ASSESSING TYPES OF SOCIAL MEDIA SIGNALS ON CROWDFUNDING CAMPAIGN SUCCESS: AN ANALYSIS OF DUTCH MUSIC PROJECTS ON INSTAGRAM

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CC4150 Master Thesis
13 June 2025

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ABSTRACT

In the context of increasing austerity for cultural funding across Europe, artists without a solid commercialization strategy (non-commercial artists) increasingly turn to alternative finance methods such as crowdfunding. This research investigates how signals external to crowdfunding platforms, such as social media signals, impact the success of cultural crowdfunding campaigns, particularly in the music industry. With a framework built on signaling theory and media richness theory, this study analyzes data from a Dutch cultural crowdfunding platform and corresponding Instagram activity in order to assess the impact of external signaling on success. Findings confirm that the quantity and richness of campaign signals—especially dynamic formats like video—positively influence both financial and social success metrics. While internal signals remain more predictive overall, this research highlights the importance of external social capital amid shifting cultural policy, as well as the need for further investigation on the effects of external signaling on crowdfunding. The study contributes to literature on cultural financing, and it suggests that artists should strategically consider external social media signaling in their crowdfunding communication.

<u>KEYWORDS</u>: crowdfunding, signaling, social media, media richness, cultural funding

Word count: 15,404

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1. Introduction

In recent decades, the public funding for culture in Europe has undergone important changes; namely, culture has been reframed as an instrument for broader intersectional "creativity" (Littoz-Monet, 2012), and countries like the Netherlands have adopted increasing austerity measures towards the public funding of the cultural and creative industries (CCIs) (Loots et al., 2024). These shifts are notable in their divergence from a previous rationale of culture as having inherent, non-economic value and thus meriting funding from a welfare perspective (Throsby, 2010). Artists and art organizations, therefore, are increasingly being pressured to find alternative, non-public means of funding (Loots et al., 2024). In the music industry, this shift has raised particular challenges for a large swath of industry agents, namely, those whose funding schemes are almost if not entirely dependent on public funding which includes most of the classical and contemporary music sectors (Emerson, 2023; Frey, 2000), as well as those whose artistic production is not yet commercially viable (Abbing, 2022). A potential fundraising solution for these non-commercial artists may lie in crowdfunding (Loots et al., 2024; Dalla Chiesa, 2022). Pursuing crowdfunding campaigns entails potentially high management costs for artists (Dalla Chiesa, 2022) and necessitates effective management of economic inputs (Eikhof & Haunschild, 2006), requiring ambidexterity from artists who, especially those in the non-commercial cohort, are likely to be untrained or ineffective at managing these "humdrum inputs" (Caves, 2002). As such, for many artists, crowdfunding is an alternative funding strategy applied only when necessary (Dalla Chiesa, 2022).

Existing literature has outlined how several factors may positively influence a crowdfunding campaign's likelihood of success (Dalla Chiesa, 2021; Handke & Dalla Chiesa, 2022), among them matchfunding, or the allocation of funds from private or public funding institutions to a crowdfunding project; number of reward incentives offered to micro-donors; and the age of the artist crowdfunding (Baeck et al., 2017; Steigenberger, 2017; Mollick, 2014). Actually managing to capitalize on these factors may be challenging or unclear to artists: the manner in which matchfunding is allocated, for instance, is largely unclear or inconsistent at times (Loots et al., 2024). As such, artists may choose to invest in different actions to attempt to improve their campaigns' chances at success.

Among these avenues is signaling, both within and beyond the crowdfunding platform. Colombo et al. (2015) make the case that both internal social capital, that is, social capital on the crowdfunding platform, and external social capital, or social capital located outside of the crowdfunding platform, are relevant to crowdfunding success. As such, signaling via external channels like social media may be a fruitful avenue to explore for artists. Though existing literature establishes a positive relation between signaling on social media platforms like Instagram and crowdfunding success (Colombo et al., 2015; Hong et al., 2015; Lu et al., 2014; Putra & Kusumasondjaja, 2022), the relevance of this relation to the highly abnormal CCIs, characterized by near-perfect product differentiation and a "symmetric ignorance" concerning information (Throsby, 2010; Caves, 2002), requires further exploration. Additionally, the effects of the types of external signals employed, be it in regards to medium or content, also necessitates greater study.

This research seeks to fill these gaps in the literature by applying a signaling and media richness theoretical framework to the external signaling of cultural crowdfunding campaigns. It poses the question, *to what extent do external social media signals impact the success of a cultural crowdfunding campaign?* Additionally, it poses the sub-question, *which types of social media signals most positively affect the success of a cultural crowdfunding campaign?* The research uses anonymized data of cultural crowdfunding campaigns privately provided upon request by a Dutch cultural crowdfunding platform and supplements it with readily-available and free-to-access data from the relevant campaigns' Instagram pages in order to document and code the signals made by the campaigning artists on the social media platform. The data underwent a quantitative analysis in the form of several multivariable, linear, stepwise regression models, testing the predictive power of variables like the number of signals posted during the campaign period to dependent variables indicating success, namely, the "financial" success indicator of amount raised and the "social" success indicator of number of donations.

The findings from this strategy allow me to confirm that external signaling of a crowdfunding campaign is significant and positively predictive of its success, both in the financial dimension regarding amount raised and the social dimension regarding number of donations. This confirms the phenomenon previously observed outside the context of the core creative industries (Throsby, 2010; Colombo et al., 2015; Putra & Kusumasondjaja, 2022). Moreover, the study demonstrates that the number of campaign signals is also significant and positively associated with both aspects of success. The study additionally finds that dynamic campaign signals like videos on social media positively predict the number of donations to a crowdfunding project, with the additional finding that more dynamic campaign signals is associated with greater number of donations. In doing so, it demonstrates the validity and applicability of media richness theory to the context of signaling cultural products (Grewal et al., 2021), establishing that the consideration of the richness of media of choice is pertinent to artists that are crowdfunding.

This research, additionally, found little significance in the effects of rhetorical campaign signaling on crowdfunding success, suggesting that the role of rhetorical signals in high-noise environments posited by Steigenberger and Wilhelm (2018) needs further evaluation and study. Finally, it confirms Colombo et al.'s (2015) proposition that internal signals and factors are more relevant to crowdfunding success than external signals and factors; however, it identifies how this relevance might shift given current cultural policy trends, in which greater austerity in public cultural funding might entail the need to reevaluate the long-term effectiveness and viability of crowdfunding strategies like matchfunding. In this way, this research contributes directly to the literature on alternative finance, specifically with regards to crowdfunding in music and the cultural and creative industries.

2. Context

This research is focused on evaluating how a crowdfunding project's social media signals impact its success; this question will thus be approached through the frame of signaling theory applied to cultural crowdfunding, specifically the crowdfunding of music. An additional aspect of media richness theory will supplement the framework. Before establishing the framework of signaling theory for this research, however, it is important to explain the context of the research itself, due unique qualities of the CCIs (Caves, 2002), the diverse motives and circumstances of cultural producers (Abbing, 2022), and the intricacies of crowdfunding markets (Loots et al., 2024). This chapter will focus on exploring the context of the music industry, as well as the role crowdfunding plays in it. This context will then serve as a base for the theoretical framework, to be presented in the following chapter. First, the stakeholders in the music industry will be grouped into cohorts; following this, changes in the valuation and commodification of music will be explored; finally, the history and significance of crowdfunding in the music industry will be analyzed.

2.1. Stakeholder cohorts in the music industry: focusing on the niches and independents

As the CCIs are not only differentiated externally (regarding other industries) but also internally according to discipline and medium (Bürger & Kleinert, 2020), it is useful to begin by elaborating on these distinctions. In their "concentric circles model," Throsby (2010) groups cultural goods in accordance with the amount of cultural content per their economic value, with the core industries exhibiting the highest ratio of cultural content to economic value and with outer layers exhibiting the lowest. The music industry is included amongst the core industries (Throsby, 2010); as such, it involves an immense number of stakeholders, each with heterogeneous activities, products, and motivations. Hans Abbing's "spheres" model is useful in grouping these diverse interests into operational categories (2022). Abbing describes cultural producers existing in four distinct spheres: the consumer-oriented sphere, the bohemian sphere, the research sphere, and the hybrid practices sphere. The consumer-oriented sphere includes producers who produce art for a sizeable, broad consumer base; as such, this sphere is perhaps the most market-focused out of all of them, as the production of cultural goods with a sizeable expected demand means that agents' business models are less dependent on structural funds (Abbing, 2022).

The non-market aspect of the cultural production of research-, Bohemian-, and hybrid practices-sphere artists necessitates that their artistic production is not economically viable, necessitating either public subsidies, hobbyism, or freelance work in non-art activities (Abbing, 2022). As such, it is possible to group stakeholders in these three spheres into a non-commercial cohort of the music industry, distinct from the market-oriented commercial-sphere stakeholders. Though each sphere in the non-commercial cohort entails different circumstances, several commonalities are likely to exist between their stakeholders. A lack of training on and experience with balancing economic and artistic logics, for instance, can be expected (Eikhof & Haunschild, 2006). Additionally, it can be inferred that artists in the non-commercial cohort do not benefit from superstar effects but are rather part of the long tail, as their inability to commercialize could stem from a lack of demand, be it due to inferior talent (Rosen, 1981) or relative lack of attention paid by audiences (MacDonald, 1988). Finally, their lack of market revenue entails potential iron cage effects as they are forced to interact with bureaucracies responsible for fund allocations or with "charismatic" agents incapable or unwilling to provide equitable remuneration, instead appealing to intrinsic motivation (Mangset et al., 2012). When considering renewed austerity measures regarding cultural funding (Loots et al., 2024) and the institutional and social reframing of cultural products as tools for economic growth rather than valued in their own right (Littoz-Monet, 2012), it becomes clear that agents in this cohort are gaining strong extrinsic motivators enter the market, but their lack of an established demand for their cultural output entails challenges to market entry, as the "nobody knows" nature of assessing the quality of cultural goods reinforces trial-and-error strategy (Caves, 2002).

2.2. The value of music

Music, as with many other artistic disciplines, primarily deals with experience goods, that is, goods whose quality can only be appraised post-consumption (Caves, 2002). A musical work in itself is not physical but ephemeral, suggesting that it exhibits public-good characteristics in its simplest form (Caves, 2002), as someone in the midst of music cannot be excluded from it, nor is the music finite such that it becomes scarcer with more listeners. As such, musical works cannot be bought or sold in and of themselves. It is first necessary, thus, that a musical work undergo a commodification regime, through which it becomes excludable and/or rival. Taylor (2016) outlines three essential commodification regimes for music: music as a live performance, in which access to the musical work is commodified in the form of ticket sales; music as a written score, in which a musical work is commodified in the form of a notation that consumers can use to reproduce the musical work themselves; and music as a recording, in which a performance of a musical work is commodified as a reproducible audio recording.

The emergence of streaming platforms in the 21st century, however, have challenged the effectiveness of these existing commodification regimes (Fleischer, 2017): as streaming platforms offer consumers access to a virtually infinite catalog of music in exchange for a monthly subscription or for free with attention payments to advertisements (Gaenssle & Budzinski, 2020a), they represent a fourth commodification regime for music, one that specifically reduces the consumer value of owning music to virtually zero (Fleischer, 2017). Only the live performance commodification regime retains its commercial viability (Bonini & Magaudda, 2024), due to the fact that the experience value of a live performance cannot be easily substituted by a recording (Vandenberg & Berghman, 2023). For artists, however, there remains a value in recording and publishing music for artists because they are forms of normative isomorphism (DiMaggio & Powell, 1983): an artist who has recorded and published albums, music videos, or scores is communicating a legitimacy to consumers that unpublished artists cannot. Additionally, a merit-good understanding of musical products, in which a non-use valuation of music could be made based on its bequest, option, or existence value, independent of its market value (Throsby, 2010). Consumers who value music in these ways may be incentivized to purchase ownable music from their preferred artists despite not deriving utility from owning said music; rather, their purchase is altruistic, effectively serving as a donation to said artist (Steigenberger, 2017).

The necessity for conducting said interaction as a purchase in the market can be attributed from social stigmas around donation-seeking behaviors for artists (Dalla Chiesa, 2022), itself perhaps a form of coercive isomorphism such that it is socially unacceptable for "serious" artists to ask for charity (DiMaggio & Powell, 1983). Limiting donations to market transactions, however, is inefficient and increases transaction costs. The necessity of exchanging a useable product in exchange for money entails potentially conflicting market and donation logics, such that price-sensitive consumers, for instance, may be deterred altogether from "donating" should they see the monetary value as significantly exceeding the useable value of the product (Kirmani & Rao, 2000). Artists, furthermore, are limited by price expectations in how much they can charge for their products, and Baumol's cost disease suggests that wage costs would increase faster than product prices would (Baumol & Bowen, 1965); with the effectively zero marginal utility of owning multiple copies of one musical work, it becomes difficult to justify repeated transactions per fan, which entails that more donors must continually be recruited to fund the same cultural output.

2.3. Crowdfunding

Crowdfunding, or the funding of a project through accumulation of donations from micro-donors, may alleviate the fundraising challenges faced by artists by creating a permission structure, that is, a justification that helps enable otherwise normatively unacceptable actions, for artists to request and receive donations to fund their projects (Handke & Dalla Chiesa, 2022). Along with this, the pay-what-you-will aspect of crowdfunding platforms entails that artists can benefit from price discrimination (Bernard, 2017). Bernard (2017) suggests, however, that, whilst the initial decision to donate to a crowdfunding project tends to follow a non-market donation logic, the decision of how much to donate more closely follows market logics. As such, it is important for artists to create incentives for higher donation amounts; this can easily be done in the form of rewards for donation amount tiers. Nevertheless, the framing of crowdfunding around donative rather than market transactions allows for prices to exceed the value of the attached reward greatly (Steigenberger, 2017); a price-sensitive consumer might have qualms over purchasing a €50 t-shirt of their favorite niche artist, but framing the transaction as a donation towards the artist's project with a t-shirt as a reward separates the value of the t-shirt from the money donated. In tandem to this is the low-risk nature of donating, as crowdfunding transactions are contingent on projects amassing a critical mass of funds in a designated period; should the project fail to amass the necessary funds, donations are returned to micro-donors (Loots et al., 2024). Therefore, the donation-based nature of its approach allows for artists to secure funds *a priori* to a finished product, mitigating their potential sunk costs on high-cost projects like studio recordings and music videos.

The benefits of crowdfunding go beyond the market: the nature of crowdfunding platforms as multi-sided markets speaks to their role in facilitating contact between artists and micro-donors (Gaenssle & Budzinski, 2020a). This allows artists to experiment with the nature of their cultural products and, should they offer reward tiers correlating to amounts donated by micro-donors, the artists additionally have the opportunity to gauge interest and the viability of their product; this contact makes crowdfunding useful for non-commercial artists' legitimization and professionalization (Dalla Chiesa, 2021). These interactions between artists and micro-donors can be understood largely through the framing of signaling theory and will thus be discussed further in the following chapter.

3. Theoretical Framework & Hypothesis Development

In the previous chapter, Abbing's "spheres" framework was used to delineate two clear cohorts of stakeholders in the music industry (2022): a commercial cohort composed of artists with an established demand for their output, such that they can viably operate in the market without need for substantial non-market revenues, and a non-commercial cohort composed of artists lacking an established or viable demand for their cultural output and thus necessitating non-market revenues to ensure cultural production. The extrinsic social and institutional push for artists to move away from public funding and commercialize their product was discussed, and crowdfunding and matchfunding were presented as valuable strategies in this transition. In order to understand why this is, a theoretical framework must be established, one exploring the strategies and nuances in signaling and screening the quality of these aforementioned musical products. This chapter will analyze each of these theoretical aspects in turn.

3.1. Signaling theory

Having established the different valuations of goods in the music industry, it is now worthwhile to explore the role that signals play in the music industry and, more specifically, in the crowdfunding of musical projects. First, a general overview of signaling theory will be provided. Following this, the signaling and screening dynamics in musical crowdfunding will each be explored in turn. Finally, relevant typologies for the study will be presented.

