H1: Word Count (log)		0.349***				0.245***
		(0.010)				(0.010)
H2: Quantitative Language (log)			0.086***			0.009
			(0.008)			(0.007)
H3: Hunter Follower Count (log)				0.170***		0.160***
				(0.002)		(0.002)
H4: Media Object Count (log)					0.331***	0.142***
					(0.016)	(0.015)
Constant	1.740***	1.168***	1.692***	1.494***	1.510***	1.004***
	(0.014)	(0.021)	(0.015)	(0.014)	(0.018)	(0.021)
Log-Likelihood	-18,735	-18,132	-18,671	-16,175	-18,516	-15,729
Adjusted R^2	0.104	0.137	0.107	0.236	0.116	0.257
N	32,026	32,026	32,026	32,026	32,026	32,026

Note: Heteroskedastic-consistent (HC3) standard errors in parenthesis.
OLS = Ordinary Least Squares
*p<0.05; **p<0.01; ***p<0.001

4.2 Hypothesis Testing

H1: *The narrative length of venture descriptions in campaigns is positively associated with endorsement*

The Word Count (log) variable was found to be significant and positively related to an increased number of upvotes (p-value < 0.001; β = 0.349 and 0.245 in Models 2 and 6, respectively). Hence there is a significant linear relationship between the number of words in venture descriptions and the number of upvotes a campaign receives. More specifically, a one log unit increase in Word Count (log) corresponded to a 0.349 and 0.245 log unit increase of Upvotes (log) for Models 2 and 6, respectively. Therefore, we find support for H1.

H2: *The presence of quantitative language in venture descriptions in campaigns is positively associated with endorsement*

The Quantitative Language (log) variable was only partly found to be positively related to an increased number of upvotes (p-value < 0.001 and > 0.01; β = 0.086 and 0.009 in Models 2 and 6, respectively). Hence, there is an inconclusive linear relationship between the relative frequency of number and money-related words in venture descriptions and the number of upvotes of a campaign. Therefore, due to the inconclusiveness of results, we deem that we do not find support for H2.

H3: *The credibility of the source of campaigns is positively associated with endorsement*

The Hunter Follower Count (log) variable was found to be significant and positively related to an increased number of upvotes (p-value < 0.001; β = 0.170 and 0.160 in Models 4 and 6, respectively). Hence there is a significant linear relationship between the number of followers of a hunter and the number of upvotes of a campaign. More specifically, a one log unit increase in Hunter Follower Count (log) corresponded to a 0.170 and 0.160 log unit increase in Upvotes (log) for Models 4 and 6, respectively. Therefore, we find support for H3.

H4: *The presence of visual cues in campaigns is positively associated with endorsement*

The Media Object Count (log) variable was found to be significant and positively related to an increased number of upvotes (p-value < 0.001; β = 0.331 and 0.142 in Models 5 and 6, respectively). Hence there is a significant linear relationship between the number of media objects and the number of upvotes of a campaign. More specifically, a one log unit increase in Media Object Count (log) corresponded to a 0.331 and 0.142 log unit increase in Upvotes (log) for Models 5 and 6, respectively. Therefore, we find support for H4.

Table 5: Overview of Hypotheses and Results.

Hypothesis	Result
Issue-Relevant Information	
H1: The narrative length of venture descriptions in campaigns will have a positive relationship with supporter endorsement	Supported
H2: The presence of quantitative language in venture descriptions in campaigns will have a positive relationship with supporter endorsement	Not Supported
Peripheral Cues	
H3: The credibility of a source in campaigns will have a positive relationship with supporter endorsement	Supported
H4: The presence of visual cues in campaigns will have a positive relationship with supporter endorsement	Supported

4.3 Robustness Tests

To ensure the structural validity of our findings, a number of robustness tests were performed pertaining to alternative model specifications and the satisfaction of regression assumptions.

As discussed in 3.4.4 Model Choice, the selected model for this study was OLS with a log-transformed dependent variable. To ensure the robustness of our findings, we also performed an alternative model specification using a generalized linear model on the pre-transformed data. As the sample did not entail any zeros of our dependent variable (see Table 2) but suffered from overdispersion, we used a negative binomial generalized linear model without zero-inflation (Cameron & Trivedi, 2013). As per the output in Appendix B, all our results hold as the independent variables remain significant in the same direction (with the exception of Quantitative Language also becoming significant (***) in Model 12 when including all independent variables).

To ensure the stability of estimators, it is important to assess the collinearity level of independent variables. Collinearity problems entail that two or more independent variables are highly intercorrelated, meaning that one variable can predict the change of another (Best & Wolf, 2014). In order to judge collinearity in our measurements, a correlation matrix was constructed (Table 3) as well as the variance inflation factor (VIF) for each independent variable was formally assessed (Table 6). There is still debate in academia on what an acceptable VIF is, as some maintain that a VIF of less than 10 is acceptable (Best & Wolf, 2014; Allison, 2012), while others argue that a VIF of more than 2.5 is problematic (Johnston et al., 2018). As shown in Table 6, all model measurements maintain a VIF of less than 2, thus fulfilling the requisite for our study.

Table 6: Variance Inflation Factor (VIF).

	VIF	Tolerance
Maker Listed	1.12	0.89
Hunter Make Count (log)	1.73	0.58
Introductory Comment	1.66	0.60
Positive Tone (log)	1.04	0.96
Word Count (log)	1.88	0.53
Quantitative Language (log	1.06	0.94
Hunter Follower Count (log)	1.75	0.57
Media Object Count (log)	1.06	0.94

Normality and the distribution of residuals of linear regression models are debated topics in academia. While there is no assumption regarding the distribution of residuals for the purpose of descriptive statistics, in statistical inference, it is presumed that the distribution of residuals follows a normal distribution despite this often being violated in social science research (Mueleman et al., 2015). A lack of normality in the distribution of residuals can theoretically impede statistical inference of regression coefficients by biasing statistical significance. However, due to the robustness against deviations of normality for statistical tests of regression parameters, particularly in the case of large sample sizes, regression coefficients will approach t-distribution despite a lack of normality in residuals as a result of the central limit theorem (Lumley et al., 2002).

Despite this, we visually assessed the distribution of our residuals through a diagnostic QQ-plot, which indicated adequate normal distribution (Figure D1). A formal D'Agostino-Pearson test was also performed, which indicated that residuals did not follow a normal distribution ($p<0.05$) (Appendix E). However, formal tests for normality of residuals with large sample sizes (when non-normality lacks considerable consequences) have been found to be oversensitive (Mueleman et al., 2015). Hence, based on the large sample size of the study ($N=32,026$) and the above discussion, we are not concerned with the result of the formal test.

In order to formally assess the variance of error terms along with differing values of independent variables, we perform a Breusch-Pagan test (Breusch & Pagan, 1979). The null hypothesis of the test that squared residuals have a constant variance is rejected ($p<0.05$), indicating that the variance in errors partly is dependent on the values of independent variables (Breusch & Pagan, 1979) (see Appendix F). Visually assessing the diagnostic plots of residuals also suggests there is some evidence of this in the model (see Appendix D). This is formally referred to as heteroskedasticity (Kaufman, 2013). While non-constant error variance still entails least squares estimators to remain unbiased, they do become inefficient, making alternative estimation procedures more efficient due to their influence on the significance and confidence intervals (Best & Wolf, 2014).