3.1.1. Information in the music industry

As elaborated in the first chapter, the experience-good nature of music entails a lack of complete information on products for consumers; Caves (2002) elaborates on this characteristic of experience goods by also pointing to the subjective appraisal of art, which signifies that stakeholders on the value chain also lack information on the quality of what they produce. This lack of information is described by Caves as the "nobody knows" principle, though it can be ventured that, as artists are more of aware of the inputs and content of their cultural output before an audience experiences it, there is an imbalance of information favoring artists. What Caves seeks to convey, however, is that despite this disparity in information between producer and consumer, producers are still largely unable to predict reliably the reception to their products, entailing that information asymmetry problems are unlikely to arise (Akerlof, 1970).

In addition to the challenges in obtaining information on cultural goods, it is worthwhile to reflect on how cultural goods and, by extension, musical goods undergo socially-interdependent demand formation. The nebulous information around cultural goods entails a degree of risk for suppliers, as it is difficult to predict the success of a cultural good before it is experienced; in this context, *known quantities,* that is, cultural producers that have released previously successful works, have an advantage over *unknown quantities,* as previous successes offer a comparatively reliable indicator of future successes for agents on the supply chain (Frank & Cook, 1996). On the demand side, low information leads to a form of *bandwagon effect*, one that stems, as Kretschmer, Klimis, and Choi describe, from a sociological desire to engage in experiences in groups (1999). This bandwagon effect can explain part of the observed crowding-in effects in cultural crowdfunding (Zúñiga-Vicente et al., 2014) alongside impure altruism, or the non-use value of voluntary donation from individuals (Andreoni, 1990), in that campaigns with significant amounts of donors may not only signal to potential micro-donors that it is worth investing in, but also that there is an existing social group of donors they may join, with the promise of future cultural experience to consume collectively. As such, network effects are vital to the success of cultural goods, in which crowdfunding campaigns are included.

Given the general lack of *a priori* information around cultural products and the importance of network effects in the market success of cultural goods, it is clear that information sharing around musical products lowers transaction costs, with signaling and screening encompassing the primary strategies for information sharing between producers and consumers (Spence, 1981; Stiglitz, 1989). In essence, signaling can be understood as information sharing from producer to consumer in a market, with screening referring to a reverse directionality. Signals and screening, therefore, both encompass a wide breadth of possible indices, with everything from the brand of an artist to the advertisements they publish communicate information on their cultural products. The following subsections will discuss each in more detail.

3.1.2. Social media and music

As this research specifically focuses on signals and screens in social media, it is important to elaborate why these channels are specifically relevant to the music industry and in musical crowdfunding projects. Similar to the disruption of streaming services on the commodification of music, social media platforms – that is, internet-based free-to-use media platforms that primarily host third-party content for their consumers or "users," content often generated by users themselves – disrupted traditional media platforms by exploiting internet technologies to offer unprecedented amounts of on-demand content to a massive pool of consumers (Gaenssle & Budzinski, 2020a). The consequence of this for content producers is that social media platforms drastically lower the transaction costs of publishing content, and their critical mass of content consumers entails that this content is available in theory to an immense consumer pool (Gaenssle & Budzinski, 2020a).

Because of the focus on the non-commercial cohort of artists and other stakeholders in the music industry, it is logical to focus on social media platform signaling specifically because of its near-zero upfront costs for content publishing, meaning that these platforms are an especially useful channel for artists with limited funding options. Additionally, the Web 2.0 design of social media platforms allows for artists to have direct feedback from users on or about the content they publish (Web 2.0 Conference, 2004), allowing for low-cost screening on the part of consumers, as well as fostering more direct communication between producers and consumers (Gaenssle & Budzinski, 2020a; Dalla Chiesa, 2021).

It bears discussing why the consideration of crowdfunding project signaling on social media platforms beyond the crowdfunding platform itself in this study. As with other platforms, crowdfunding platforms can be understood as multi-sided markets, acting as mediators between distinct yet interdependent demand groups in situations where direct contact between groups would be prohibitive (Gaenssle & Budzinski, 2020a; Handke & Dalla Chiesa, 2022). The role of platforms as facilitators, as well as the scope of their userbases, initially appears to suggest that gatekeeping effects are diminished and that the search costs specifically are lowered for consumers to find projects and products relevant to them (Anderson, 2006; Bannerman, 2020). Empirical research, however, demonstrates that this not the case (Gaenssle & Budzinski, 2020b; Duffy et al., 2019); rather, the sheer amount of content available begins to raise search costs for users, necessitating platform employment of algorithmic search and recommendation services (SRS) to connect consumers to relevant products, leading to similar gatekeeping effects but with the platform as gatekeeper instead of traditional gatekeepers (Gaenssle & Budzinski, 2020a; Evans & Schmalensee, 2013).

Smaller, local cultural crowdfunding platforms have emerged (Loots et al., 2024), whose smaller scope mitigates the issue of search costs from content saturation whilst also posing limits to platform utility for creators, given their smaller user pool. As such, artists have incentive to utilize social media platforms with a bigger userbase, in which they already may have a presence and following, to send signals for crowdfunding projects, thus mobilizing their followers to the crowdfunding platforms. It is for this reason that this study will examine social media signals and their impact on crowdfunding projects.

3.1.3. A broad classification of signals

In order to discuss the scope and methodology of this research, it is necessary to elaborate first on signal types. Kirmani and Rao (2000) set forth a useful categorization of signals concerning unobservable product quality (Table 1), especially relevant to culture sectors and music, by extension, given the infinite heterogeneity and subjective quality of its goods (Caves, 2002). Differentiating between default-independent signals, that is, signals whose costs are incurred regardless of whether the firm defaults on claims, from default-contingent signals, in which costs are incurred only when default occurs, it is possible to separate the vast array of signals into analytical categories (Kirmani & Rao, 2000). In this framing, therefore, a crowdfunding campaign itself would be classified as a default-contingent cost-risking signal because of the requirement that a campaign meet its goal in order to receive its funds. The product, the campaign's description of the product, and the allocation of matching funds to the campaign, the latter of which has been observed to correlate positively with campaign success (Baeck et al., 2017; Fang et al., 2021), in contrast, all could be classified as default-contingent revenue-risking signals: should the quality of the final project be deemed significantly inferior by micro-donors to their amount donated, they may be reticent in donating to future projects or even purchasing products of the creator(s) in question (Kirmani & Rao, 2000).

Table 1

Kirmani & Rao's signal typology according to default and sale independence (2000).

Characteristics of Signals

	Default-Independent Signals		Default-Contingent Signals	
	Sale-Independent	**Sale-Contingent**	**Revenue-Risking**	**Cost-Risking**
Examples	Advertising Brand name Retailer investment in reputation	Low introductory price Coupons Slotting allowances	High price Brand vulnerability	Warranties Money-back guarantees
Characteristic	Publicly visible expenditures before sale	Private expenditures during sales transaction	Future revenues at risk	Future costs at risk
Repeat purchase	Is important	Is important	Is important	Irrelevant
Monetary loss	Fixed	Variable or semi-variable	In the future	In the future
Secondary benefits	Buyer does not receive direct utility	Buyer receives direct utility	Buyer does not receive direct utility	Buyer receives direct utility
Appropriate when	Buyer cannot be identified easily	Buyer can be identified easily	Frequently purchased nondurables	Durables
Potential for abuse by consumer	None	High	None	High

Because crowdfunding projects themselves are default-contingent revenue-risking signals, and because the *a priori* nature of crowdfunding, along with cultural products' perfect heterogeneity, makes tracking future revenue loss especially difficult, this research will primarily track default-independent signals, as these can be used as a sort of meta-signal for the crowdfunding project itself and can thus impact their success (Harris et al., 2021; Nian & Sundararajan, 2022). Within this category, the most predominant sale-contingent signals in crowdfunding are tier-specific rewards, which can be classified as either *use rewards,* that is, rewards that are goods with intrinsic use value, or *non-use rewards,* that is, rewards that are goods without intrinsic use value (Snowball, 2008). Examples of use rewards include branded apparel, posters, or exclusive content such as recordings or other such content that is or will not be published; non-use rewards can include recordings of music already widely published or personal messages from the artists, among others. Given this research's focus on social media, this avenue of signals will not be explored thoroughly.

3.2. Signals on social media and media richness theory

The most common sale-independent signal in crowdfunding projects is social media content (SMC). Though crowdfunding sites are platforms in themselves, there is significant literature establishing a positive correlation between signaling a project on external social media platforms and project success (Colombo et al., 2015; Hong et al., 2015; Lu et al., 2014; Putra & Kusumasondjaja, 2022). Additionally, the impact of signals on specific platforms varies according to good types, with private-good crowdfunding projects favoring Twitter over Facebook due to its facilitation of more objective information gathering and with public-good projects favoring Facebook due to its facilitation of interpersonal connections (Hong et al., 2015). As music exhibits both public- and private-good characteristics (Throsby, 2010), and as it is primarily an experience good (Caves, 2002), Instagram was selected as the external platform of study because of its facilitation of interpersonal connection akin to Facebook and its focus on visual and audiovisual content, which can be useful for providing quality signals of experience goods. In this frame of signaling theory, the following hypotheses emerge:

> ***H1a. Crowdfunding artists that have a presence on social media are more likely to be successful than artists that do not signal on social media.***
> ***H1b. Crowdfunding artists that have a greater presence on social media are more likely to be successful than artists with a lesser presence.***
> ***H2a. Cultural crowdfunding campaigns that have a presence on social media are more likely to be successful than campaigns that do not signal on social media.***
> ***H2b. Cultural crowdfunding campaigns that have a greater presence on social media are more likely to be successful than campaigns with a lesser presence.***

In the context of these hypotheses, "success" is defined along two dimensions. First is the apparent dimension of success in crowdfunding, or "financial success." Secondly, however, is also the dimension of "social success," rooted in the focus of crowdfunding on micro-donations; in this context, crowdfunding provides artists the opportunity to experiment with their artistic product and how it can be commercialized, receiving economic and interest signals from micro-donors (Handke & Dalla Chiesa, 2022; Dalla Chiesa, 2021). As such, a relevant success metric for artist can also be the number of donations they receive, each representing a positive response from current or prospective audience-members on their cultural product. Additionally, the decision to frame Hypothesis 1 around artists with crowdfunding campaigns rather than the campaigns themselves is due to the fact that artists could provide audiences signals for investing in a campaign by promoting themselves generally, without need to mention the campaign specifically (Kirmani & Rao, 2000).

Given the diversity of content medium, that is, medium in the sense of images, text, or videos, as well as in the information contained within the content, which could involve glimpses of the project, interviews, and production stories, among others, a typology for SMC signals is necessary, as both of these dimensions may influence a signal's effectiveness (Steigenberger & Wilhelm, 2018; Eisenbeiss et al., 2022). In regard to the latter, the rhetorical-substantive distinction made by Steigenberger and Wilhelm (2018) provides a useful framework for delineating the information conveyed by SMC; here, *rhetorical* information refers to relevant language-based information "that is equally costly for low-quality and high-quality senders" (p. 529), whilst *substantive* information refers to that which is "more costly for low-quality senders than high-quality senders" (p. 529). More simply, rhetorical signals could be understood as communicating factual information about a crowdfunding project such as project specifications, scope, and release or performance date, whereas substantive signals involve information demonstrating the quality of the project such as rehearsal footage, trailers, or "sneak peeks" of recordings.

In order to sort SMC signals into analyzable categories, the typology featured in Table 2 has been adopted. One axis corresponds to SMC signal medium, separated into text, image, audio with static image, and video (Table 2). The relevance of this axis corresponds to the framing provided by media richness theory, which will be discussed further in the following paragraphs. The other axis corresponds to SMC signal information, separated into rhetorical and substantive categories (Table 2).

In the context of Instagram specifically, this typology can be further simplified. Because the platform does not allow for posting text without an image or video file to accompany it, a signal cannot be solely text-based. Likewise, it is also impossible to post audio on Instagram without an image or a video file. As such, a simpler dichotomy of medium arises, between *static* signals, or posts involving a static image, and *dynamic* signals, characterized by their having a non-zero duration in the form of static image with audio or full video. This simplified typology is represented below (Table 3).

Table 2

Typology of SMC signals. Enriched from theory of Steigenberger & Wilhelm (2018) and Grewal et al. (2021).

SIGNAL MEDIUM: The medium of a signal.	SIGNAL CONTENT: The nature of the content of a signal.	
	1. Rhetorical	**2. Substantive**
a. Text-based	The signal involves primarily written information about the project.	The signal primarily involves an external link to a substantive signal of the project, like a video or image.
b. Static Image	The signal is an image containing information on the project (e.g. a concert tour poster containing only dates and branding images).	The signal is a static image of content from the project.
c. Audio with static image	The signal is an audio recording containing information on the project, accompanied with an image (e.g. an artist interview about the project)	The signal is an audio recording of content from the project, accompanied by an image (e.g. a sneak peek of a single or a new song)
d. Video	The signal is a video primarily containing information about the project (e.g. a call-to-action post, a video interview of artists involved)	The signal is a video primarily composed of content from the project.

Table 3

Simplified typology of SMC signals for Instagram.

SIGNAL MEDIUM: The medium of a signal.	SIGNAL CONTENT: The nature of the content of a signal.	
	1. Rhetorical	**2. Substantive**
a. Static	The signal is an image containing information on the project (e.g. a concert tour poster containing dates and branding images).	The signal is a static image of content from the project.
b. Dynamic	The signal is a video or a static image with audio primarily containing information about the project (e.g. a call-to-action post, a video interview of artists involved)	The signal is a video or a static image with audio primarily composed of content from the project.

3.2.1. Media richness theory

As Nelson (1974) argues, experience goods differ from search goods in that their quality valuation by consumers cannot be determined fully before consumption, and signals such as advertising can help alleviate this information asymmetry (Akerlof, 1970). Here, the arguments presented by media richness theory are relevant, as it refers to the ability of a media source to transmit cues to consumers (Grewal et al., 2021). In this theoretical frame, *richer media,* which includes face-to-face communication, audio, and video media (Grewal et al., 2021), allows for the transmission of more information to consumers as well as more immediate information to consumers than *leaner media* (Keating & Latane, 1976)*,* which includes text-based forms (Kahai & Cooper, 2003) and, in modern digital contexts, static images (Grewal et al., 2021). Thus, dynamic signals, which transmit audio as well as video images, have potential to transmit greater information to audiences and thus have greater potential to alleviate asymmetries than the leaner static signals, which are limited to transmitting a singular image (Akerlof, 1970; Spence, 1981).

Furthermore, it is meaningful to consider the relevance of media richness to musical products specifically: because music is an aural product, that is, a product that is consumed as a listening experience, dynamic signals allow artists to transmit musical content itself, effectively revealing a part of the experience good itself to audiences, alleviating asymmetries and potentially reducing risk (Akerlof, 1970). This is not possible with static signals. Given these factors, the following hypothesis emerges:

H3a. Cultural crowdfunding campaigns that employ dynamic SMC signals on social media are more likely to have more donations than campaigns that do not.
H3b. Cultural crowdfunding campaigns that employ more dynamic SMC signals on social media are more likely to have more donations than campaigns that employ less.

3.2.2. Signal content in crowdfunding

Having explored the theoretical expectations regarding the dimension of signal medium, it is now worthwhile to elaborate on the significance of signal content. Traditional signaling theory emphasizes the role of substantive signals in analysis over rhetorical signals specifically because substantive signals are more costly for low-quality producers than high-quality producers (Connelly et al., 2011; Steigenberger & Wilhelm, 2018), thus aiding consumers in determining good quality as low-quality producers are disincentivized from providing substantive signals altogether (Kirmani & Rao, 2000; Akerlof, 1970). This cost disparity, however, presumes that producers have the ability to assess the quality of their product accurately; the near-perfect heterogeneity of cultural goods and the symmetric ignorance of cultural markets (Caves, 2002) entail that this disparity cannot be assumed to exist for cultural goods. In cultural markets, therefore, rhetorical signals may play a more prominent role, especially given the importance of rhetoric as a tool for conveying information in interpersonal interactions (Steigenberger & Wilhelm, 2018; Suddaby & Greenwood, 2005) as well as for organizational legitimization (Harmon et al., 2015).

It is also important to consider the context of SMC signals of crowdfunding campaigns. Unlike signals on the crowdfunding platform itself, SMC signals are published on an external social media platform. As such, rather than leveraging the *internal social capital* of artists and micro-donors already on the platform and thus familiar with its functionality, SMC signals are transmitted and targeted to the audience of the artist beyond the crowdfunding platform and thus leverages their *external social capital* (Colombo et al., 2015). Because this external audience cannot be expected to be familiar with the dynamics of the crowdfunding platform or even with an initial awareness of the crowdfunding campaign itself, it experiences higher transaction costs than the internal audience already familiar and active in the mediated crowdfunding platform market (Gaenssle & Budzinski, 2020a). As such, SMC signals not only provide information on product quality but also information to alleviate these higher transaction costs (Akerlof, 1970; Spence, 1981). As the cost of alleviating transaction costs for external audiences is not dependent on product quality and is thus equally costly for both high- and low-quality campaigns, rhetorical SMC signals can be expected to be important to a campaign's success (Steigenberger & Wilhelm, 2018).

An additional consideration to be made regarding the content of SMC signals is how they are perceived and assessed by consumers. Whereas traditional signaling theory focuses primarily on isolated signals (Bergh et al., 2014; Steigenberger & Wilhelm, 2018), research on signal perception in high-noise environments such as crowdfunding markets (Ahlers et al., 2015), that is, environments in which consumers are presented with a significant amount of often simultaneous signals (Steigenberger & Wilhelm, 2018), suggests that consumers perceive and interpret signals holistically (Evans, 2008; Steigenberger & Wilhelm, 2018). In this context, existing literature suggests that inclusion of rhetorical signals in these "signal portfolios" play an important role in complementing substantive signals (Steigenberger & Wilhelm, 2018), as they may strengthen or weaken their effectiveness. Therefore, I hypothesize the following:

> ***H4. Cultural crowdfunding campaigns that employ rhetorical SMC signals are more likely to have more donations than campaigns that do not.***

4. Methods and Data Collection

4.1. Research Context

There is extensive literature discussing the recent emergence of crowdfunding platforms in Europe (Loots et al., 2024; Rykkja & Bonet, 2023; Shneor et al., 2023). The decision to focus the scope of this research of the Netherlands, therefore, is relevant to discuss. The Netherlands market is first in Crowdfunding Market Readiness (Shneor et al., 2023); this, along with the country's moving away from public cultural funding to alternative schemes in recent years (Loots et al., 2024), are the primary reasons for its selection as the scope of the study. For the research, the Dutch cultural crowdfunding platform Voordekunst was selected. It is the largest cultural crowdfunding platform in the country, and its partnerships with private and public funding bodies, along with its services providing advice and guidance to artists with campaigns, make it specifically interesting for study, as its intermediary role with matchfunding bodies and educational services suggest it may be particularly useful for the non-commercial cohort of artists discussed earlier. As Voordekunst is an all-or-nothing model crowdfunding platform, payouts of campaign sums are contingent on the campaign reaching at least an 80% threshold of fundraising; failing this, funds are returned to micro-donors. Additionally, successful projects may increase their target amount with a stretch goal.

Instagram was selected as the external social media platform of study. Colombo et al. (2015) emphasize the importance of early donations to the success of a crowdfunding project, entailing that artists that can effectively mobilize their existing following to donate to the project may generate crowding-in effects; in this regard, signaling a campaign on external social media is important for leveraging artists' existing external social capital to donate and subsequently generating internal social capital within the crowdfunding platform (Hong et al., 2015). Instagram was specifically selected because of its posting format, necessitating either an image or a video, meaning that it is well-suited for experience-good signaling.

4.2. Data Collection

This study builds on an existing database of all projects on a reward-based platform from 2021 to 2023, directly provided by the platform upon request. This database includes information for all crowdfunding campaigns on the platform from that period, including their cultural industry, the amount raised, the proportion of funds stemming from matchfunding, the number of matchfunding bodies per project (if any), the word count of campaign pages, the number of rewards offered, the number of donations and donors, and the number of updates by campaigners, among other data from the campaigns. Over 2000 campaigns are included in the full dataset, though only the campaigns pertaining to music were studied (n=595), which together make up the "large sample" (Table 4).

Using information readily and publicly available on the platform of each campaign, I cross-referenced each campaign with information readily available on Instagram in order to determine whether each project had an Instagram page, how frequently they posted during the campaign period, and how many of those SMCs signaled the campaign. In total, the observations made from this sample were n=1643: all 595 campaigns were checked for Instagram presence, of which n=524 artists (88%) had publicly accessible Instagram pages; from these, the number of posts – both general and campaign-specific – made whilst the campaign was active were also counted. Out of 524 campaigners with public Instagram pages, n=351 of them (67%) signaled the crowdfunding campaign.

Table 4

Summary of data groups of this research.

	DATA GROUP		
	1. Large sample	**2. Subsample**	**3. Signals of subsample**
Description	Sample composed of all musical crowdfunding campaigns on Dutch cultural crowdfunding platform from 2021 to 2023 (provided by platform).	Sample with cases randomly selected from large sample for more in-depth analysis of campaign signals.	Group composed of all Instagram signals posted by the cases in the subsample that referenced crowdfunding campaigns.
Size	n=595	n=99	n=527
Relevant data	Instagram signal data per campaign (e.g. number of signals, number of signals per campaign), crowdfunding campaign data (e.g. amount raised)	Grouped signal data from "signals of subsample" according to campaign (e.g. total/ mean dynamic signals per campaign, total/ mean likes per campaign), crowdfunding campaign data	SMC signal typology coding per campaign signal, engagement (e.g. signal medium, signal content type), engagement data per signal (number of likes, comments)
Relevant hypotheses	H1, H2	H3, H4	

From this group of n=351 campaigns that did promote on Instagram, a subsample of n=99 campaigns was randomly selected for further analysis (Table 4). The total number of observations – in the form of SMC signals posted by artists specifically referencing the crowdfunding campaign – in this subsample were n=527. Each one of these SMC signals was coded according to the simplified SMC typology (Table 3), meaning that each signal was classified as either static or dynamic, as well as either rhetorical or substantive. The full coding guidebook is available in Appendix A. Of these, n=328 signals (62%) of signals were static signals, that is, posts of static images; n=199 signals (38%) were dynamic signals, that is, posts of videos or of static images with audio; n=317 (60%) were substantive signals; and n=210 (40%) were rhetorical signals. The dual medium-content typing of each signal was also observed, yielding the following data: n=236 (44.8%) were both static and substantive, n=92 (17.5%) were both static and rhetorical, n=81 (15.4%) were both dynamic and substantive, and n=118 (22.4%) were both dynamic and rhetorical.

The *engagement,* or audience interaction, for each signal was also documented. Eliminating n=7 signals without readily-available like counts, the remaining n=520 signals had a cumulative 24,464 likes, with a mean of 47.04 likes; of the n=189 dynamic signals with available view count, a cumulative 251,356 and mean 1329.92 views were observed; and all n=527 signals had a sum of 989 comments and a mean of 1.88 comments. All three of these indicators exhibited a positive skewness and a kurtosis of over 15, suggesting a non-normal distribution. Additionally, the day of the campaign each signal was published was recorded. After standardizing the values by expressing the publishing day as a ratio over the duration of the campaign, a mean publishing moment of 51.1% into the campaign was observed, with a skewness of .061 and a kurtosis of -1.185.

These signals were then grouped by campaign in the subsample. The average likes, views, and comments were calculated for each campaign, along with percentages of each engagement metric and signal type for each campaign. In total, this research involved the coding of 595+527 or 1122 coding units, 595 being crowdfunding cases used in the large sample and 527 being signals used in the subsample. Appendix E, attached separately, contains the full raw dataset.

4.3. Descriptive Statistics and Variables

This study is primarily focused on two dependent variables (DVs): *Amount Raised* (a) and *Number of Donations* (b), each representing an operationalized concept from the hypotheses. *Amount Raised* corresponds to the concept of “financial success,” whereas *Number of Donations* corresponds to the concept of "more donors." Along with these dependent variables are four binary independent variables (IVs): *General Signaling Binary* (c), *Campaign Signaling Binary* (d), *Dynamic Binary* (e), and *Rhetorical Binary* (f). In order to conduct more in-depth analysis, three continuous IVs are also included in the study: *Number of Total Signals* (g), *Number of Campaign Signals* (h), *Number of Dynamic Signals* (i). Control variables included the binary variables *Randstad Dummy* (j) and *Netherlands Dummy* (k), along with the following continuous variables: *Matchfunding Amount* (l), *Number of Days* (m), *Word Count* (n), *Number of Reward Tiers* (o), *Preparation Time* (p), *Artist Age* (q), *Average Day Ratio* (r), and *Average Likes* (s). Appendix B provides a description of each of these variables.

Unweighted indicators were selected as DVs over weighted indicators, like the percentage of target amount raised, due to the low variance of the latter in both samples: the vast majority of projects (97% of the n=99 subsample, 95.8% of the n=595 sample) succeeded, meaning that they reached the minimum 80% funding threshold required by the crowdfunding platform in order to receive the funds. Additionally, all continuous variables used in this study – except for the *Number of Reward Tiers, Artist Age,* and *Average Day Ratio* variables*,* the latter being the average moment a campaign published SMC signals, expressed as the ratio of number of days posted over total days the campaign was active – underwent a logarithmic (base-10) transformation. The reason for this is twofold: since all variables that were logarithmically transformed had significantly non-normal distribution, the logarithmic transformation provided a means to curb residual effects in data analysis, and logarithmic transformation allows for more robust interpretation of the regression, as it makes possible to determine the percentage increase in DVs for every 1% increase in the IVs and controls. Tables 5 outlines the descriptive data of the dummy variables employed in the study, Table 6 provides the descriptive data for continuous variables before logarithmic transformation, and Table 7 provides the descriptive data for continuous variables after logarithmic transformation. Finally, Appendix B provides a list of all variables used and a description of what they measure.

Table 5

Descriptive Data of Binary Variables

(n=595)	**Frequency Value: 0**	**Frequency Value: 1**
Dummy_GeneralSignal	0.156	0.844
Dummy_CampaignSignal	0.41	0.59
Dummy_Randstad	0.548	0.452
Dummy_Netherlands	0.054	0.946
(n=99)		
Dummy_DynamicSignal	0.273	0.727
Dummy_RhetSignal	0.202	0.798
Dummy_Randstad	0.566	0.434
Dummy_Netherlands	0.04	0.96

Table 6

Descriptive Data of Continuous Variables

(n=595)	Min	FirstQuart	Median	Mean	ThirdQuart	Max	StdDev
AmountRaised	0	3613	5601	6874.55	8327	102455	6658.799
N_Donations	2	50	81	97.28	112	1925	106.820
N_TotalSignals*	0	1	5	7.29	10	65	8.483
N_CampaignSignals*	0	0	2	3.57	5	40	4.956
AmountMF	0	0	750	1110.31	1400	43000	2192.857
N_Days	8	34	37	40.43	44	105	12.468
WordCount	523	1006	1193	1291.46	1460	3601	433.332
PrepTime	0	14	30	56.1	64	640	78.343
N_Rewards	1	6	7	7.3	8	18	2.086
Age_Artist	17	30	37	49.04	49	82	13.147
(n=99)							
AmountRaised	100	4070	6650	7208.35	9065	32298	4564.303
N_Donations	3	56	91	104.10	127	728	86.088
N_DynamicSignals	0	0	1	2.01	3	20	2.901
AmountMF	0	350	750	1199.92	750	6325	1315.046
N_Days	8	34	37	40.18	43	96	12.093
WordCount	762	1082	1267	1416.92	1704	3118	505.364
PrepTime	0	14	33	62.95	80.5	632	83.886
N_Rewards	3	6	7	7.64	8.75	15	2.183
Age_Artist	19	29	36	36.77	33	73	10.085
Avg_DayRatio	0	0.29	0.4762	0.4382	0.562	0.8824	0.1941
Avg_Likes	2	18.67	39	58.8	73	552	73.77

*Results are only reported for campaigns whose artists have an instagram page that is readily available, that is, not private (n=502).

Table 7

Descriptive Data of Continuous Variables post-Logarithmic Transformation

(n=595)	Min	FirstQuart	Median	Mean	ThirdQuart	Max	StdDev
Log_AmtRaised	0	3.5580	3.7483	3.7168	3.9205	5.01	0.369
Log_NDonations	0.48	1.7076	1.9138	1.8793	2.0531	3.28	0.31897
Log_NTotalSignals*	0	0.3010	0.7782	0.7095	1.0414	1.82	0.45181
Log_NCampaignSigs*	0	0	0.4771	0.47	0.7782	1.61	0.39877
Log_AmountMF	0	0	2.8756	2.0371	3.1464	4.63	1.46898
Log_N_Days	0.95	1.5441	1.5798	1.6013	1.6532	2.06	0.11433
Log_WordCount	2.72	3.0030	3.0770	3.0905	3.1647	3.62	0.13170
Log_PrepTime	0	1.1761	1.4914	1.5024	1.8129	2.81	0.46885
Log_Age_Artist	1.26	1.4914	1.5798	1.5919	1.6990	1.92	0.13539
(n=99)							
Log_AmtRaised	2	3.6097	3.8229	3.77	3.9574	4.51	0.33180
Log_NDonations	0.6	1.7559	1.9638	1.9169	2.1072	2.86	0.32198
Log_NDynamicSigs	0	0	0.301	0.3579	0.6021	1.32	0.30286
Log_AmountMF	0	2.5453	2.8756	2.3834	3.2177	3.8	1.31454
Log_N_Days	0.95	1.5441	1.5798	1.5975	1.6435	1.99	0.12543
Log_WordCount	2.88	3.0346	3.1031	3.1277	3.2317	3.49	0.14149
Log_PrepTime	0	1.1761	1.5315	1.5467	1.9191	2.80	0.49841
Log_Avg_Likes	0.48	1.2937	1.6021	1.5849	1.8692	2.74	0.41125

*Results are only reported for campaigns whose artists have an instagram page that is readily available, that is, not private (n=502).

Having briefly discussed the variables used and presented their descriptive statistics, it is now worthwhile to cover the nuances of each type of variable in detail.

4.3.1. Dependent variables

The dependent variables of *Amount Raised* and *Number of Donations* are both ratio variables, with each designating a different dimension of success: *Amount Raised* indicates financial success, and *Number of Donations* indicates success in terms of the number of supporters and/or micro-donors an artist can mobilize.

4.3.2. Independent variables

This research features seven IVs, with four IVs corresponding to the large sample and three to the subsample. For the n=595 sample, first is the *General Signaling Binary,* which is a binary variable measuring whether the campaigning artist published one or more signals during the duration of the campaign on Instagram, regardless of whether the signal(s) promote the crowdfunding campaign. In this regard, the *General Signaling Binary* variable serves to measure an artist's general presence on Instagram beyond merely having an account. The second IV for the n=595 sample is the *Campaign Signaling Binary,* which is a binary variable measuring whether there are one or more signals on Instagram specifically promoting a crowdfunding campaign. The third and fourth independent variables employed, the *Number of Total Signals* and *Number of Campaign Signals,* represent respective continuous versions of the aforementioned binary variables. *Number of Total Signals* pertains to the number of signals published on Instagram by a campaign's artist, regardless of whether these signals pertain to the campaign or not, and *Number of Campaign Signals* is the number of signals published on Instagram that do mention the campaign. Each of these has been logarithmically transformed such that the version of the IVs employed are the natural logarithms of the number of total signals and campaign signals, respectively. As such, the names of these variables shall henceforth refer specifically to the logarithmic transformations in the following sections of this study.

The fifth and sixth independent variables correspond to the n=99 subsample, and each has to do with the simplified signal typology (Table 3). One, the *Dynamic Binary*, measures whether a campaign employs at least one dynamic signal. Alternatively, the *Rhetorical Binary* measures whether a campaign employs at least one rhetorical signal. The specific process by which each signal was coded can be found in Appendix A. The final IV also corresponds to the subsample, and it is the continuous variable *Number of Dynamic Signals*, which specifies the number of dynamic signals published by each campaign. Like the other continuous independent variables, it has also undergone logarithmic transformation, and the name will henceforth refer to the logarithmically transformed data.