A common way researchers manage the presence of heteroskedasticity is through transformations of the dependent variable, which is particularly relevant in the case of skewed distributions (Kaufman, 2013). As elaborated on in section 3.4.1 Dependent Variable, the dependent variable has already been log-transformed due to its skewed distribution, making any further transformations excess. Instead, a common practice in managing and correcting heteroskedasticity in OLS regressions is through the use of heteroskedastic-consistent (robust) standard errors (Kaufman, 2013). In all model specifications, we use robust standard errors (HC3), addressing the problem of incorrectly calculated standard errors. The (HC3) variation was selected as it has been found to outperform alternative versions (Long & Ervin, 2000; Kaufman, 2013).

In pursuit of investigating the cause for heteroskedasticity, scatter plots of dependent to independent variables were visually assessed, which indicated a cluster of lower value observations of the variable Hunter Follower Count (log). When replicating the six primary regressions and excluding this subset of campaigns where the hunter had seven or fewer followers (21.8% of the sample), we find that the model becomes homoskedastic upon performing an additional Breusch-Pagan test ($p>0.05$) (see Table G1). With this alternative sample (N=25,046), all of our results hold in these regressions as independent variables remained significant in the same direction (with the exception of Quantitative Language (log) also becoming partially significant (*) in the Model 18, including all independent variables (see Table G2). These results reassure us of our findings but are, however, further discussed in section 5.4 Limitations and Future Research.

Finally, as mentioned in 3.4.2 Independent Variable, the Hunter Follower Count (log) variable is not time-adjusted for the date and time when a campaign was made due to this time-adjusted data not being available from the Product Hunt API. We conducted an additional number of alternative model specifications to ensure robustness in our findings when only including the latest campaigns made by a hunter. By only including the latest campaigns made by a hunter, we ensure that frequent posters are only based on the performance of their latest campaign rather than campaigns dating far back in time, thus increasing the accuracy of the Hunter Follower Count variable. These regressions replicate the six primary models but with a sample made up only of the latest campaign by each hunter (N=16,780). In this, Hunter Follower Count (log) remained significant (***) both when tested alone in Model 22 and with all independent variables in Model 24 (see Appendix H). Based on the general stability of our results in these alternative models' specifications, we are further reassured about the robustness of the findings from the study.

5. Discussion

The following chapter will analyze and discuss the findings of the study in relation to the ELM and previous literature. First, a general discussion of the results of the study will be had in relation to the ELM (5.1). Following this, the study's theoretical contributions (5.2) and practical implications (5.3) will be explored. Lastly, a reflective discussion will be had, covering the limitations of the study and providing suggestions for future research (5.4).

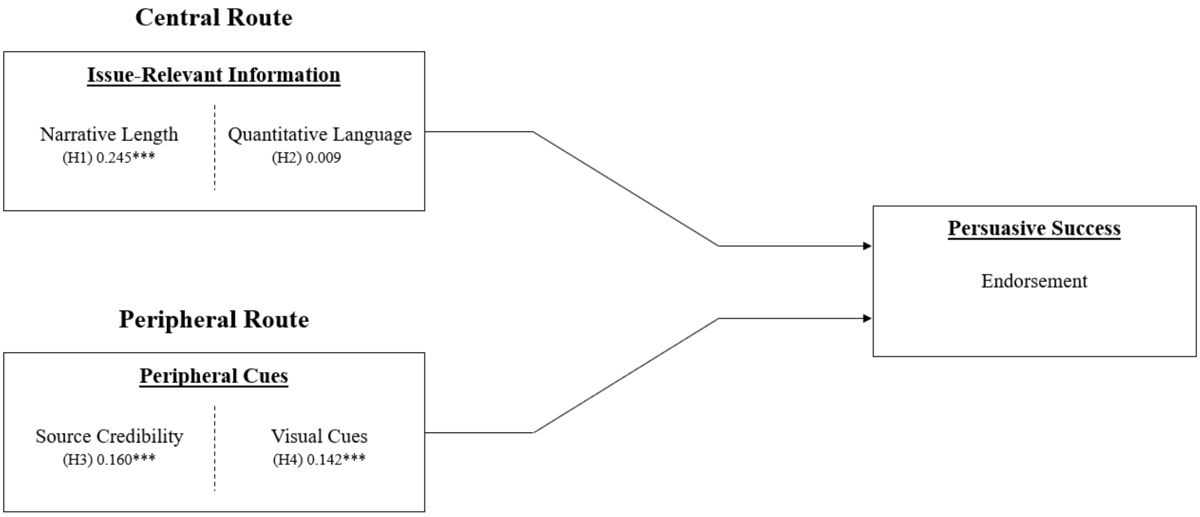
5.1 Discussion of Results

In our review of the literature, it has been shown that in this digital age, entrepreneurs commonly turn to online platforms to acquire resources and support for their ventures (e.g., Meurer et al., 2022; Zhao et al., 2019). While entrepreneurs commonly utilize crowdfunding to acquire financial resources from supporters, it is evident that new ventures also need non-financial support in their development.

We set out to identify how entrepreneurs successfully persuade supporters on online crowdvoting platforms to endorse their ventures through the use of issue-relevant information and peripheral cues, as per the ELM. We utilize crowdfunding research as a basis in our hypothesis generation due to the novelty of literature on persuasion on crowdvoting platforms.

The results of the study show support for three of our hypotheses indicating that the narrative length of venture descriptions, source credibility, and visual cues are positively related to the amount of endorsement a campaign receives. A visual summary of the hypotheses and their relationship to supporter endorsement is presented in Figure 4 below.

Figure 4: Conceptual Model and Results of Hypotheses in Model 6



*p<0.05; **p<0.01; ***p<0.001

5.1.1 Issue-Relevant Information

Hypothesis 1 proposed that longer venture descriptions would be positively related to more endorsement from supporters. The results of our study also indicate that is the case as campaigns with longer venture descriptions perform better than shorter ones. The rationale for this claim comes from the notion that more elaborate venture descriptions enable entrepreneurs to include more persuasive arguments and details on their venture, thus reducing uncertainty about the product's quality for potential supporters (Bi, Liu, & Usman, 2017). The results suggest that the arguments of the ELM, being that issue-relevant information increases the persuasiveness of a message, are applicable in this context (Petty & Cacioppo, 1986). The results are also in line with findings from previous research on success in crowdfunding platforms (Bi, Liu, & Usman, 2017; Moradi & Badrinarayanan, 2021). To conclude, increased length of venture descriptions provides supporters with more issue-relevant information, allowing them to more easily discern the value and benefits of a venture's product, which appears to also increase the level of support for that venture itself.