4.3.3. Controls

The control variables were selected due to their theoretical impact as predictors in crowdfunding as established by the literature (Mollick, 2014; Steigenberger, 2017; Baeck et al., 2017). These include factors pertaining to the campaigning artist such as whether the artist is Dutch or residing in the Randstad as well as their age, to the campaign itself such as the duration of the campaign and preparation time as well as the number of reward incentives, and to additional phenomena, such as the amount of matchfunding provided to projects and amount of engagement on external social media.

Of these, the *Amount of Matchfunding, Project Duration, Average Ratio of Signal Date to Project Duration, Average Likes, Word Count, Number of Reward Incentives, Artist Age,* and *Preparation Time* are continuous variables, with all except *Project Duration* and *Preparation Time* being ratio variables. Additionally, all of these except for *Average Ratio of Signal Date* and *Number of Reward Incentives* have undergone logarithmic transformation, and the names of these variables will be used to refer specifically to the logarithmically transformed data henceforth. The control *Artist Age* also underwent logarithmic transformation in the case of the large sample, given its non-normal distribution, but the subsample exhibited more normal patterns, and as such, the raw, untransformed data was used in the subsample. The reason *Average Ratio of Signal Date* and *Number of Reward Incentives* did not undergo logarithmic transformation is due to the data's already normal or close to normal distribution; as such, it was decided that logarithmic transformation was not necessary.

4.4. Validity Tests

First, T-tests were conducted in order to determine whether there were meaningful differences between the categories of the binary independent variables. Three out of four independent variables returned significant differences ($\alpha = .05$), with only the *Rhetorical Binary* not returning a significant difference in mean between binary groups. From there, a Variance Inflation Factor (VIF) was conducted for each model, that is, each regression analysis with respect to a DV. All potential variables with a VIF higher than 2, such as the "year" control variable, were removed; this high VIF would indicate a high level of multicollinearity, which could potentially reduce the validity of the study as a whole. As such, the decision was made to exclude them from the regression models, with independent variables with high VIFs being recoded into workable, lower VIF variables. Regarding skew, the argument of the Central Limit Theorem was used (Hogg et al., 2019), meaning that skewed data in the sample or population was not excessively normalized given the presumption that the distribution of sample means is normal as the size of the sample increases. As such, logarithmic transformation was applied for the primary purpose of allowing for more in-depth evaluations of regressions, for example, facilitating establishing the percentage of predictive power between continuous IVs and DVs. Tables 8 through 11 present the Pearson Correlation Matrices of the variables for each regression model employed in the study.

Table 8

Pearson Correlation Matrix for Variables Used in Model 1

(n=595)	Amt_Raised	N_Donations	GenSignal Binary	Campaign Signal Binary	Amount MF	N_Days	WordCount	N_Rewards	Randstad Dummy	Netherlands Dummy	PrepTime	(Log) Age_Artist
Amt_Raised	1											
N_Donations	0.767	1										
GenSignal Binary	0.084	0.05	1									
Campaign Signal Binary	0.220	0.219	0.441	1								
AmountMF	0.285	0.121	0.111	0.123	1							
N_Days	0.16	0.056	0.008	-0.002	0.097	1						
WordCount	0.333	0.258	0.095	0.219	0.108	-0.024	1					
N_Rewards	0.392	0.394	0.148	0.253	0.121	-0.005	0.525	1				
Randstad Dummy	0.036	0.026	0.053	0.057	0.119	-0.058	0.126	0.026	1			
Netherlands Dummy	0.022	0.039	0.050	0.013	0.226	-0.033	-0.051	-0.048	0.217	1		
PrepTime	0.041	0.019	-0.010	0.072	0.028	0.047	0.090	0.039	-0.002	0.034	1	
(Log) Age_Artist	0.052	0.051	-0.184	-0.090	-0.060	0.077	-0.090	-0.064	-0.135	0.021	-0.062	1

Table 9

Pearson Correlation Matrix for Variables Used in Models 2 and/or 3

(n=595)	Amt_ Raised	N_Donations	N_Posts Total	N_Posts Campaign	Amount MF	N_Days	Word Count	N_ Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	(Log) Age_Artist
Amt_Raised	1											
N_Donations	0.767	1										
N_Posts Total	0.219	0.189	1									
N_Posts Campaign	0.303	0.335	0.775	1								
AmountMF	0.285	0.121	0.144	0.170	1							
N_Days	0.16	0.056	0.194	0.082	0.097	1						
WordCount	0.333	0.258	0.182	0.270	0.108	-0.024	1					
N_Rewards	0.392	0.394	0.219	0.319	0.121	-0.005	0.525	1				
Randstad Dummy	0.036	0.026	0.025	0.035	0.119	-0.058	0.126	0.026	1			
Netherlands Dummy	0.022	0.039	-0.057	0.007	0.226	-0.033	-0.051	-0.048	0.217	1		
PrepTime	0.041	0.019	-0.018	0.01	0.028	0.047	0.090	0.039	-0.002	0.034	1	
(Log) Age_Artist	0.052	0.051	0.068	0.036	-0.060	0.077	-0.090	-0.064	-0.135	0.021	-0.062	1

Table 10

Pearson Correlation Matrix for Variables Used in Model 4

(n=99)	N_Donations	Dynamic Binary	Rhet Binary	Amount MF	N_ Days	Word Count	Avg Day Ratio	Avg Likes	N_ Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	Age_ Artist
N_Donations	1												
Dynamic Binary	0.252	1											
Rhet Binary	-0.016	0.483	1										
AmountMF	0.06	0.285	0.034	1									
N_Days	-0.238	-0.021	0.032	-0.1	1								
WordCount	0.210	0.172	0.053	0.042	-0.039	1							
Avg DayRatio	0.147	0.101	0.142	0.033	0.041	0.117	1						
Avg Likes	0.320	0.152	-0.115	-0.002	-0.153	-0.017	-0.126	1					
N_Rewards	0.441	0.054	0.008	0.094	-0.217	0.552	0.106	0.014	1				
Randstad Dummy	0.034	0.171	0.035	0.095	-0.061	0.094	0.092	0.157	0.006	1			
Netherlands Dummy	0.051	0.220	0.025	0.197	-0.104	-0.024	-0.152	0.094	-0.034	0.180	1		
PrepTime	-0.207	-0.164	-0.043	-0.05	0.162	0.088	0.02	0.027	-0.184	0.159	-0.126	1	
Age_ Artist	0.162	-0.075	-0.029	-0.061	0.017	0.034	0.198	-0.371	0.300	-0.063	-0.286	-0.087	1

Table 11

Pearson Correlation Matrix for Variables Used in Model 5

(n=99)	N_Donations	N_ Dynamic Signals	Amount MF	N_ Days	Word Count	Avg Day Ratio	Avg Likes	N_ Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	Age_ Artist
N_Donations	1											
N_Dynamic Signals	0.291	1										
AmountMF	0.06	0.151	1									
N_Days	-0.238	0.119	-0.1	1								
WordCount	0.210	0.280	0.042	-0.039	1							
Avg DayRatio	0.147	0.331	0.033	0.041	0.117	1						
Avg Likes	0.320	0.005	-0.002	-0.153	-0.017	-0.126	1					

Table 11 (continued)

Pearson Correlation Matrix for Variables Used in Model 5

(n=99)	N_Donations	N_Dynamic Signals	Amount MF	N_Days	Word Count	Avg Day Ratio	Avg Likes	N_Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	Age_Artist
N_Rewards	0.441	0.149	0.094	-0.217	0.552	0.106	0.014	1				
Randstad Dummy	0.034	0.113	0.095	-0.061	0.094	0.092	0.157	0.006	1			
Netherlands Dummy	0.051	0.081	0.197	-0.104	-0.024	-0.152	0.094	-0.034	0.180	1		
PrepTime	-0.207	-0.136	-0.05	0.162	0.088	0.02	0.027	-0.184	0.159	-0.126	1	
Age_ Artist	0.162	-0.030	-0.061	0.017	0.034	0.198	-0.371	0.300	-0.063	-0.286	-0.087	1

These Pearson correlation matrices yield some curious results. High correlations ($R > .7$) can be observed between *Amount Raised* and *Number of Donations* in the large sample, which is to be expected given that both are indexes of success of campaigns and, due to them being separate dependent variables, do not greatly affect the regression models. Additionally, Table 9 shows how the *Number of Total Signals* and the *Number of Campaign Signals* variables are also highly correlated. This is also an expected result, as both are numerical indices of a campaign's frequency of posting; however, because of this high correlation, it would be unwise to model them simultaneous in a multivariate regression model. As such, they have been separated into distinct regression models, namely, Models 2 and 3. The following section will discuss regression modeling in detail. Besides these results, the highest correlation is between *Number of Reward Incentives* and *Word Count;* as the latter corresponds to the word count of a campaign's page on the crowdfunding platform, it is logical that pages that offer more rewards will have greater word counts, as the need to explain each reward may entail a positive marginal word count for each additional reward incentive offered.

Similarly worth observing is the inverse relationship between some variables. Negative correlations between *Artist Age* and variables corresponding to social media, such as *General Signaling Binary, Average Likes,* and *Number of Dynamic Signals* may evidence a generational difference in level of familiarity and presence on social media sites. *Preparation Time,* notably, was inversely related to most of the dependent and independent variables. This could suggest that more time to prepare a crowdfunding campaign does not translate to greater likelihoods of success. Observing these relations in the regression models may yield more information on these points.

4.5. Regression Analysis

This study consists of five multivariate linear regression models (Models 1, 2, 3, 4, and 5), a method of analysis with precedence in crowdfunding literature (Shneor & Vik, 2020). Using SPSS software to run calculations, a two-step forced-entry regression analysis was conducted, first run excluding control variables, which are re-added on a second run. Models 1 through 3 are built using the large n=595 sample, and they measure both DVs (*Amount Raised* and *Number of Donations*), whereas Models 4 and 5 are built using the n=99 subsample and only measure the *Number of Donations* DV. Similarly, the IVs of each model are distinct: Model 1 measures the *General Signaling Binary* and *Campaign Signaling Binary* variables, with Model 2 measuring the *Number of Total Signals* variable, Model 3 the *Number of Campaign Signals* variable, Model 4 the *Dynamic Signal Binary* and *Rhetorical Signal Binary* variables, and Model 5 the *Number of Dynamic Signals* variable. A detailed breakdown of each model is presented in Table 12.

Table 12

Index and Description of Linear Regression Models

Model	Hypotheses	Sample	DVs	IVs
1	H1a, H2a	Large (n=595)	*Amount Raised* (1a), *Number of Donations* (1b)	*General Signaling Binary, Campaign Signaling Binary*
2	H1b	Large (n=595)	*Amount Raised* (2a), *Number of Donations* (2b)	*Number of Total Signals*
3	H2b	Large (n=595)	*Amount Raised* (3a), *Number of Donations* (3b)	*Number of Campaign Signals*
4	H3a, H4	Subsample (n=99)	*Number of Donations*	*Dynamic Binary, Rhetorical Binary*
5	H3b	Subsample (n=99)	*Number of Donations*	*Number of Dynamic Signals*

By structuring the regression analysis in this manner, it is possible to measure each hypothesis with clear, focused variables. As shown in Table 12, Model 1 tests Hypothesis 1a, that *crowdfunding artists that have a presence on social media are more likely to be successful than artists that do not signal on social media,* and Hypothesis 2a, that *Cultural crowdfunding campaigns that have a presence on social media are more likely to be successful than campaigns that do not signal on social media*, with the "success" concept being operationalized in two dimensions by the DVs *Amount Raised* (Model 1a) and *Number of Donations* (Model 1b), and with the concepts "artist presence on social media" and "campaign presence on social media" operationalized by the IVs *General Signaling Binary* and *Campaign Signaling Binary*, respectively. Expanding on the first model, Model 2 tests Hypothesis 1b, that *Crowdfunding artists that have a greater presence on social media are more likely to be successful than artists with a lesser presence,* operationalizing "success" once again with the DVs *Amount Raised* (Model 2a) and *Number of Donations* (Model 2b). and with "greater artists presence on social media" operationalized in the IV *Number of Total Signals*. Model 3 operates in the same manner, different from Model 2 in that it tests Hypothesis 2b, that *Cultural crowdfunding campaigns that have a greater presence on social media are more likely to be successful than campaigns with a lesser presence,* with "greater campaign presence on social media" operationalized with the IV *Number of Campaign Signals*. All of these employ control variables described in Appendix B and Section 4.3 of this chapter, and the specific control variables can also be found in Tables 8 and 9.

Unlike Models 1 through 3, Models 4 and 5 utilize data from the subsample (n=99) and test Hypotheses 3 and 4. Given that these hypotheses do not deal with a two-dimensional conceptualization of crowdfunding success, the sole dependent variable tested in Models 4 and 5 is *Number of Donations* as a rather clear operationalization of the concept "number of donations." Model 4 tests Hypothesis 3a, that *cultural crowdfunding campaigns that employ dynamic SMC signals on social media are more likely to have more donations than campaigns that do not,* as well as Hypothesis 4, that *cultural crowdfunding campaigns that employ rhetorical SMC signals are more likely to have more donations than campaigns that do not*; it operationalizes the concept "employs dynamic SMC signals" with the IV *Dynamic Binary* and the concept "employs rhetorical SMC signals" with the IV *Rhetorical Binary.* Finally, Model 5 tests Hypothesis 3b, that *cultural crowdfunding campaigns that employ more dynamic SMC* *signals on social media are more likely to have more donations than campaigns that employ less*, and it operationalizes the concept of "more dynamic SMC signals" with the IV *Number of Dynamic Signals*.

5. Findings

Running the models, the seven independent variables were tested against the two dependent variables along with several control variables in order to arrive at answers for all four hypotheses. Each model will be discussed in its own separate section.

5.1. Model 1: Effect of social media presence on crowdfunding success.

In Model 1, shown in Table 13, Hypotheses 1a and 2a are tested, applying the IVs *General Signal Binary* and *Campaign Signal Binary*. With its DV of *Amount Raised,* Model 1a tests the "financial success" dimension of Hypothesis 1a and 2a, whilst Model 1b tests the "social success" dimension of Hypothesis 1a and 2a via the DV *Number of Donations*.

5.1.1. Model 1a

Model 1a tests the predictive power of a crowdfunding's social media signaling over the amount of money it raises, with and without controls. When controls are not considered, the regression model explained a mere 4.5% of the variance in the amount raised, though with a high statistical significance (F = 15.100, p < .001). The *General Signaling* insignificantly affected success according to the model (β = -0.019, p > .05), whereas the *Campaign Signaling* variable did positively affect success in funding with very high significance (β = 0.17, p < .001). The AIC values indicate that the more reliable model is with control, however. With the addition of control variables, the regression model explained 25.5% of the variance, a 21% improvement in the model's goodness-of-fit. The *General Signaling* p-value decreased from 0.713 to 0.487 and thus remains largely insignificant in the model. The *Campaign Signaling* variable, however, remains significant and positive (β = .084, p < 0.01), though the degree of significance is eclipsed by control variables of *Matchfunding Contribution* (β = .055) *Number of Days* (β = .444), *Word Count* (β = .448), and *Number of Reward Incentives* (β = .047), all with p < .001. The implications of such significance from the control variables bears discussion in later sections, but it is possible to say that, whereas artist presence on social media is insignificant to the amount raised for crowdfunding campaigns, the presence of campaign signals on social media leads to higher amounts fundraised. Considering the DV has been logarithmically transformed, it is possible to say, within the 25.5% of the variance explained by the regression, that that campaigns that are signaled on Instagram can be predicted to be $(10^{.084} - 1)\%$ or 21.3% more financially successful.

Table 13

Model 1 Results of the Two-step Linear Regression Analysis

Model 1a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 1b:** DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	3.633***	0.756	(Intercept)	1.836***	0.434
SE	0.043	0.433	SE	0.037	0.394
GenSignal Dummy	-0.019	-0.032	GenSignal Dummy	-0.057	-0.060
SE	0.051	0.046	SE	0.044	0.042
Campaign Signal Binary	0.170***	0.084**	Campaign Signal Binary	0.158***	0.097***
SE	0.033	0.031	SE	0.029	0.028
Matchfunding Amount		0.055***	Matchfunding Amount		0.012
SE		0.009	SE		0.009
N_Days		0.444***	N_Days		0.132
SE		0.116	SE		0.105
Word Count		0.448***	Word Count		0.156
SE		0.119	SE		0.108
N_Rewards		0.047***	N_Rewards		0.051***
SE		0.008	SE		0.007
Randstad Dummy		-0.001	Randstad Dummy		-0.001
SE		0.027	SE		0.025
Netherlands Dummy		-0.005	Netherlands Dummy		0.067
SE		0.061	SE		0.056
PrepTime		0.001	PrepTime		-0.008
SE		0.028	SE		0.026
Age_Artist		0.248*	Age_Artist		0.188*
SE		0.100	SE		0.091

Table 13 (continued)

Model 1 Results of the Two-step Linear Regression Analysis

Model 1a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 1b:** DV Number of Donations *Predictors*	**IVs**	**Control**
N_Obs	595	595	*N_Obs*	595	595
R^2 Adjusted	**0.045**	**0.255**	***R^2 Adjusted***	**0.047**	**0.178**
ANOVA F	15.100***	21.352***	***ANOVA F***	15.690***	13.878***
AIC	-1210.996	-1350.793	***AIC***	-1383.204	-1463.310
Schwarz-Bayesian Criterion	-1197.830	-1302.519	***Schwarz-Bayesian Criterion***	-1370.043	-1415.054
*p<.05, **p<.01, ***p<.001					

5.1.2. Model 1b

Model 1b tests the predictive power of a crowdfunding campaign's social media signaling over the number of donations it receives. The initial regression model explained 4.7% of the variance in the amount raised with a very high statistical significance ($F = 15.690$, $p < .001$). The *General Signaling Binary* variable negatively yet insignificantly affected success according to the model ($\beta = -.057$, $p = .199$), whereas the *Campaign Signaling* variable did significantly and positively affect number of donations ($\beta = .158$, $p < .001$). Given that Model 1b once again exhibits a lower AIC in the regression with controls than the one without controls, however, the controlled regression should be preferred for accuracy over the one without controls.

With the addition of control variables, the regression model explained 17.8% of the variance, an 13.1% improvement in the model's goodness-of-fit. Though the *p*-value of the *General Signaling* decreased from .199 to .150, it remains largely insignificant in the model, though it now exhibits a negative $\beta = -.060$. The *Campaign Signaling* variable, however, remains significant and positive ($\beta = .097$, $p < .001$). Notable here is that, unlike Model 1a, Model 1b has the *Campaign Signaling Binary* and the *Number of Reward Incentives* as the most significant variables, with only *Artist Age* any sort of significant results ($p < .05$). This entails that the relevance of signaling a campaign on social media is more relevant in the social dimension than the financial dimension, though it is significant in both. As such, it is possible to say that the presence of campaign signals on social media leads to higher numbers of donations, such that it is possible to claim, within the 17.8% of the variance explained by the regression model, that signaling a campaign at least once on Instagram may predict a $(10^{.097} - 1)\%$ or 25.03% increase in its number of donations.

When considering both of its sub-models, Model 1 demonstrates that the first hypothesis (H1a) *"Crowdfunding artists that have a presence on social media are more likely to be successful than artists that do not signal on social media"* is not confirmed, as the IV *General Signaling Binary,* which measures whether an artist made at least one post during the crowdfunding period, has a low significance in the tests of both the "financial" (p = .487) and "social" (p = .170) dimensions of success. In contrast, the second hypothesis (H2a) "*Cultural crowdfunding campaigns that have a presence on social media are more likely to be successful than campaigns that do not signal on social media"* can, in fact, be confirmed, given the positive coefficient and high significance of the *Campaign Signaling* variable in the tests for both "financial" (β = .084, p < 0.01) and "social" (β = .097, p < .001) dimensions of success.

5.2. Model 2: Effect of amount of general artistic signaling on success

Though Hypothesis 1a was not confirmed, it is relevant to know whether the *amount* of signals an artist publishes on social media has an impact on success. In Model 2, shown in Table 14, Hypothesis 1b is tested, applying the IV *Number of Total Signals*. With its DV of *Amount Raised,* Model 2a tests the "financial" dimension of success, whilst Model 2b tests the "social" dimension of success with the DVs *Amount Raised* (Model 2a) and *Number of Donations* (Model 2b).

Model 2a tests the predictive power of the number of total signals a crowdfunding artist posts during the campaign on the amount of money the campaign raises, with and without controls. The regression model that does not factor controls predicts 4.6% of the variance in the *Amount Raised* variable, with high statistical significance according to the ANOVA test (F = 25.312, p < .001). In this uncontrolled model, the variable *Number of Total Signals* is a positive predictor and a very significant one as well (β = .164, p < .001). However, the AIC of the regression without controls (-1119.209) higher than the regression with controls (-1234.972). The regression with controls predicts 25.3% of the variance, with high statistical significance (*F*

= 19.984, $p < .001$). In this model, however, the significance of the *Number of Total Signals* variable drops ($p = .139$), with *Matchfunding Amount, Number of Days, Word Count, Number of Reward Incentives,* and *Artist Age* more statistically significant ($p < .001$ for all except for *Artist Age*, whose $p < .05$). As such, it is possible to say that the "financial" dimension of Hypothesis 1b cannot be confirmed. This result is consistent with the findings in Model 1a regarding Hypothesis 1.

Model 2b, which tests the predictive power of the number of total signals a crowdfunding artist posts during the campaign on the amount of money the campaign raises, exhibits a similar pattern of results. Though the regression without controls exhibits a high degree of significance and positive correlation ($\beta = .135$, $p < .001$) for the IV *Number of Total Posts*, the AIC indicates that the regression with controls ($AIC = -1237.889$) should be preferred over the regression without controls ($AIC = -1160.200$). In the controlled regression, however, the IV is insignificant ($p = .084$); instead, most significant is *Number of Reward Incentives* ($\beta = .054$, $p < .001$), with *Matchfunding Amount* ($\beta = .02$, $p < .05$) and *Artist Age* ($\beta = .215$, $p < .05$) also exhibiting significant results. Therefore, the Hypothesis 1b, that *Crowdfunding artists that have a greater presence on social media are more likely to be successful than artists with a lesser presence,* cannot be confirmed due to insignificant results in the IV *Number of Total Posts* in regressions testing both "financial" ($p = .139$) and "social" ($p = .084$) dimensions of success (Model 2). Because neither Hypothesis 1a nor Hypothesis 1b were confirmed by the models, Hypothesis 1 is not confirmed.

Table 14

Model 2 Results of the Two-step Linear Regression Analysis

Model 2a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 2b:** DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	3.614***	0.797	(Intercept)	1.788***	0.163
SE	0.027	0.427	SE	0.026	0.426
N_TotalSignals	0.164***	0.045	N_TotalSignals	0.135***	0.053
SE	0.033	0.031	SE	0.031	0.030
Matchfunding Amount		0.051***	Matchfunding Amount		.020*
SE		0.009	SE		0.009
N_Days		0.527***	N_Days		0.108
SE		0.121	SE		0.120
Word Count		0.411***	Word Count		0.220
SE		0.117	SE		0.116
N_Rewards		0.044***	N_Rewards		0.054***
SE		0.008	SE		0.008
Randstad Dummy		0.013	Randstad Dummy		-0.003
SE		0.027	SE		0.027
Netherlands Dummy		-0.014	Netherlands Dummy		0.045
SE		0.062	SE		0.062
PrepTime		0.006	PrepTime		0.000
SE		0.027	SE		0.027
Age_Artist		0.221*	Age_Artist		0.215*
SE		0.101	SE		0.101
N_Obs	502	502	*N_Obs*	502	502
R^2 Adjusted	**0.046**	**0.253**	***R^2 Adjusted***	**0.034**	**0.184**
ANOVA F	25.312***	19.984***	***ANOVA F***	18.687***	13.669***
AIC	-1119.209	-1234.972	***AIC***	-1160.200	-1237.889
Schwarz-Bayesian Criterion	-1110.756	-1192.707	***Schwarz-Bayesian Criterion***	-1151.746	-1195.623

*p<.05, **p<.01, ***p<.001

5.3. Model 3: Effect of amount of campaign signaling on success

Expanding on the results of Hypothesis 2a as showcased by Model 1, Model 3 tests the predictive power of the amount of campaign social media signals published on the campaign's success, thus corresponding to Hypothesis 2b. Table 15 contains the results of Model 3, which measures success via the *Amount Raised* and *Number of Donations* DVs, against the IV *Number of Campaign Signals* as well as the same control variables as Models 1 and 2. Like Model 2, the number of experimental cases is n=502, smaller than the full sample size. This is due to the variable *Number of Campaign Signals* only having values for campaigns that had a readily-available presence on Instagram; in other words, this group is composed of all n=502 campaigns that had a value of 1 for the *General Signaling Binary* variable. In this manner, only campaigns whose number of signals during the campaign period could be verified were included.

Model 3a tests the "financial" dimension of success via the DV *Amount Raised.* Without controls, the regression model explains 9% of the variance in the *Amount Raised* variable (F = 50.402, $p < .001$). Because the AIC of the regression with controls (-1232.142) is less than that of the control-less regression (-1131.698), however, the regression with controls, which explains 26.6% of the variance in the DV, is preferred for analysis. Regardless, in both, the IV exhibits a positive coefficient and a significant value, albeit with a higher significance ($\beta = .257$, $p < .001$) in the regression excluding controls than the one including controls ($\beta = .112$, $p < .01$). As might be expected from the previous regression models, the IV is once again exhibiting weaker significance than the controls *Matchfunding Amount* ($\beta = .047$), *Number of Days* ($\beta = .538$), and *Number of Rewards* ($\beta = .041$), such that for all of these $p < .001$. Nevertheless, the significance of the IV makes it possible to state, within the 26.6% of variance explained by the regression formula, that a 1% increase in campaign signals on Instagram predicts a .112% increase in amount of money raised for the crowdfunding campaign with 99% confidence ($p < .01$).

Model 3b test the "social" dimension of success, using the DV *Number of Donations.* Excluding controls, the regression explains 11.1% of the variance in the *Number of Donations* variable, and with controls, 21.7% of the regression is explained. Once again, the AIC for the control-inclusive regression (-1252.143) is less than the control-exclusive one (-1196.068), indicating that it is preferred for analysis. In both regressions, the IV *Number of Campaign Signals* exhibits a positive coefficient ($\beta = .27$ without controls, $\beta = .162$ with) and a very high significance in both ($p < .001$). Additionally, only the *Number of Reward Incentives* control had significance (β = .049, p < .001), and with a lower coefficient than the IV, suggesting that the IV is the most powerful of the significant predictors in the regression. Given this, it is possible to state, within the 21.7% of the variance in the DV explained by the regression formula and with more than 99% confidence, that a 1% increase in the number of campaign signals predicts a .162% increase in the number of donations to the crowdfunding campaign. Finally, as both dimensions of success tested in the model had positive coefficients and high significance for the IV *Number of Donations,* representing "amount of campaign presence on social media," Hypothesis 2b, that *cultural crowdfunding campaigns that have a greater presence on social media are more likely to be successful than campaigns with a lesser presence,* is confirmed. Given that Hypotheses 2a and 2b have been confirmed by Models 1 and 3, respectively, it is possible to state that Hypothesis 2 has been fully confirmed by the data.

Table 15

Model 3 Results of the Two-step Linear Regression Analysis

Model 3a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 3b:** DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	3.610***	0.915*	(Intercept)	1.757***	0.344
SE	0.022	0.427	SE	0.021	0.419
N_CampaignSignals	0.257***	0.112**	N_CampaignSignals	0.270***	0.162***
SE	0.036	0.035	SE	0.034	0.034
Matchfunding Amount		0.047***	Matchfunding Amount		0.013
SE		0.009	SE		0.009
N_Days		0.538***	N_Days		0.135
SE		0.119	SE		0.116
Word Count		0.380**	Word Count		0.166
SE		0.117	SE		0.115
N_Rewards		0.041***	N_Rewards		0.049***
SE		0.008	SE		0.007
Randstad Dummy		0.012	Randstad Dummy		-0.002
SE		0.027	SE		0.027
Netherlands Dummy		-0.006	Netherlands Dummy		0.062
SE		0.063	SE		0.062
PrepTime		0.006	PrepTime		0.005
SE		0.027	SE		0.027
Age_Artist		0.199	Age_Artist		0.172
SE		0.101	SE		0.099
N_Obs	502	502	*N_Obs*	502	502
R^2 Adjusted	**0.090**	**0.266**	***R^2 Adjusted***	**0.111**	**0.217**
ANOVA F	50.402***	21.221***	***ANOVA F***	63.254***	16.424***
AIC	-1131.698	-1232.142	***AIC***	-1196.068	-1252.143
Schwarz-Bayesian Criterion	-1123.260	-1189.956	***Schwarz-Bayesian Criterion***	-1187.631	-1209.957
*p<.05, **p<.01, ***p<.001					

5.4. Model 4: Effect of signal type on number of donations

In Model 4 (Table 16), Hypotheses 3a and 4 are tested via a two-step linear regression analysis that employs the DV *Number of Donations* and the IVs *Dynamic Binary* and *Rhetorical Binary*, along with a several control variables. The initial "step" of the model does not account for controls; this version of the regression model has an adjusted R-squared value of .069, meaning that 6.9% of the variance in the number of donations can be explained by the *Dynamic Binary* and *Mixed Substantive/Rhetorical Binary* variables. Additionally, this version of the regression model has an $F = 4.655$ ($p < .05$), entailing that these findings are significant. The first of the IVs employed, the *Dynamic Binary*, has a beta-value of .244 ($p < .01$), signifying that it has a very significant and positive effect on the amount raised, whilst the *Rhetorical Binary* IV has a negative coefficient and is insignificant ($\beta = -0.143$, $p = .110$). This entails that, when compared only with each other, *Dynamic Binary* is a more positive and significant predictor of number of donations than the *Rhetorical Binary.* This result is consistent with the initial t-tests described in Section 4.4 of the methodologies in that the *Rhetorical Binary* did not have a significant difference in means between groups.

When deciding whether the control-exclusive or control-inclusive regression should be preferred, several factors must be considered. Importantly, the results of the AIC indicate that the regression with controls (-250.155) should be preferred to the one without controls (-228.558), but the Schwarz Bayesian Criterion (also described as BIC) indicates the opposite, with the control-exclusive regression (-220.773) scoring lower than the inclusive one (-216.418). Given that the control-inclusive regression has a higher R-square value (.318), however, it will be preferred, as the AIC indicates it has greater predictive power and the R-square value entails that it explains a greater part of the variance (31.8%) in the number of donations. The control-inclusive regression also exhibits a higher degree of significance ($F = 4.8$, $p < .001$) compared to the control-exclusive regression ($F = 4.655$, $p < .05$).

The control-inclusive model therefore represents a 24.9% increase in variance explained. When factoring in controls, the IV *Dynamic Binary* retains a positive coefficient ($\beta = 0.165$) and significance ($p = .042$), albeit less so than in the control-exclusive "step." The *Rhetorical Binary* IV, in contrast, remains insignificant and negatively related to the DV ($\beta = -0.080$, $p = .319$). Of the controls, only *Average Likes per Campaign Signal* ($\beta = .268$, $p < .001$) and *Number of Reward Incentives* ($\beta = .049$, $p < .01$) were significant, albeit both more significant than the

Dynamic Binary. Interesting here is that the *Average Likes* value has the highest coefficient of the significant values, indicating that level of engagement on Instagram is potentially an important predictor of crowdfunding success. As it was not logarithmically transformed, it can be stated, within the 31.8% of the variance explained by the model, that for every increase in average likes by 1, a $(10^{.268} - 1)\%$ or 85% increase in number of donations may be predicted, compared to the $(10^{.165} - 1)\%$ or 46.2% predicted increase in donation number for campaigns that publish at least one dynamic signal.