In contrast, hypothesis 2, which proposed that increased use of quantitative language in venture descriptions would result in more endorsement from supporters, was not supported. Quantitative language can be considered as issue-relevant information that, according to the ELM, should increase the persuasive efficiency of a message when individuals process information through the central route (Petty & Cacioppo, 1986; Lee et al., 2019). Similarly, crowdfunding literature has shown that the use of quantitative language increases persuasiveness as it helps potential supporters to understand the financial viability of ventures and thus reduces uncertainty and risk (Larrimore, 2011; Lee et al., 2019). Our findings suggest that this information used to reduce uncertainty and risk is not as influential when supporters are asked to endorse ventures compared to when they are asked to provide financial resources and seek a monetary return. As such, our results appear to indicate that non-financial supporters in this empirical setting are not processing messages to the same extent through the central route in their decision to endorse a venture or not.

5.1.2 Peripheral Cues

Hypothesis 3 proposed that the level of credibility a source has would be influential in the decision to endorse a venture for supporters. The results from our study indicate that source credibility is positively related to increased levels of endorsement from supporters, as campaigns created by hunters with a larger following count receive more endorsement than those with a lower count.

These results are in line with the ELM, arguing that the credibility of a message source influences the persuasive efficiency of a message when arguments are processed through the peripheral route (Petty & Cacioppo, 1986). The results are further in line with previous findings in crowdfunding success, showing that the characteristics of the source can influence the persuasive efficiency in receiving financial resources (Wang et al., 2021; Wang & Yang, 2019;

Allison et al., 2017). The results indicate that using a source with higher credibility can enhance the perceived quality of a venture and trust that it will fulfill its claims and proposed plans (Wang et al., 2021; Buttice et al., 2017). Additionally, our results further support the findings of Cheng and Ho (2015), showing that follower count can be used as an indicator of source credibility, which has an effect on the persuasiveness of a message. Hence, we can conclude that source credibility increases persuasiveness when entrepreneurs seek endorsement for their ventures on online crowdvoting platforms.

Hypothesis 4 proposed that the use of visual cues would be positively related to endorsements from supporters. Our findings suggest that this is also the case as campaigns with more visual cues also had more endorsements from supporters.

The finding is in line with the ELM, arguing that visual cues can provide individuals with a mental shortcut, and in this case to form a judgment concerning a venture (Petty & Cacioppo, 1986). One reason why visual content is positively associated with endorsement could be that the ability to process all issue-relevant information presented in venture descriptions is limited due to the immense amount of ventures competing for attention in this empirical setting. Hence, as visual content was posited to be processed through the peripheral route it is processed faster and requires less cognitive effort than textual information (Pieters & Wedel, 2004). Furthermore, our results find support for previous findings from research on crowdfunding success, showcasing that the use of visual content improves funding performance (Bi et al., 2017; Wang et al., 2021; Li et al., 2016). In line with those studies, we thus find support for the claim that the use of visual content thus attracts attention, is easier to process than detailed venture descriptions and can enhance positive attitudes regarding a venture's campaign. Taken together, our results appear to indicate that non-financial supporters in this empirical setting to a greater extent process messages through the peripheral route in their decision to endorse a venture or not.

The ELM posits that what route a message is processed through is determined by an individual's motivation to engage in elaboration and the ability to understand the respective arguments (Petty & Cacioppo, 1986). As established, in the case of both *motivation* and *ability* to process message arguments being high, individuals will process information through the central route and be more persuaded by issue-relevant information than peripheral cues. Supporters engaging on these non-financial platforms do not engage in pursuit of financial returns but rather appear to do so out of sheer interest and passion for entrepreneurial ventures. These are individuals interested and knowledgeable in tech and the development of new ventures. More specifically, given that the user base of the empirical setting largely is made up of product enthusiasts with well-founded technical acumen (Cao et al., 2021; Cao, 2021), one could presume that their *ability* to process the arguments presented as part of campaigns is high.

The *motivation* to process arguments is another key component of ELM in determining whether supporters process information through the central or peripheral route. As established there is a financial risk associated with supporting a venture in crowdfunding that is not present on crowdvoting platforms. Moreover, the motivation for supporting ventures in crowdvoting is also not derived from a pursuit of a tangible return, as is partly the case in crowdfunding. As such, one could posit that these financial aspects influence the underlying motivations and dynamics of participation amongst supporters. Adding on to this, given the competitive nature and abundance of ventures seeking support in this empirical setting, the *motivation* to process arguments may perhaps not always be as high for supporters as in a crowdfunding context.

This could perhaps be one explanation as to why the significance of quantitative language did not hold across all model specifications. It is possible that non-financial supporters, to a lesser extent care about the uncertainty and risk related to a venture and hence are less interested in elaborating on the more objective, quantitative information part of campaigns than financial supporters. The decision whether to support a venture or not hence appears to be less dependent on the viability of the venture than other factors.

Taken together, this line of argumentation could hence lead one to postulate that an emphasis on issue-relevant information consisting of objective quality arguments highlighting the value of a venture's offering perhaps should be less important for these types of supporters. While having an elaborate description of one's venture is important, our findings indicate that peripheral cues also carry much significance in the decision-making of supporters, more so than the quantification of benefits and value.

5.2 Theoretical Contributions

This study examines how entrepreneurs successfully persuade supporters on online crowdvoting platforms to endorse their ventures through the use of issue-relevant information and peripheral cues. As a result of the selected empirical setting, theoretical application, and methodological choice, this study has contributed to the theoretical domain in three overarching themes.

First, the study contributes to the growing research on entrepreneurial support and acquisition of resources for early-stage ventures through online platforms. Prior research has largely focused on how entrepreneurs acquire financial support for their ventures by means of crowdfunding platforms. However, non-financial support still has significant implications for venture growth and the support of entrepreneurs in their journeys. Thus, we advance the theoretical understanding of venture support in online platforms by extending our study to a setting that previously has largely been overlooked.

Second, we contribute to the theoretical domain of the Elaboration Likelihood Model and persuasion in online platforms by extending the theory to an empirical setting to which it has not previously been applied. While persuasion and communication have received much attention in the marketing domain, crowdfunding, and customer reviews, the application in acquiring non-financial support is limited. With our study, we thus extend the understanding of issue-relevant information and central route processing, as well as peripheral cues in its information processing. We show that in comparison to the acquisition of financial support from crowdfunding platforms, issue-relevant information appears to not be as influential in the persuasion of potential supporters. While issue-relevant information and central route processing are partly apparent, non-financial supporters providing endorsement thus rather appear to be more persuaded through peripheral cues.

Lastly, through our application of the ELM and operationalization of constructs in this setting, we contribute to the robustness of the constructs and how these can be operationalized in online community-like platforms. In the case of source credibility specifically, we deepen the understanding of how this construct can be operationalized based on platform-specific credibility for supporters.

5.3 Practical Implications

In our purpose of this study, we also set out to provide practical guidance on how entrepreneurs shall construct their message strategies in pursuit of endorsement for their ventures. The results of our study entail several implications for entrepreneurs of early-stage ventures seeking support from online contexts.

Firstly, our findings indicate that persuasion and how one constructs their messages on online platforms fundamentally matter. We show that constructs derived from persuasion theory influence the level of endorsement ventures receive on online platforms. Thus, entrepreneurs planning on appealing to potential supporters in this context should carefully consider this before engaging online. Moreover, as has been shown from previous research, having a successful outcome in this specific empirical setting has significant implications for new ventures in their future acquisition of resources (Cao, 2021). As a result, the sheer implication that message strategy influences success in this context furthers an entrepreneur's ability to acquire resources for their venture successfully and improves the probability of success.