The significance and positive beta-value of the *Dynamic Binary* IV entails that publishing at least one dynamic campaign signal on social media positively relates to the number of donations. Therefore, Hypothesis 3a, that *cultural crowdfunding campaigns that employ dynamic SMC signals on social media are more likely to have more donations than campaigns that do not,* is confirmed. In contrast, the lack of significance and negative coefficient of the *Rhetorical Binary* IV signifies that Hypothesis 4, namely, that *cultural crowdfunding campaigns that employ rhetorical SMC signals are more likely to have more donations than campaigns that do not,* is not confirmed.

Regarding Models 1 through 3, it is worth commenting that all exhibit an R^2 value under .3; though studies in field of crowdfunding have exhibited low results for R^2, around .3 or .4 (Shneor & Vik, 2020), regression results lower than .3 greatly limit what can be affirmed from the data. It is still relevant to mention coefficient valuations and significance levels, as I have done, yet it is important to remember that the ultimate predictive power is weakened by the low R^2 values. Models 4 and 5 feature higher values for R^2, entailing that more can be affirmed from the results.

Table 16

Model 4 Results of the Two-step Linear Regression Analysis

Model 4: DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	1.854***	1.306
SE	0.073	0.861
Dynamic Binary	0.244**	0.165*
SE	0.080	0.080
Rhetorical Binary	-0.143	-0.080
SE	0.089	0.080
Matchfunding Amount		-0.011
SE		0.022
N_Days		-0.270
SE		0.227
Word Count		-0.028
SE		0.248
Average Day Ratio		0.219
SE		0.146
Average Likes		0.268***
SE		0.077
N_Rewards		0.049**
SE		0.017
Randstad Dummy		0.085
SE		0.152
Netherlands Dummy		-0.036
SE		0.058
PrepTime		-0.050
SE		0.060
Age_Artist		0.006
SE		0.003
N_Obs	99	99
R^2 Adjusted	**0.069**	**0.318**
ANOVA F	4.655*	4.800***
AIC	-228.558	-250.155
Schwarz-Bayesian Criterion	-220.773	-216.418
*p<.05, **p<.01, ***p<.001		

5.5. Model 5: Effect of number of dynamic signals on number of donations

Given that Model 4 established a significant and positive relationship between publishing dynamic campaign signals on social media and number of donations or "social" crowdfunding success, it is worth exploring whether the *amount* of dynamic campaign signals similarly affects success. Model 5 (Table 17) tests this hypothesis (3b), evaluating the predictive power of the IV *Number of Dynamic Signals* on the DV *Number of Donations* with and without controls.

A similar phenomenon to Model 4 can be observed, as the AIC and Schwarz Bayesian Criteria offer differing indications of preference. As the control-exclusive regression only explains 7.5% of the variance in *Number of Donations* ($R^2 = .075$, $p = .004$) opposed to the 34.2% of the control-inclusive regression ($R^2 = .342$, $p < .001$), the control-inclusive regression will be preferred for analysis. The *Number of Dynamic Signals* variable has a positive beta-value and significance in both the control-exclusive ($\beta = .309$, $p < .01$) and control-inclusive ($\beta = .262$, $p = .011$) steps of the model, though it notably lessens in significance in the latter. Of the controls, *Average Likes* is most significant with the highest coefficient ($\beta = .303$, $p < .001$), with *Number of Reward Incentives* ($\beta = .044$, $p < .01$) and *Artist Age* ($\beta = .007$, $p = .030$) also exhibiting significance, though this latter control bears a lower coefficient and significance than the IV.

These results are relatively consistent with those from Model 4, and the trend of *Number of Rewards* being among the strongest predictors of *Number of Donations* remains consistent across all models. In light of the results of the IV, and considering that it and the DV have both undergone logarithmic transformation, it is possible to state with 95% confidence that, considering the 34.2% of the variance in *Number of Donations* explained by the regression model, every 1% increase in the number of dynamic signals of a campaign on Instagram predicts a 0.262% increase in the number of donations to the campaign. As such, Hypothesis 3b, that *cultural crowdfunding campaigns that employ more dynamic SMC signals on social media are more likely to have more donations than campaigns that employ less*, is confirmed. Seeing as the results of Model 4 confirmed Hypothesis 3a in both "financial" and "social" success dimensions and Model 5's results confirmed Hypothesis 3b, it is possible to say that Hypothesis 3 is confirmed.

Table 17

Model 5 Results of the Two-step Linear Regression Analysis

Model 5: DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	1.806***	1.429
SE	0.048	0.845
Number of Dynamic Signals	0.309**	0.262*
SE	0.103	0.101
Matchfunding Amount		-0.004
SE		0.021
N_Days		-0.353
SE		0.226
Word Count		-0.058
SE		0.244
Average Day Ratio		0.107
SE		0.150
Average Likes		0.303***
SE		0.072
N_Rewards		0.044**
SE		0.017
Randstad Dummy		0.110
SE		0.148
Netherlands Dummy		-0.035
SE		0.056
PrepTime		-0.045
SE		0.058
Age_Artist		0.007*
SE		0.003
N_Obs	99	99
R^2 Adjusted	**0.075**	**0.342**
ANOVA F	8.944**	5.641***
AIC	-230.126	-254.693
Schwarz-Bayesian Criterion	-224.936	-223.551
*p<.05, **p<.01, ***p<.001		

6. Discussion

The five linear regression models provide empirical insight with which to confirm the hypotheses previously posed. Of the four hypotheses, only the second (H2) and third (H3) were fully confirmed by the regression models. Hypothesis 1b (H1b) might have been confirmed when not factoring for control variables, but the controlled step of Model 2 demonstrates that, when factoring for other control variables, the effect of the IV *Number of Total Signals* on the amount raised becomes insignificant. The first (H1) and fourth (H4) hypotheses, therefore, are clearly not confirmed by the regression models. The implications of these results bear examining in the context of the existing literature.

6.1. Promoting the artist versus the campaign

First, it is worthwhile to discuss the implication of the results of the first two hypotheses. Hypothesis 1a posits that the presence of an artist that is crowdfunding on social media positively affects their crowdfunding campaign's success, with Hypothesis 1b suggesting that the more an artist is present on social media, the greater the effect on the campaign's success. Conversely, Hypothesis 2a states that the presence of the *campaign* itself on social media affects its success, with Hypothesis 2b similarly positing that greater presence of the campaign leads to greater chances at success. These hypotheses are grounded in the notion that the external social capital of an artist (Colombo et al., 2015) is relevant, if not as much as their internal social capital, to the success of their campaign. Similar evidence for artist and campaign presence on Instagram can be found in Putra and Kusumasondjaja (2022) as well as Hong et al. (2015), such that a connection between signals on the crowdfunding platform itself and on external social media platform are interrelated.

The findings of this research develop this connection further; because hypothesis 1 was not confirmed but hypothesis 2 was confirmed, the findings from the regression model suggest that general signals published by crowdfunding artists during their campaigns are largely insignificant to the campaigns' success, but that signals specifically referencing and pertaining to the campaigns do have a significant impact on success. Additionally, the confirmation of Hypothesis 2b entails that publishing more campaign signals also predicts greater chances of campaign success. This could be a consequence of the low-information nature of the CCIs (Caves, 2002), such that familiarity and high-quality evaluations of previous works by an artist does not necessarily translate into quality of a future work. Instead, artists must dedicate resources towards signaling the quality of the new work in order to alleviate transaction costs and receive financial support (Akerlof, 1970).

Another perspective to these results could be that they indicate a disconnect between general engagement of audiences on social media and specific fundraising goals, such that audiences require clear calls-to-action in order to translate passive interest and support for an artist into tangible, financial support. As such, the notion could be put forth that artists may benefit from marketing strategies more centered around the project being crowdfunded than their artistic oeuvre. A campaign-centric promotional strategy carries the additional benefit of being applicable beyond the existing audience of the artist: should a compelling narrative for the campaign be developed, it may be efficient for artists to promote via collaborations with influencers, as well as beyond social media with more grassroots initiatives involving community outreach. Though this expanded marketing strategy may generate positive network effects for artists, in turn growing their following as the campaign grows (Gaenssle & Budzinski, 2020a), it also entails potentially significant increases in humdrum inputs and the weight of economic logics in the artists' work (Caves, 2002; Eikhof & Haunschild, 2006), which may prove prohibitive for some long-tail artists. Thus, though the relevance of external signaling of a campaign to its success is evident, the cost burden of such an approach should be considered carefully by artists, especially considering the already comparatively significant labor costs of cultural crowdfunding itself (Dalla Chiesa, 2022).

6.2. Internal versus external crowdfunding signaling

Having discussed the cost implications of different external signaling strategies, it is worth discussing additional costs to signaling crowdfunding campaigns, namely, the opportunity costs of signaling externally on social media compared to internally on the crowdfunding platform. In Models 1a, 2a, and 3a, that is, the models that tested variables against the DV *Amount Raised,* the controls *Matchfunding Amount, Word Count, Number of Days,* and *Number of Reward Incentives* featured very high significance, at times even higher than the IVs being tested. These results confirm the validity and relevance of the controls in the regressions, as established by previous research (Mollick, 2014; Steigenberger, 2017; Baeck et al., 2017). Additionally, given that they all pertain to signals and parameters within the crowdfunding platform, they may confirm the relative importance of internal social capital and thus internal signaling over external social capital (Colombo et al., 2015). As such, concerning financial success, it is probable that internal aspects of crowdfunding campaigns are and remain primary focuses for artists, whilst external signaling should be a secondary or supplemental concern; the research suggests, for instance, that artists should invest more time and labor in securing matchfunding and developing effective reward incentives than in promoting a campaign on social media, as the predictive significance and power for these internal aspects remains higher than that of external aspects.

There is, however, an important difference in the results observed when *Number of Donations* is the DV (Models 1b, 2b, 3b, 4, and 5), that is, when the dimension of "social" crowdfunding success is being tested as opposed to that of "financial" success. In these models, only the control *Number of Reward Incentives* proved consistently significant, though very highly so. This, along with the confirmation of Hypothesis 2, Hypothesis 3a ("*cultural crowdfunding campaigns that employ dynamic SMC signals on social media are more likely to have more donations than campaigns that do not*"), and Hypothesis 3b ("*cultural crowdfunding campaigns that employ more dynamic SMC signals on social media are more likely to have more donations than campaigns that employ less*"), suggests that external campaign signaling is more relevant than many of the internal controls to its social success. Given that crowdfunding is first and foremost a financing strategy, it is likely that financial success is a primary target for most, if not all, crowdfunding artists, whereas social success is a secondary target. It is pertinent, however, to consider several contextual factors regarding these results.

As has been described in earlier chapters, important shifts in European funding approaches and framing have occurred (Littoz-Monet, 2012; Loots et al., 2024), such that austerity regarding cultural funding is increasing in countries such as the Netherlands (Loots et al., 2024). It is in this context that crowdfunding and, by extension, matchfunding, emerged as viable funding strategies for cultural projects (Loots et al., 2024; Baeck et al., 2017). Should austerity measures continued to be pushed, it is not unimaginable that public funds for culture continue to diminish, which may affect the availability of matching funds for crowdfunding. In this scenario, securing matchfunding may prove a more costly focus for artists, in which case increasing the number of donations may become a more cost-effective strategy. In this framing, designing reward incentives and setting appropriate campaign durations, but both of these aspects essentially fixed costs: careful planning of reward incentives and campaign durations mean they may only need to be done once. This entails that activities with significant marginal costs are updates to the campaign's page and its social media signaling; therefore, should costs to obtaining matchfunding become prohibitive under increasing austerity, artists may be incentivized to investing greater resources towards external signaling, as its significance to "social" success in the form increasing donations may translate to more significant "financial" success. As it stands, in the immediate context, external signaling is largely secondary to internal signaling for artists.

6.3. Impact of signal type and content on crowdfunding success

Models 4 and 5 represent regressions run on the subsample data (n=99), which was derived randomly from all cases that did promote the campaign on social media, so as to test Hypotheses 3a, that signaling a campaign on social media with dynamic signals led to more donations, 3b, that a greater amount of dynamic campaign signals led to more donations, and 4, that using rhetorical signals to signal a campaign on social media led to more donations. As discussed in the Findings chapter, the results of Models 4 and 5 meant that Hypothesis 3 was fully confirmed, whereas Hypothesis 4 was not confirmed. The implications of these results bear discussing in detail.

Dynamic signals proved to be significant positive predictors of donation numbers, both in their general application as well as in the number of dynamic signals published. This corresponds to the observations of Grewal et al. (2021) and Keating and Latané (1976) that richer media is more efficient and effective at information transmission than leaner media. In the context of this study, it suggests that signaling crowdfunding through videos significantly and positively affect the campaign's "social" success. There may be additional explanations behind this observation, namely, in music's temporal nature as a medium (Throsby, 2010), meaning that similar observations may be observed in industries like theater and dance, but industries corresponding to media that is not dependent on time to experience may exhibit different results.

It bears discussion, however, on why tests of rhetorical campaign signaling on number of donations were consistently insignificant. An argument could be made that, even with the peculiarities of the CCIs (Caves, 2002), substantive signals are more significant signals to campaign success, as traditional signaling theory suggests (Bergh et al., 2014); alternatively, the argument could be made that, because crowdfunding is a high-noise environment (Ahlers et al., 2015), whether and how campaigns mixed rhetorical and substantive signals in their signal portfolios are more relevant and significant indicators (Steigenberger & Wilhelm, 2018). A cursory t-test of a *Substantive Binary* variable, that is, a dummy variable regarding whether or not a campaign publishes at least one substantive signal, however, returns insignificant results ($p = .079$). Similarly, a t-test of a *Mixed Substantive/Rhetorical Binary* variable, that is, a variable describing whether or not a campaign publishes both substantive and rhetorical signals, also returns insignificant results ($p = .158$). As such, there is little evidence in the data that different configurations might yield different results.

Instead, a different explanation seems plausible. As Steigenberger and Wilhelm (2018) discuss, in bundled signal portfolios, it is possible that rhetorical signals may positively or negatively affect the impact of substantive signals. As such, it seems evident from the data that the *classification* of the signal is largely irrelevant; instead, the specific, qualitative information that the signal is communicating may lead to a difference in success. From this perspective, whether or not a project posts images of reward incentives on social media, or whether they provide information on how to donate and updates on campaign progress, is largely irrelevant, should the content of the message being transmitted not matter to consumers. This resonates with what was discussed in Section 6.1, such that *how* campaigns are signaled appears to be of central importance. In this regard, the notion that artists benefit from having a compelling narrative for their campaign, as well as clear calls-to-action is once again relevant. As such, the importance of having a well-constructed campaign, with clear internal incentives and messages, is once again highlighted, suggesting that micro-donors donate to campaigns because they resonate with the project, not because they were signaled to. In any case, more nuanced study of campaign signals, with room for some normative interpretation of its semantic content, is necessary in order to confirm these points.

7. Conclusions

This study set out to find the extent to which social media signaling can positively impact the success of crowdfunding campaigns, as well as to determine which types of social media signals most impact campaigns' success. First, the relevant context was examined, evaluating how non-commercial musicians in the CCIs face unique and steep challenges towards commercialization, how recent technological disruptions have limited the avenues of revenue generation for musicians, and how crowdfunding represents a relatively new avenue for cultural fundraising rooted in altruism and non-pecuniary valuations of culture. Second, preceding literature was reviewed, and the framework rooted in signaling theory was adopted, with aspects of media richness theory supplementing the research frame, and four hypotheses were posited. The methodology of the research was outlined, utilizing quantitative processes and two-step multivariate linear regression models to generate clear analytical conclusions from the data collected. These results were described, first focusing on the confirmation of hypotheses; finally, the findings were interpreted within the broader research context and compared to those of the body of literature.