Secondly, by identifying the specific technical factors related to persuasive success in pursuit of endorsement, entrepreneurs could implement our findings when constructing their campaigns in pursuit of non-financial support online. We showcase that the elaborateness of a venture description, the number of followers of a source, and the use of visual content in a campaign significantly improve the performance and level of endorsement it receives. Moreover, while entrepreneurs may commonly be schooled in emphasizing the quantitative benefits and value of their venture's product(s), we find that this practice appears to not yield the same results in a context without financial implications for supporters.

5.4 Limitations and Future Research

Due to the scope and design of the study, we acknowledge that there are certain limitations related to the findings. In this chapter, we aim to reflect on those limitations and suggest future research opportunities that can address those limitations.

First, the sample of the study was collected from only one platform, Product Hunt. As the platform does not easily allow for distinguishing for-profit ventures from non-profit ventures or campaigns of mature ventures, the sample may include campaigns outside of the core scope of the study. We hence propose future research to explore if there are any differences in the persuasive mechanisms at play for supporters between these types of ventures.

There are not many platforms, to our knowledge, that entail the same purpose and mechanisms as Product Hunt. This, in conjunction with previous research showing that it can be tricky to generalize across platforms as they can differ in terms of users and driving factors (Dushnitsky, 2018), raises questions about the generalizability of our findings. We acknowledge this and understand that we cannot naively claim our findings to be more generalizable than the previous works of other authors. However, this study is a first step in exploring the realm of entrepreneurial support in online non-financial contexts, and as such, we believe it offers a strong foundation to build upon and further explore similar platforms of this purpose.

Furthermore, we utilize previous research on primarily crowdfunding as guidance in selecting the issue-relevant information and peripheral cues that could be influential in persuading potential supporters to endorse ventures. Future work should investigate what other factors may influence the persuasiveness of campaigns. That could, for example, be how the results differ depending on what type of products a venture offers, or the perceived quality of these. In addition, future work could also investigate how issue-relevant information and peripheral cues relate to each other. It would be of great practical value to understand whether certain peripheral cues such as source credibility act as an enabler for supporters to elaborate more on the issue-relevant information. For example, as there are so many campaigns available, some supporters might only read and elaborate on the issue-relevant information from campaigns with a credible source. Exploring these dynamics could be a fruitful avenue for further research.

As discussed in 4.3 Robustness Tests, upon visually assessing data, we found there to be an atypical pattern for campaigns with a very low follower count of hunters. When excluding this subsample and rerunning our models, our results hold and show that heteroskedasticity is no longer present by performing a Breusch-Pagan test ($p>0.05$) (see Table G1). This indicates that there may be some uncontrollable phenomenon happening likely outside of the platform, such as marketing or social media campaigns, causing certain campaigns of hunters with low follower counts to overperform. While we acknowledge that this is a limitation in our study as a result of the type of data, we have taken steps to minimize its influence on the results and performed additional robustness tests showing our results hold. However, this finding presents an interesting opportunity for future research to try and explore what the phenomenon is and potentially control for it. Future work could incorporate third-party data such as Twitter followers of the hunter, or website visitors of a venture, similar to the work of Cao (2021), to explore what this cause might be related to.

Another avenue for research could be examining the motivations behind why supporters and entrepreneurs are active on online non-financial platforms like Product Hunt. There have been done numerous studies exploring the motivations of entrepreneurs and supporters in crowdfunding (e.g., Gerber & Hui, 2013; Ordanini et al., 2011). However, the research concerning motivations for participation in entrepreneurially-focused crowdvoting platforms is, to our knowledge, non-existent. Understanding why users are active on the platform and why they choose to support certain ventures can help formulate future research questions on how to persuade these supporters.

Moreover, it would be interesting to understand what a launch on Product Hunt entails, both in terms of tangible benefits and company decisions. For example, Cao (2019) showed that a successful launch on Product Hunt entailed significant benefits in regard to funding and exposure for new ventures. Further research could, as such, examine closer what these benefits are and the influence they have had on new ventures through surveys or interviews with entrepreneurs. Additionally, as has become evident from exploring the data of this study, supporters and entrepreneurs frequently utilize the discussion section of campaigns to exchange information, give feedback, and offer advice on how ventures and products can be improved. Given this crowdsourcing channel for direct feedback from supporters and potential customers, we believe it could be fruitful to explore how ventures utilize the feedback they receive. Particularly interesting would be understanding whether companies change direction and "pivot" as a result of the feedback they get on the platform, entailing either smaller product and design changes or more strategic market changes. All in all, we believe there are many new avenues for potential research of this specific empirical setting due to the richness of data available through the API and the potential implications this setting has for new ventures.

6. Conclusion

The purpose of this study was to commence the exploration of the novel context of entrepreneurially-focused crowdvoting platforms utilized for non-financial support. More specifically, by studying the phenomenon through the theoretical perspective of the ELM, we set out to uncover how entrepreneurs successfully persuade supporters to endorse their ventures through the use of issue-relevant information and peripheral cues in their messages.

Our findings show that both the central and peripheral routes are at play in persuading supporters. For issue-relevant information, pertaining to the central route, the narrative length of venture descriptions in campaigns was found to be significant and positively related to supporter endorsement. Elaborate venture descriptions containing more words appear to enable entrepreneurs to convey more issue-relevant information to supporters, resulting in increased persuasive success. The use of quantitative language was found to have a significant positive relationship to supporter endorsement when isolated in Model 3 but not in Model 6, including all independent variables. While the results show some evidence of venture descriptions emphasizing quantitative language being related to supporter endorsement, the limited significance inhibits any claims to be made with confidence regarding its persuasive influence on supporters.

For peripheral cues, pertaining to the peripheral route, both source credibility and visual cues were found to be significant and positively related to supporter endorsement. The amount of platform-specific followers a source has, as well as the use of images and videos, all appear to influence the persuasiveness of campaigns.

To summarize, supporters appear to be persuaded through both the central and peripheral routes when deciding to endorse entrepreneurial ventures on online crowdvoting platforms. Statistically sound relationships have been found between campaign characteristics and supporter endorsement. Entrepreneurs must thus carefully consider this when constructing their campaigns in pursuit of acquiring support for the ventures. Both issue-relevant information by means of longer venture descriptions as well as peripheral cues pertaining to source credibility and visual cues are positively related to the endorsement and support one receives for their venture.

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8. Appendices

Appendix A

Table A1: D'Agostino-Pearson Test for Normality of Variables Before Adjustments.

Concept	Variable	Statistic	Significance
Endorsement	Upvotes	55,026	< 0.05
-	Maker Listed	22,128	< 0.05
-	Hunter Make Count	42,230	< 0.05
-	Introductory Comment	6,633	< 0.05
-	Positive Tone	8,482	< 0.05
Narrative Length	Word Count	12,516	< 0.05
Quantitative Language	Quantitative Language	23,527	< 0.05
Source Credibility	Hunter Follower Count	30,828	< 0.05
Visual Cues	Media Object Count	28,234	< 0.05

Note: As part of 3.3.2 Data Processing. Test conducted before outlier removal and log-transformation
Control Variables listed as '-'

Appendix B

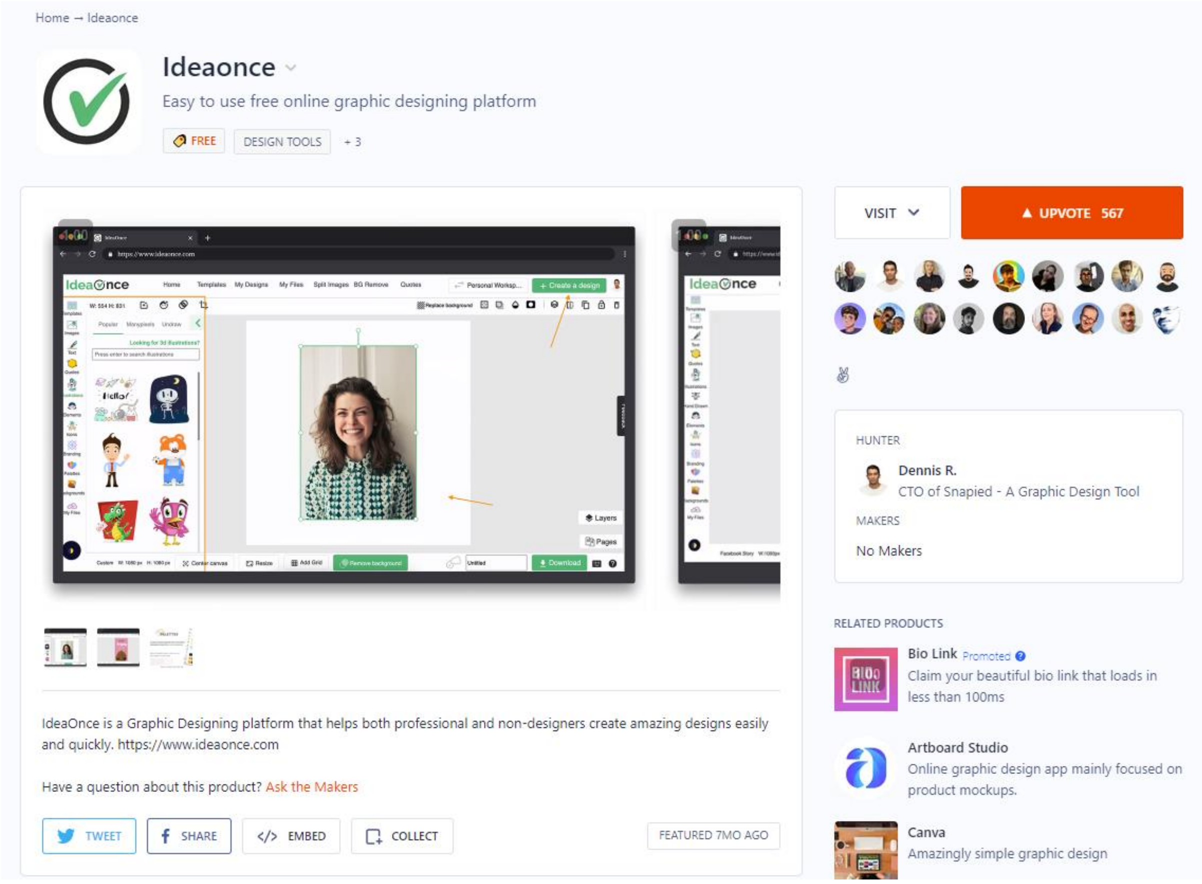
Table B1: Regression Coefficients of Campaign Characteristics on Upvotes with Alternative Specification of Negative Binomial Generalized Linear Model.

	Model 7	Model 8	Model 91	Model 10	Model 11	Model 12
	(NBGLM)	**(NBGLM)**	**(NBGLM)**	**(NBGLM)**	**(NBGLM)**	**(NBGLM)**
	Dependent Variable: Upvotes					
Control Variables						
Maker Listed	0.424***	0.316***	0.425***	0.425***	0.411***	0.326***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Hunter Make Count	0.038***	0.037***	0.038***	0.027***	0.037***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Introductory Comment	-0.064***	-0.309***	-0.064***	-0.060***	-0.077***	-0.279***
	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)
Positive Tone	-0.004	0.010***	-0.002	-0.004	-0.004	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Independent Variables						
H1: Word Count		0.002***				0.002***
		(0.0001)				(0.0001)
H2: Quantitative Language			0.013***			0.007***
			(0.002)			(0.002)
H3: Hunter Follower Count				0.00002***		0.00002***
				(0.00000)		(0.00000)
H4: Media Object Count					0.053***	0.030***
					(0.003)	(0.003)
Constant	4.772***	4.709***	4.723***	4.765***	4.540***	4.552***
	(0.026)	(0.026)	(0.027)	(0.026)	(0.028)	(0.029)
Log-Likelihood	-202,203	-201,659	-202,178	-201,941	-201,998	-201,375
(Pseudo) Adjusted R^2	0.006	0.009	0.026	0.008	0.007	0.011
N	32,026	32,026	32,026	32,026	32,026	32,026

Note: Standard errors in parenthesis. (Pseudo) Adjusted R^2 is McFadden.
NBGLM = Negative Binomial Generalized Linear Model
*p<0.05; **p<0.01; ***p<0.001