Of the four hypotheses tested, only the second, pertaining to the influence and degree that signaling a crowdfunding campaign on social media has on its success, and third, pertaining to the influence and degree thereof that publishing dynamic signals of a crowdfunding campaign on social media has on its number of donations, were confirmed by the regression models. The first, regarding the impact of crowdfunding artists' generic signaling on social media over the success of their campaigns, and fourth, on the effect of rhetorical signaling of crowdfunding campaigns on their success, were not confirmed by the findings of this research. These results may be interpreted in the following ways:

- Signaling an artist leading a crowdfunding campaign is not enough to predict success, but signaling the campaign does lead to greater chances of success, and
- Signaling crowdfunding campaigns with dynamic signals like videos improves the chances the campaign will succeed, but
- Social media signaling is generally a weaker predictor of campaign success than internal crowdfunding platform factors, like securing matchfunding, number of reward incentives offered, and campaign duration; finally,

- The *message* transmitted by campaign signals is more significant than the specific content type of the signals, such that audiences likely resonate with campaigns they find compelling rather than with any campaign they see.

Thus, this research reveals important implications for musicians, especially non-commercial musicians. If the costs of investing in signaling campaigns on social media are not prohibitive, they are incentivized to pursue this avenue, as it is statistically likely to positively affect the success of their campaigns. Additionally, should the current climate of austerity continue, such that funds become even scarcer, the relative opportunity cost of external campaign signaling may decrease, incentivizing more artists to pursue it as part of a general campaign strategy. For artists seeking to develop an audience as a primary concern, additionally, signaling their campaign on external social media may be a very effective strategy to this end. As funding options in the CCIs continue to change, artists will need to pursue different economic-logic strategies to ensure viability, which may entail simultaneous leveraging of external and internal social capital for fundraising initiatives like crowdfunding campaigns.

7.1. Limitations and future study

This research faced many limitations, primarily those consisting of factors beyond the control of the research. First among these is due to the nature of an analysis of social media signals for projects that are not currently active, as this entails that factors like deletion of old posts and accounts may hinder the precision of the data collected. It is completely possible that an artist may have published extensive signals for their campaign on Instagram whilst it was going on and later decided to delete it; it is impossible to determine whether this happened without asking the artist directly, making the scale of this research prohibitive. This problem is additionally expressed in the fact that a common manner of posting on Instagram is completely inaccessible to the researcher, namely, Instagram stories. As stories are videos that are automatically deleted 24 hours after publishing, any story published during these campaigns is completely inaccessible, as years have passed.

The research's focus on a single crowdfunding in the Netherlands may also limit the applicability of findings to other contexts or regions. Replicating this research with crowdfunding in different countries, as well as conducting a comparative analysis across platforms, could be viable and interesting avenues for further research. The dynamics of how social media influences funding is also highly dependent on location, given that the userbases of social media platforms themselves can vary greatly across countries. The same can be said for funding, entailing that a non-commercial musician on a Dutch crowdfunding platform may have significantly different resources at their disposal than, say, a non-commercial musician in the United States or Japan. As such, comparative analyses across locations and social media platforms are relevant and possible avenues for further study.

An additional limitation to the research was the available time window for data collection and completion. As this thesis must be prepared and researched in a manner of months, there was insufficient time to compare crowdfunding signals on several different social media platforms, something that would have likely greatly enriched the analysis and findings. This limitation, however, provides a clear follow-up for future research, with there being potential for a comparative analysis of crowdfunding signals across different social media platforms like Facebook, YouTube, and TikTok. Additionally, a future longitudinal study of crowdfunding social media signaling seems promising, as it may allow for tracking real-time effects on donations from specific social media signals. This would, of course, necessitate significant time and resources, but may yield powerful findings regarding the specific causality of social media signaling on crowdfunding. Finally, there is room for a mixed-methods or qualitative approach to social media signaling of crowdfunding campaigns, which would allow for an in-depth, normative exploration of which types of signal content are most effective.

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Appendix A
Coding Guidebook

In this appendix, the process for coding both the cases of the large sample (n=595) and the signals later grouped according to campaign in the subsample (n=99). First, the coding instructions for the large sample will be outlined.

A1. Guide for Coding Campaigns (n=595)

The purpose of this methodology is to enumerate how the variables *General Signaling Binary, Campaign Signaling Binary, Number of Total Signals,* and *Number of Campaign Signals* were derived. Each case was coded at a time, with the variables each coded in the sequence presented above. As such, the process for each will be outlined.

A1.1. General Signaling Binary

First, go to the link of the crowdfunding campaign of the case in question. If there is a hyperlink to an Instagram page listed, click on that link. If it links to an existing Instagram page, then the crowdfunding artist of this case has an Instagram page; therefore, the case has a *General Signaling Binary* value of 1. The next variable may now be coded. If the hyperlink returns a dead page or an error statement from Instagram, continue to the next paragraph.

Check to see if an artist name is provided in the description of the campaign. If so, search for said artist on Instagram. If there is an account listed under the search entry, click to view its page. If the images posted by the account or the profile picture appear to have the same people as subjects, or a logo that is also present on the crowdfunding page as images, then this is very likely the artist's Instagram page; therefore, this case has a *General Signaling Binary* of 1. If it is not possible to make a connection with images, check for textual descriptions on the Instagram page that are similar to that of the crowdfunding page, such as instruments played, genre descriptions, cultural activities, or otherwise. If there is such a description, then *General Signaling Binary* is 1. If not, it is unlikely that this is the artist. Continue to the next paragraph.

Check the name of the project host in the crowdfunding campaign page. Conduct the same process as the previous paragraph but searching with this name. If a connection can be made with an Instagram page, then *General Signaling Binary* is 1. If not, conduct the same Instagram search with the name of the project. If it is not found by this point, the value of

General Signaling Binary is set as 0 for this case. At any point in this process, if any Instagram page is found but has private access, then it cannot be considered that the artist has an Instagram presence, as the privacy filter makes assessment impossible without requesting to follow the artist. Because this information is not readily accessible, additionally, the *General Signaling Binary* must be 0. It is possible to search for alternative accounts of the artist or the project. Having completed the coding of *General Signaling Binary,* continue to the next subsection.

A1.2. Campaign Signaling Binary

If the *General Signaling Binary* value of the case was determined to be 0, then *Campaign Signaling Binary* must necessarily be set at 0. Otherwise, scroll on the artist page down until the first signal made during the campaign is found. This can be ascertained by entering Instagram on a computer as opposed to a phone and clicking on a post. Below the like count, the date of posting is available. Figure A1 presents an example of this, in very small print at the bottom right of the image.

Figure A1

Example location of Date on Instagram Publication

If there are no posts made during the time period the campaign was active, then the *Campaign Signaling Binary* must be 0. The next variable may now be coded. If there are posts made during the duration of the campaign, then each post must be checked for any reference to the campaign. These references include the Voordekunst logo, any mention of Voordekunst in the description, as hashtags, profile tags, or simple text. The Vdk abbreviation is also indicative. Barring references to the platform, explicit mentions of the word "crowdfunding" can count. Barring this, mentions of percentage of completion, percentage amounts to go, days left (that align with the campaign's timing), the mention of the word "donate" or "doneer" in Dutch, the mention of "support" or "steun" in Dutch, or mentions of a link in bio can serve as identifiers of a campaign signal. They may be present in the signal itself or the textual description of the signal. These latter signs, however, should be approached with caution. Mention of the link in bio, for instance, is insufficient confirmation that a post is a campaign signal, unless the link in the biography of the artist links to the crowdfunding platform page, or unless there are additional indicators of crowdfunding like the "doneer" and "steun ons" language. If any of these signs are present in any signal made during the campaign, then *Campaign Signal Binary* is 1 for this case. Otherwise, it has a value of 0.

A1.3. Number of Total Signals

If *General Signal Binary* is 0, then *Number of Total Signals* cannot be coded. This case must be excluded from the count, as the value of *General Signaling Binary* is entailing that the crowdfunding artist has no presence on Instagram. If they are coded as 0, it suggests they do have an Instagram presence but have simply not posted. If the *General Signaling Binary* is 1, then it is possible to code *Number of Total Signals.* Simply count the number of posts made during the time period the campaign was active. Whatever that value is, that is the *Number of Total Signals* value. Once completed, proceed to the final variable.

A1.4. Number of Campaign Signals

If the *General Signaling Binary* is 1, then *Number of Campaign Signals* can be coded. If *General Signaling Binary* is 1, but *Campaign Signaling Binary* is 0, then the *Number of Campaign Signals* is 0. If *Campaign Signaling Binary* is 1, then the following steps should be conducted. Count the number of posts made during the time period the campaign was active that reference the crowdfunding campaign. The index by which to determine whether a post references the campaign is the same elaborated in subsection A1.2. If no posts reference the campaign, then *Number of Campaign Signals* is 0. Otherwise, the value of *Number of Campaign Signals* is equal to the number of signals referencing the campaign during the time period it was active. For ease of coding, personal, private notes should be made with the link to each campaign signal, as it may be relevant for the next stage of coding.

A2. Guide for Coding Signals (n=527)

The subsample selects 99 campaigns randomly from the pool of campaigns with *Campaign Signaling Binary* values of 1. In the case of this research, this subsample involved a total of 527 signals. The following is a guide on how to code each of those signals for the variables according to medium and content. Each one of these codes informs variables used in the subsample.

A2.1. Coding according to medium

Each signal has an option to be one of two types of medium: static, or dynamic. As such, go to the link of the signal in question. If the signal is a static image, then the medium code is reported as 0 (0 pertaining to "static" medium posts). If the signal is a static image, but with audio, then it is coded as 1. Similarly, if the signal is a video file, then it is coded as 1. If the image involves several discrete images or videos, its code is assigned according to the first file in the set: if it is a static image, then the value is 0; if it is a video, then the value is 1. Code each signal in this manner.

A2.2. Coding according to content

Each signal is assigned a code according to whether it transmits rhetorical or substantive content. As this valuation is highly subjective, and as most signals showcase aspects of both, the criteria for classification have been set up so that any evidence of rhetoric forces the signal to be classified as rhetorical. Note that the description has been excluded from all of these evaluations; only the signal image and audio will be used. If there is any written mention of the crowdfunding project, such as the logo of the platform, a countdown of how many days left, or a percentage indicator of funds raised, then the signal is coded as rhetorical. If the image is dynamic, and there is audio of someone speaking, if they mention calls to support, donate, or any other signals referencing the crowdfunding project, then it is a rhetorical signal. Calls to help are included among these.

Exceptions to these principles include testimonials from donors, such that there is no overt use of the word "crowdfunding," and logos from funding bodies that have provided matching funds. However, if the other signs of rhetorical content are present, the signal must be coded as rhetorical.

A3. Guide for Grouping Signal Codes in Subsample (n=99)

Having coded each campaign signal published by the cases in the subsample, the results can be used to generate variables per campaign in the subsample. The variables *Dynamic Binary* and *Rhetorical Binary,* for instance, are assigned values of 1 should any campaign signals employed by the case during the campaign period have a medium value or a content value of 1, respectively. The variable *Number of Dynamic Signals* corresponds to the amount of campaign signals that were dynamic-medium signals. The variable, *Average Likes,* for instance, is calculated by finding the sum of all likes on campaign signals published on Instagram during the campaign, divided by the *Number of Campaign Signals* value.

The *Average Day Ratio* involves a slightly more complex process. First, the amount of days after the beginning of a campaign a signal was published is recorded for each campaign signal. This amount is divided by the *Number of Days* value, to get a decimal value between 0 and 1 representing when the signal was published over the course of the campaign. Then, the average value for each campaign is found, summing the decimal value for each signal, then dividing by the number of campaign signals. The manner in which all other values were calculated should be clear.

Appendix B

List of Variables

This appendix includes a comprehensive list of all variables used in the study, along with a brief description of what they represent, what their measurement levels are, and in which models and samples they were applied. The parenthetical (log) indicates that a variable was logarithmically transformed. All logarithmic transformations utilize the common logarithm, or log-base-10, adding 1 to the value of the variable before log-transforming to ensure that variables with value 0 before transforming would have value 0 after transforming.

B1. Dependent variables

a. ***Amount Raised*** (log). The total amount of funds raised by a crowdfunding project (in euros). Provided by the crowdfunding platform. Ratio variable. Utilized in Models 1a, 2a, and 3a. Utilized in the large sample (n=595) and subsample (n=99).
b. ***Number of Donations*** (log). The total number of donations received by a crowdfunding project. Provided by the crowdfunding platform. Ratio variable. Utilized in Models 1b, 2b, 3b, 4, and 5. Utilized with data from the large sample (n=595) and subsample (n=99).

B2. Independent variables

c. ***General Signaling Binary***. Indicates whether the artist crowdfunding in question is present on Instagram in the form of an Instagram page. Dummy variable. Utilized in Models 1a and 1b. Utilized in the large sample (n=595). Referenced in Table 5 as Dummy_GeneralSignal.
d. ***Campaign Signaling Binary.*** Indicates whether crowdfunding campaign in question is signaled on Instagram at least once in the form of a published post. Dummy variable. Utilized in Models 1a and 1b. Utilized in the large sample (n=595). Referenced in Table 5 as Dummy_CampaignSignal.
e. ***Dynamic Binary.*** Indicates whether a crowdfunding campaign published at least one dynamic campaign signal on Instagram. Dummy variable. Utilized in Model 4. Utilized in the subsample (n=99). Referenced in Table 5 as Dummy_DynamicSignal.

f. ***Rhetorical Binary.*** Indicates whether a crowdfunding campaign published at least one rhetorical campaign signal on Instagram. Dummy variable. Utilized in Model 4. Utilized in the subsample (n=99). Reference in Table 5 as Dummy_RhetBinary.

g. ***Number of Total Signals*** (log)**.** The total amount of signals published by a crowdfunding artist on Instagram in the time period that the campaign was active. Ratio variable. Utilized in Models 2a and 2b. Utilized in the large sample (n=595).

h. ***Number of Campaign Signals*** (log). The total amount of signals published by a crowdfunding artist on Instagram in the time period that the campaign was active, that specifically signal the campaign. Ratio variable. Utilized in Models 3a and 3b. Utilized in the large sample (n=595).

i. ***Number of Dynamic Signals*** (log). The total amount of dynamic-medium campaign signals published by a crowdfunding artist on Instagram in the time period that the campaign was active. Ratio variable. Utilized in Model 5. Utilized in the subsample (n=99).

B3. Control variables

Control variables included the binary variables *Randstad Dummy* (j) and *Netherlands Dummy* (k), along with the following continuous variables: *Matchfunding Amount* (l), *Number of Days* (m), *Word Count* (n), *Number of Reward Tiers* (o), *Preparation Time* (p), *Artist Age* (q), *Average Day Ratio* (r), and *Average Likes* (s).

j. ***Randstad Dummy.*** Indicates whether the crowdfunding artist is based in the Randstad. Dummy variable. Utilized in all models. Utilized in both sample groups.

k. ***Netherlands Dummy.*** Indicates whether the crowdfunding artist is originally from the Netherlands. Dummy variable. Utilized in all models. Utilized in both sample groups.

l. ***Matchfunding Amount*** (log). The amount of funds raised by a crowdfunding campaign presented by a public or private funding body (in euros). Ratio variable. Utilized in all models. Utilized in both sample groups.

m. ***Number of days*** (log). The number of days a crowdfunding campaign was active. Ratio variable. Utilized in all models. Utilized in both sample groups.

n. ***Word Count*** (log). The number of words on a crowdfunding campaign's page on the crowdfunding platform. Ratio variable. Utilized in all models. Utilized in both sample groups.

o. ***Number of Reward Incentives***. Also called "Number of Reward Incentives" or "N_Rewards." Number of reward incentive tiers offered by the crowdfunding campaign on the crowdfunding platform page. Ratio variable. Utilized in all models. Utilized in both sample groups.

p. ***Preparation Time*** (log). The number of days between when a crowdfunding page was made for a campaign, and when the campaign became active. Ratio variable. Utilized in all models. Utilized in both sample groups.

q. ***Artist Age*** (log in large sample n=595, untransformed in subsample n=99). The age of the crowdfunding artist, in years. Ratio variable. Utilized in all models. Utilized in both sample groups.

r. ***Average Day Ratio.*** Refers to the average moment campaign signals were posted for a campaign, represented as a decimal value between 0 (start of campaign) and 1 (end of campaign). Ratio variable. Utilized in models 4 and 5. Utilized in subsample (n=99).

s. ***Average Likes.*** Refers to the average number of likes on campaign signals published by a crowdfunding artist. Ratio variable. Utilized in models 4 and 5. Utilized in subsample (n=99).