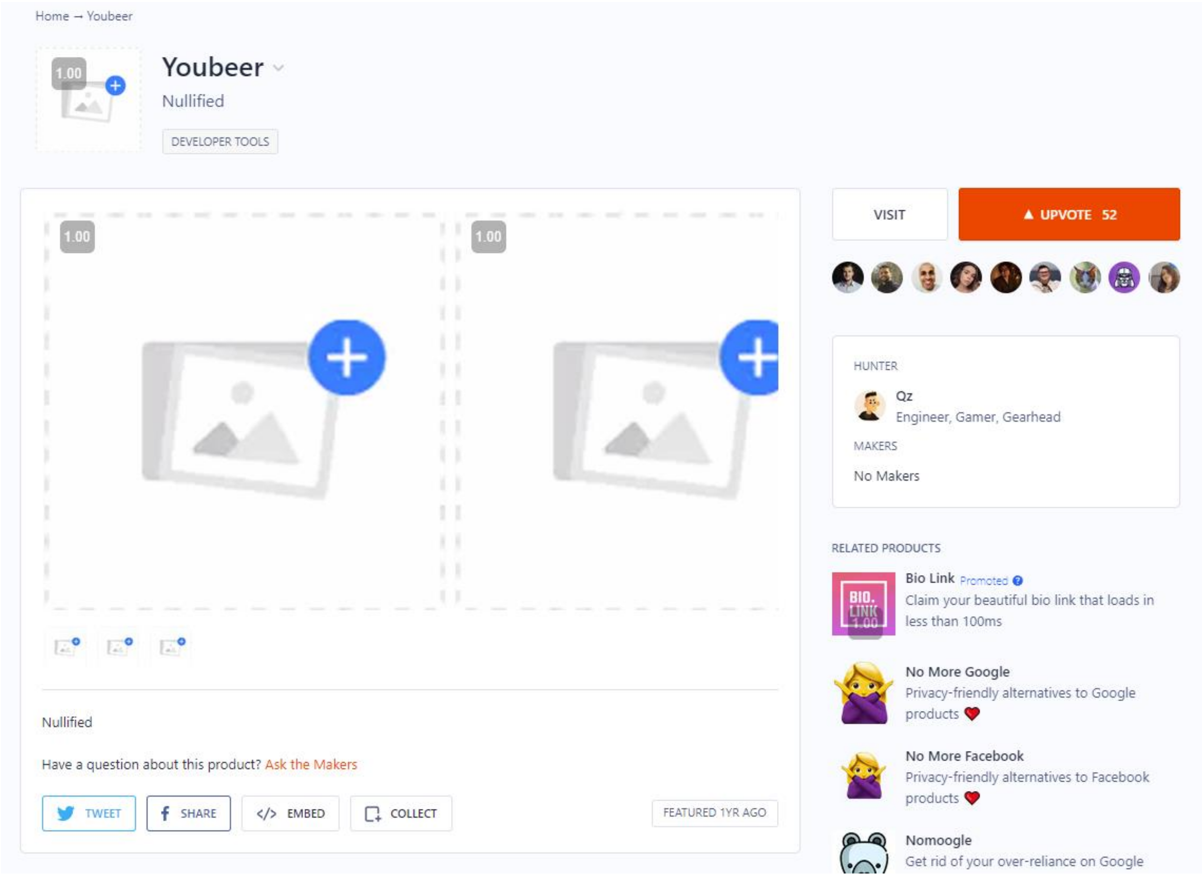
Appendix C

Figure C1: Ideaonce's Campaign.



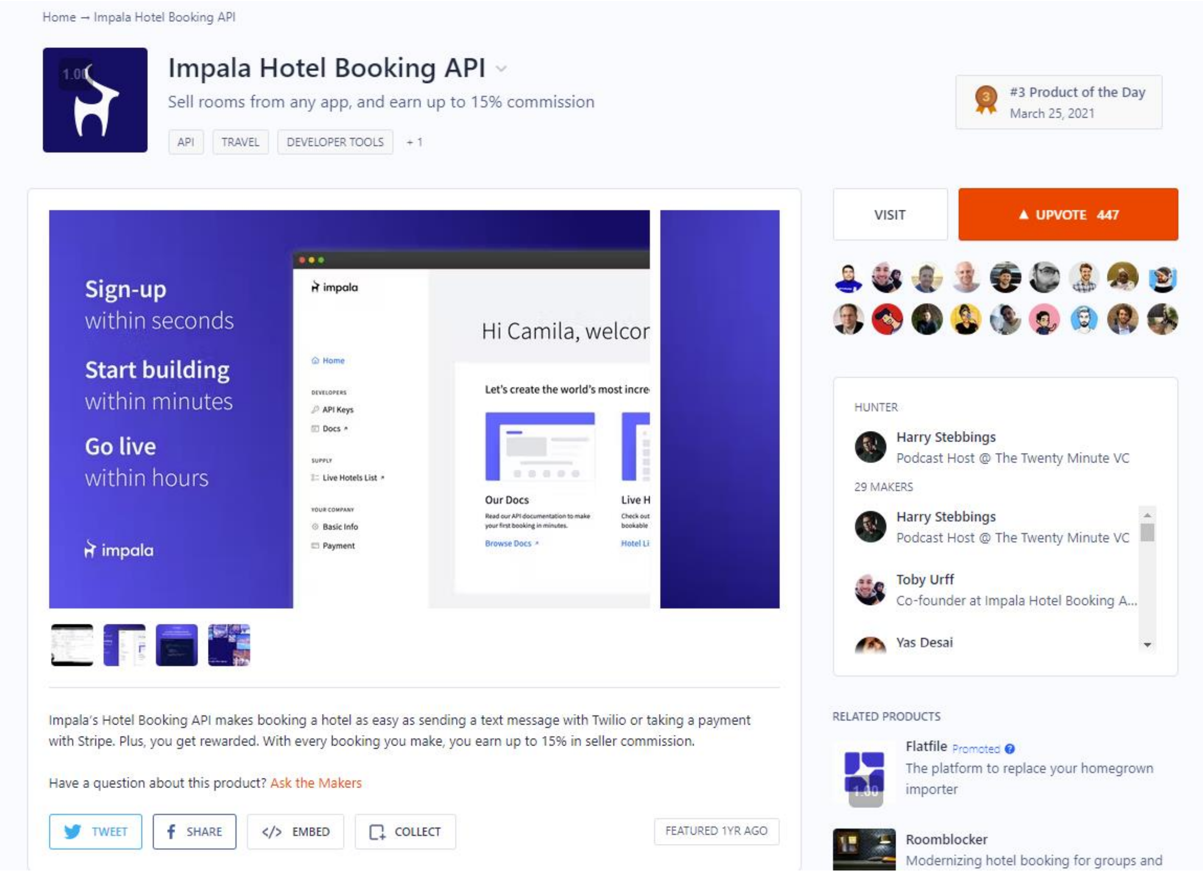
The first example is that of Ideaonce (Figure C1). The returned value for the number of media objects of Ideaonce's campaign was a total of 44, which is very high compared to the rest of the data (mean of 4.79 and median of 4 post-outlier removal, in 4.1 Descriptive Statistics). Upon visually assessing the ventures page it became evident that the data returned from the API was errorful as the page only had three images.

Figure C2: Youbeer's Campaign.



The second example is Youbeer (Figure C2), which returned a mere word count of just two words. This is also very low compared to the mean of 165.56 and median of 138 post-outlier removal (see 4.1 Descriptive Statistics). Having looked at the launch page it was confirmed that the data and campaign as a whole appeared to be faulty.

Figure C3: Impala Hotel Booking API's Campaign.



A final example is that of Impala Hotel Booking API (Figure C3). Here, the hunter had been listed as a maker 329 times, an extremely high value compared to the mean and medians of 5.67 and 3 respectively, post-outlier removal (see 4.1 Descriptive Statistics). Upon investigating this further it became evident that the hunter in this case historically had created new campaigns every time the user had created a new episode for his podcast. Further, having researched Impala Hotel Booking API we could not find any evidence to support the claim that this hunter was in fact also operational as a maker, making the data faulty, perhaps as a result of human error.[3]

[3] Having looked at the team page on the venture's website, LinkedIn and conducted thorough Google searches

Appendix D

Figure D1: QQ-Plot of Residuals for Model 6

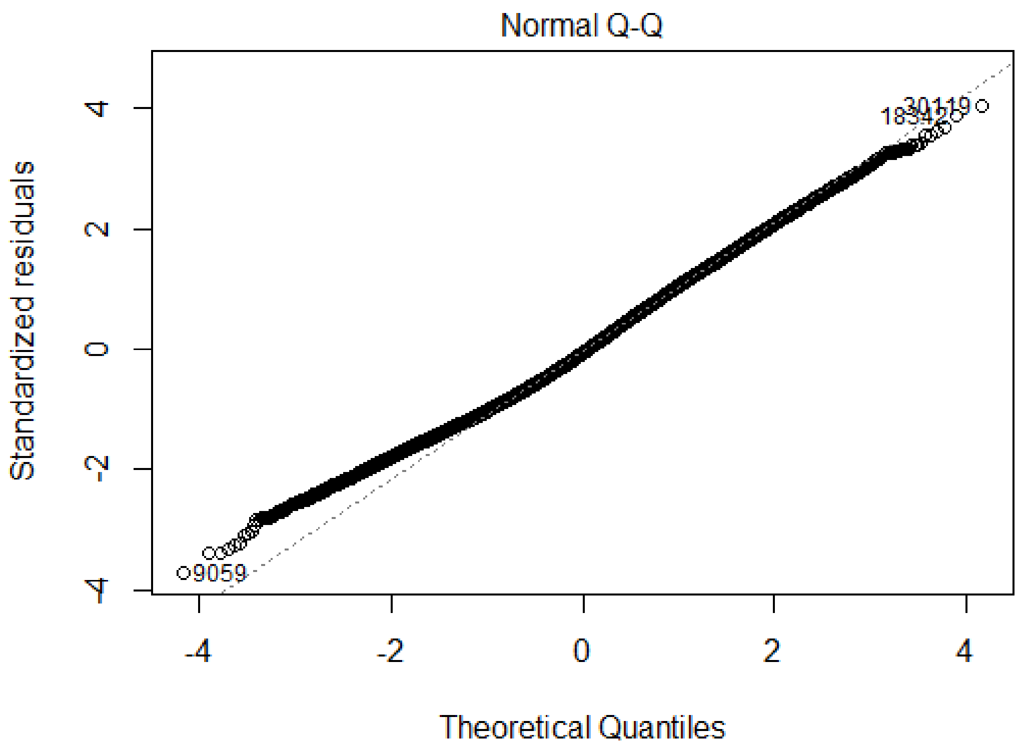


Figure D2: Residuals vs Leverage Plot for Model 6

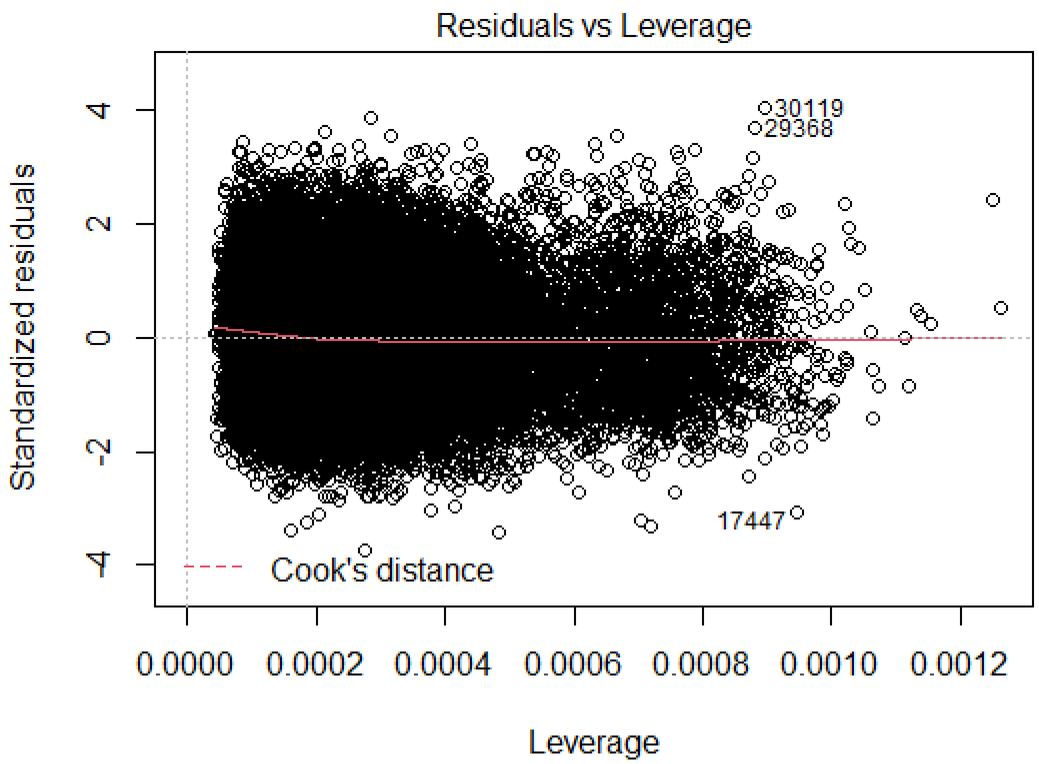


Figure D3: Residuals vs Fitted Plot for Model 6

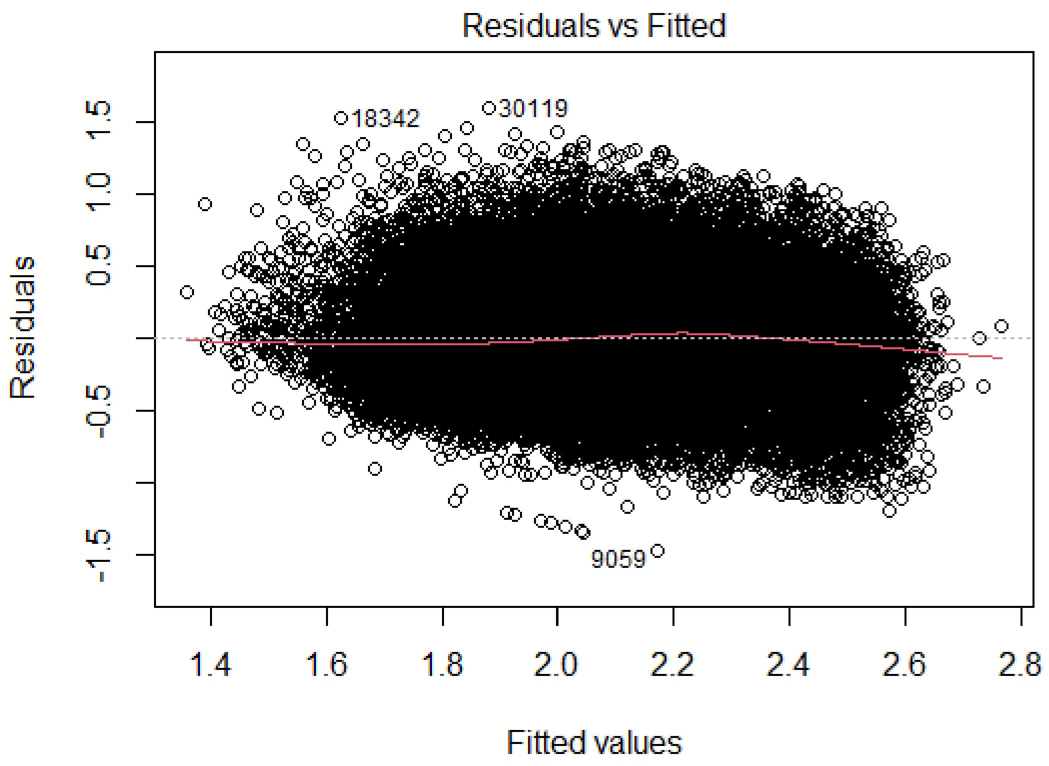
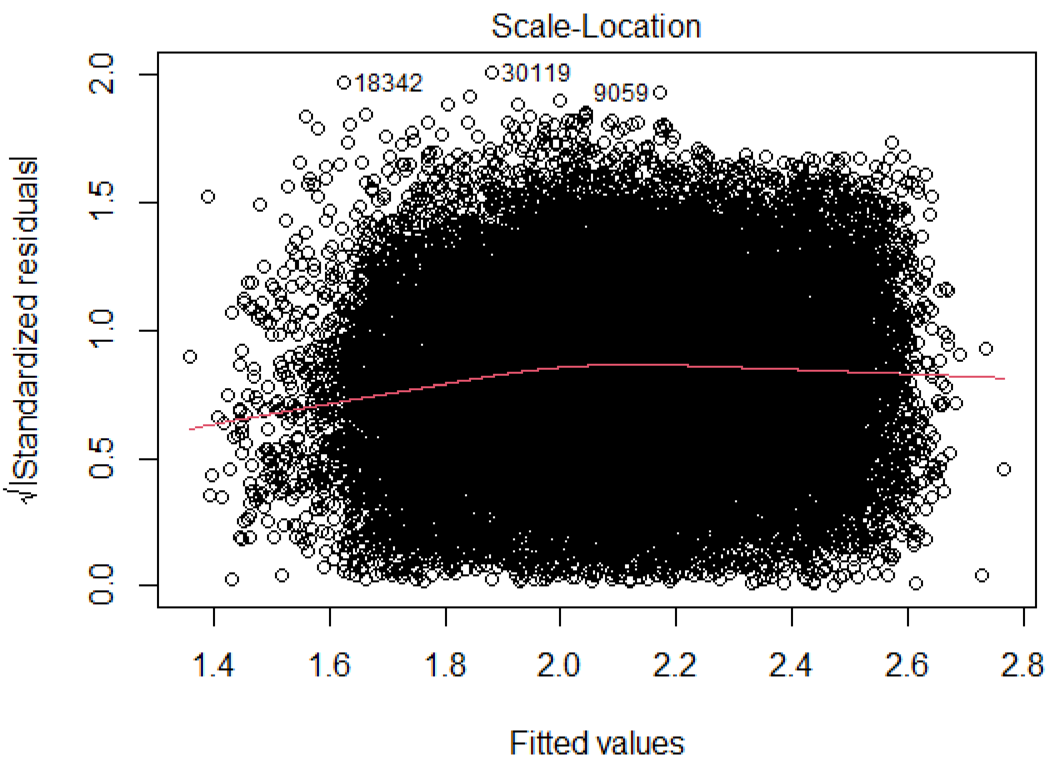


Figure D4: Scale-Location Plot for Model 6



Appendix E

Table E1: D'Agostino-Pearson Test for Normality of Residuals in Model 6.

Model 6	**Statistic**	**Significance**
Residuals	428.827	< 0.05

Appendix F

Table F1: Breusch-Pagan Test for Heteroskedasticity in Model 6.

	Model 6
Statistic	268.867
Degrees of Freedom	8
Significance	< 0.05

Appendix G

Table G1: Breusch-Pagan Test for Heteroskedasticity in Model 6, Excluding Campaigns from Hunters with Seven or Fewer Followers.

	Model 6
Statistic	13.290
Degrees of Freedom	8
Significance	> 0.05

Table G2: Regression Coefficients of Campaign Characteristics on Upvotes Excluding Campaigns from Hunters with Seven or Fewer Followers.

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
	(OLS)	**(OLS)**	**(OLS)**	**(OLS)**	**(OLS)**	**(OLS)**
	Dependent Variable: Upvotes (log)					
Control Variables						
Maker Listed	0.221***	0.149***	0.220***	0.289***	0.218***	0.225***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Hunter Make Count (log)	0.230***	0.229***	0.228***	0.031***	0.227***	0.043***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)
Introductory Comment	-0.025**	-0.194***	-0.032***	-0.015*	-0.032***	-0.157***
	(0.008)	(0.010)	(0.008)	(0.007)	(0.007)	(0.009)
Positive Tone (log)	0.006	0.075***	0.024	0.013	-0.001	0.069***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)
Independent Variables						
H1: Word Count (log)		0.322***				0.259***
		(0.011)				(0.011)
H2: Quantitative Language (log)			0.087***			0.018*
			(0.009)			(0.008)
H3: Hunter Follower Count (log)				0.132***		0.122***
				(0.003)		(0.003)
H4: Media Object Count (log)					0.372***	0.197***
					(0.018)	(0.018)
Constant	1.818***	1.291***	1.768***	1.541***	1.558***	0.992***
	(0.016)	(0.024)	(0.017)	(0.017)	(0.020)	(0.025)
Log-Likelihood	-14,359	-13,960	-14,308	-13,472	-14,137	-13,060
Adjusted R^2	0.059	0.088	0.062	0.123	0.075	0.151
N	25,046	25,046	25,046	25,046	25,046	25,046

Note: Sample excludes campaigns made by hunters with seven or fewer followers. Heteroskedastic-consistent (HC3) standard errors in parenthesis.
OLS = Ordinary Least Squares
*p<0.05; **p<0.01; ***p<0.001

Appendix H

Table H1: Regression Coefficients of Campaign Characteristics on Upvotes Only Including Hunters' Most Recent Campaign.

	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
	(OLS)	**(OLS)**	**(OLS)**	**(OLS)**	**(OLS)**	**(OLS)**
	Dependent Variable: Upvotes (log)					
Control Variables						
Maker Listed	0.048**	0.006	0.048**	0.128***	0.043**	0.095***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Hunter Make Count (log)	0.331***	0.313***	0.330***	-0.081***	0.340***	-0.069***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)
Introductory Comment	-0.059***	-0.226***	-0.063***	-0.064***	-0.064***	-0.173***
	(0.009)	(0.011)	(0.009)	(0.008)	(0.009)	(0.010)
Positive Tone (log)	0.015	0.085***	0.025	0.007	0.012	0.049**
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.016)
Independent Variables						
H1: Word Count (log)		0.332***				0.212***
		(0.013)				(0.012)
H2: Quantitative Language (log)			0.051***			-0.004
			(0.010)			(0.009)
H3: Hunter Follower Count (log)				0.212***		0.203***
				(0.003)		(0.003)
H4: Media Object Count (log)					0.260***	0.159***
					(0.021)	(0.019)
Constant	1.792***	1.228***	1.764***	1.610***	1.611***	1.149***
	(0.020)	(0.030)	(0.021)	(0.019)	(0.025)	(0.029)
Log-Likelihood	-9,024	-8,712	-9,011	-7,346	-8,947	-7,130
Adjusted R^2	0.033	0.069	0.035	0.209	0.042	0.229
N	16,780	16,780	16,780	16,780	16,780	16,780

Note: Sample only includes the most recent campaign made by hunters. Heteroskedastic-consistent (HC3) standard errors in parenthesis.
OLS = Ordinary Least Squares
*p<0.05; **p<0.01; ***p<0.001