Appendix C

List of Tables

Table C1

Kirmani & Rao's signal typology according to default and sale independence (2000).

Characteristics of Signals

	Default-Independent Signals		Default-Contingent Signals	
	Sale-Independent	Sale-Contingent	Revenue-Risking	Cost-Risking
Examples	Advertising Brand name Retailer investment in reputation	Low introductory price Coupons Slotting allowances	High price Brand vulnerability	Warranties Money-back guarantees
Characteristic	Publicly visible expenditures before sale	Private expenditures during sales transaction	Future revenues at risk	Future costs at risk
Repeat purchase	Is important	Is important	Is important	Irrelevant
Monetary loss	Fixed	Variable or semi-variable	In the future	In the future
Secondary benefits	Buyer does not receive direct utility	Buyer receives direct utility	Buyer does not receive direct utility	Buyer receives direct utility
Appropriate when	Buyer cannot be identified easily	Buyer can be identified easily	Frequently purchased nondurables	Durables
Potential for abuse by consumer	None	High	None	High

Table C2

Typology of SMC signals. Enriched from Steigenberger & Wilhelm, 2018.

SIGNAL MEDIUM: The medium of a signal.	SIGNAL CONTENT: The nature of the content of a signal. 1. Rhetorical	2. Substantive
a. Text-based	The signal involves primarily written information about the project.	The signal primarily involves an external link to a substantive signal of the project, like a video or image.
b. Static Image	The signal is an image containing information on the project (e.g. a concert tour poster containing only dates and branding images).	The signal is a static image of content from the project.
c. Audio with static image	The signal is an audio recording containing information on the project, accompanied with an image (e.g. an artist interview about the project)	The signal is an audio recording of content from the project, accompanied by an image (e.g. a sneak peek of a single or a new song)
d. Video	The signal is a video primarily containing information about the project (e.g. a call-to-action post, a video interview of artists involved)	The signal is a video primarily composed of content from the project.

Table C3

Simplified typology of SMC signals for Instagram.

SIGNAL MEDIUM: The medium of a signal.	SIGNAL CONTENT: The nature of the content of a signal. 1. Rhetorical	2. Substantive
a. Static	The signal is an image containing information on the project (e.g. a concert tour poster containing dates and branding images).	The signal is a static image of content from the project.
b. Dynamic	The signal is a video or a static image with audio primarily containing information about the project (e.g. a call-to-action post, a video interview of artists involved)	The signal is a video or a static image with audio primarily composed of content from the project.

Table C4

Summary of data groups of this research.

	DATA GROUP		
	1. Large sample	**2. Subsample**	**3. Signals of subsample**
Description	Sample composed of all musical crowdfunding campaigns on Dutch cultural crowdfunding platform from 2021 to 2023 (provided by platform).	Sample with cases randomly selected from large sample for more in-depth analysis of campaign signals.	Group composed of all Instagram signals posted by the cases in the subsample that referenced crowdfunding campaigns.
Size	n=595	n=99	n=527
Relevant data	Instagram signal data per campaign (e.g. number of signals, number of signals per campaign), crowdfunding campaign data (e.g. amount raised)	Grouped signal data from "signals of subsample" according to campaign (e.g. total/ mean dynamic signals per campaign, total/ mean likes per campaign), crowdfunding campaign data	SMC signal typology coding per campaign signal, engagement (e.g. signal medium, signal content type), engagement data per signal (number of likes, comments)
Relevant hypotheses	H1, H2	H3, H4	

Table C5

Descriptive Data of Binary Variables

(n=595)	**Frequency Value: 0**	**Frequency Value: 1**
Dummy_GeneralSignal	0.156	0.844
Dummy_CampaignSignal	0.41	0.59
Dummy_Randstad	0.548	0.452
Dummy_Netherlands	0.054	0.946
(n=99)		
Dummy_DynamicSignal	0.273	0.727
Dummy_RhetSignal	0.202	0.798
Dummy_Randstad	0.566	0.434
Dummy_Netherlands	0.04	0.96

Table C6

Descriptive Data of Continuous Variables

(n=595)	Min	FirstQuart	Median	Mean	ThirdQuart	Max	StdDev
AmountRaised	0	3613	5601	6874.55	8327	102455	6658.799
N_Donations	2	50	81	97.28	112	1925	106.820
N_TotalSignals*	0	1	5	7.29	10	65	8.483
N_CampaignSignals*	0	0	2	3.57	5	40	4.956
AmountMF	0	0	750	1110.31	1400	43000	2192.857
N_Days	8	34	37	40.43	44	105	12.468
WordCount	523	1006	1193	1291.46	1460	3601	433.332
PrepTime	0	14	30	56.1	64	640	78.343
N_Rewards	1	6	7	7.3	8	18	2.086
Age_Artist	17	30	37	49.04	49	82	13.147
(n=99)							
AmountRaised	100	4070	6650	7208.35	9065	32298	4564.303
N_Donations	3	56	91	104.10	127	728	86.088
N_DynamicSignals	0	0	1	2.01	3	20	2.901
AmountMF	0	350	750	1199.92	750	6325	1315.046
N_Days	8	34	37	40.18	43	96	12.093
WordCount	762	1082	1267	1416.92	1704	3118	505.364
PrepTime	0	14	33	62.95	80.5	632	83.886
N_Rewards	3	6	7	7.64	8.75	15	2.183
Age_Artist	19	29	36	36.77	33	73	10.085
Avg_DayRatio	0	0.29	0.4762	0.4382	0.562	0.8824	0.1941
Avg_Likes	2	18.67	39	58.8	73	552	73.77

*Results are only reported for campaigns whose artists have an instagram page that is readily available, that is, not private (n=502).

Table C7

Descriptive Data of Continuous Variables post-Logarithmic Transformation

(n=595)	Min	FirstQuart	Median	Mean	ThirdQuart	Max	StdDev
Log_AmtRaised	0	3.5580	3.7483	3.7168	3.9205	5.01	0.369
Log_NDonations	0.48	1.7076	1.9138	1.8793	2.0531	3.28	0.31897
Log_NTotalSignals*	0	0.3010	0.7782	0.7095	1.0414	1.82	0.45181
Log_NCampaignSigs*	0	0	0.4771	0.47	0.7782	1.61	0.39877
Log_AmountMF	0	0	2.8756	2.0371	3.1464	4.63	1.46898
Log_N_Days	0.95	1.5441	1.5798	1.6013	1.6532	2.06	0.11433
Log_WordCount	2.72	3.0030	3.0770	3.0905	3.1647	3.62	0.13170
Log_PrepTime	0	1.1761	1.4914	1.5024	1.8129	2.81	0.46885
Log_Age_Artist	1.26	1.4914	1.5798	1.5919	1.6990	1.92	0.13539
(n=99)							
Log_AmtRaised	2	3.6097	3.8229	3.77	3.9574	4.51	0.33180
Log_NDonations	0.6	1.7559	1.9638	1.9169	2.1072	2.86	0.32198
Log_NDynamicSigs	0	0	0.301	0.3579	0.6021	1.32	0.30286
Log_AmountMF	0	2.5453	2.8756	2.3834	3.2177	3.8	1.31454
Log_N_Days	0.95	1.5441	1.5798	1.5975	1.6435	1.99	0.12543
Log_WordCount	2.88	3.0346	3.1031	3.1277	3.2317	3.49	0.14149
Log_PrepTime	0	1.1761	1.5315	1.5467	1.9191	2.80	0.49841
Log_Avg_Likes	0.48	1.2937	1.6021	1.5849	1.8692	2.74	0.41125

*Results are only reported for campaigns whose artists have an instagram page that is readily available, that is, not private (n=502).

Table C8

Pearson Correlation Matrix for Variables Used in Model 1

(n=595)	Amt_Raised	N_Donations	GenSignal Binary	Campaign Signal Binary	Amount MF	N_Days	WordCount	N_Rewards	Randstad Dummy	Netherlands Dummy	PrepTime	(Log) Age_Artist
Amt_Raised	1											
N_Donations	0.767	1										
GenSignal Binary	0.084	0.05	1									
Campaign Signal Binary	0.220	0.219	0.441	1								
AmountMF	0.285	0.121	0.111	0.123	1							
N_Days	0.16	0.056	0.008	-0.002	0.097	1						
WordCount	0.333	0.258	0.095	0.219	0.108	-0.024	1					
N_Rewards	0.392	0.394	0.148	0.253	0.121	-0.005	0.525	1				
Randstad Dummy	0.036	0.026	0.053	0.057	0.119	-0.058	0.126	0.026	1			
Netherlands Dummy	0.022	0.039	0.050	0.013	0.226	-0.033	-0.051	-0.048	0.217	1		
PrepTime	0.041	0.019	-0.010	0.072	0.028	0.047	0.090	0.039	-0.002	0.034	1	
(Log) Age_Artist	0.052	0.051	-0.184	-0.090	-0.060	0.077	-0.090	-0.064	-0.135	0.021	-0.062	1

Table C9

Pearson Correlation Matrix for Variables Used in Models 2 and/or 3

(n=595)	Amt_ Raised	N_Donat ions	N_Posts Total	N_Posts Campaign	Amount MF	N_Days	Word Count	N_ Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	(Log) Age_Arti st
Amt_Raised	1											
N_Donation s	0.767	1										
N_Posts Total	0.219	0.189	1									
N_Posts Campaign	0.303	0.335	0.775	1								
AmountMF	0.285	0.121	0.144	0.170	1							
N_Days	0.16	0.056	0.194	0.082	0.097	1						
WordCount	0.333	0.258	0.182	0.270	0.108	-0.024	1					
N_Rewards	0.392	0.394	0.219	0.319	0.121	-0.005	0.525	1				
Randstad Dummy	0.036	0.026	0.025	0.035	0.119	-0.058	0.126	0.026	1			
Netherlands Dummy	0.022	0.039	-0.057	0.007	0.226	-0.033	-0.051	-0.048	0.217	1		
PrepTime	0.041	0.019	-0.018	0.01	0.028	0.047	0.090	0.039	-0.002	0.034	1	
(Log) Age_Artist	0.052	0.051	0.068	0.036	-0.060	0.077	-0.090	-0.064	-0.135	0.021	-0.062	1

Table C10

Pearson Correlation Matrix for Variables Used in Model 4

(n=99)	N_Donations	Dynamic Binary	Rhet Binary	Amount MF	N_ Days	Word Count	Avg Day Ratio	Avg Likes	N_ Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	Age_ Artist
N_Donations	1												
Dynamic Binary	0.252	1											
Rhet Binary	-0.016	0.483	1										
AmountMF	0.06	0.285	0.034	1									
N_Days	-0.238	-0.021	0.032	-0.1	1								
WordCount	0.210	0.172	0.053	0.042	-0.039	1							
Avg DayRatio	0.147	0.101	0.142	0.033	0.041	0.117	1						
Avg Likes	0.320	0.152	-0.115	-0.002	-0.153	-0.017	-0.126	1					
N_Rewards	0.441	0.054	0.008	0.094	-0.217	0.552	0.106	0.014	1				
Randstad Dummy	0.034	0.171	0.035	0.095	-0.061	0.094	0.092	0.157	0.006	1			
Netherlands Dummy	0.051	0.220	0.025	0.197	-0.104	-0.024	-0.152	0.094	-0.034	0.180	1		
PrepTime	-0.207	-0.164	-0.043	-0.05	0.162	0.088	0.02	0.027	-0.184	0.159	-0.126	1	
Age_ Artist	0.162	-0.075	-0.029	-0.061	0.017	0.034	0.198	-0.371	0.300	-0.063	-0.286	-0.087	1

Table C11

Pearson Correlation Matrix for Variables Used in Model 5

(n=99)	N_Donations	N_ Dynamic Signals	Amount MF	N_ Days	Word Count	Avg Day Ratio	Avg Likes	N_ Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	Age_ Artist
N_Donations	1											
N_Dynamic Signals	0.291	1										
AmountMF	0.06	0.151	1									
N_Days	-0.238	0.119	-0.1	1								
WordCount	0.210	0.280	0.042	-0.039	1							
Avg DayRatio	0.147	0.331	0.033	0.041	0.117	1						
Avg Likes	0.320	0.005	-0.002	-0.153	-0.017	-0.126	1					

Table C11 (continued)

Pearson Correlation Matrix for Variables Used in Model 5

(n=99)	N_Donations	N_ Dynamic Signals	Amount MF	N_ Days	Word Count	Avg Day Ratio	Avg Likes	N_ Rewards	Randstad Dummy	Netherlands Dummy	Prep Time	Age_ Artist
N_Rewards	0.441	0.149	0.094	-0.217	0.552	0.106	0.014	1				
Randstad Dummy	0.034	0.113	0.095	-0.061	0.094	0.092	0.157	0.006	1			
Netherlands Dummy	0.051	0.081	0.197	-0.104	-0.024	-0.152	0.094	-0.034	0.180	1		
PrepTime	-0.207	-0.136	-0.05	0.162	0.088	0.02	0.027	-0.184	0.159	-0.126	1	
Age_ Artist	0.162	-0.030	-0.061	0.017	0.034	0.198	-0.371	0.300	-0.063	-0.286	-0.087	1

Table C12

Index and Description of Linear Regression Models

Model	Hypotheses	Sample	DVs	IVs
1	H1a, H2a	Large (n=595)	*Amount Raised* (1a), *Number of Donations* (1b)	*General Signaling Binary, Campaign Signaling Binary*
2	H1b	Large (n=595)	*Amount Raised* (2a), *Number of Donations* (2b)	*Number of Total Signals*
3	H2b	Large (n=595)	*Amount Raised* (3a), *Number of Donations* (3b)	*Number of Campaign Signals*
4	H3a, H4	Subsample (n=99)	*Number of Donations*	*Dynamic Binary, Rhetorical Binary*
5	H3b	Subsample (n=99)	*Number of Donations*	*Number of Dynamic Signals*

Table C13

Model 1 Results of the Two-step Linear Regression Analysis

Model 1a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 1b:** DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	3.633***	0.756	(Intercept)	1.836***	0.434
SE	0.043	0.433	SE	0.037	0.394
GenSignal Dummy	-0.019	-0.032	GenSignal Dummy	-0.057	-0.060
SE	0.051	0.046	SE	0.044	0.042
Campaign Signal Binary	0.170***	0.084**	Campaign Signal Binary	0.158***	0.097***
SE	0.033	0.031	SE	0.029	0.028
Matchfunding Amount		0.055***	Matchfunding Amount		0.012
SE		0.009	SE		0.009
N_Days		0.444***	N_Days		0.132
SE		0.116	SE		0.105
Word Count		0.448***	Word Count		0.156
SE		0.119	SE		0.108
N_Rewards		0.047***	N_Rewards		0.051***
SE		0.008	SE		0.007
Randstad Dummy		-0.001	Randstad Dummy		-0.001
SE		0.027	SE		0.025
Netherlands Dummy		-0.005	Netherlands Dummy		0.067
SE		0.061	SE		0.056
PrepTime		0.001	PrepTime		-0.008
SE		0.028	SE		0.026
Age_Artist		0.248*	Age_Artist		0.188*
SE		0.100	SE		0.091

Table C13 (continued)

Model 1 Results of the Two-step Linear Regression Analysis

Model 1a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 1b:** DV Number of Donations *Predictors*	**IVs**	**Control**
N_Obs	595	595	*N_Obs*	595	595
R^2 Adjusted	**0.045**	**0.255**	***R^2 Adjusted***	**0.047**	**0.178**
ANOVA F	15.100***	21.352***	***ANOVA F***	15.690***	13.878***
AIC	-1210.996	-1350.793	***AIC***	-1383.204	-1463.310
Schwarz-Bayesian Criterion	-1197.830	-1302.519	***Schwarz-Bayesian Criterion***	-1370.043	-1415.054

*p<.05, **p<.01, ***p<.001

Table C14

Model 2 Results of the Two-step Linear Regression Analysis

Model 2a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 2b:** DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	3.614***	0.797	(Intercept)	1.788***	0.163
SE	0.027	0.427	SE	0.026	0.426
N_TotalSignals	0.164***	0.045	N_TotalSignals	0.135***	0.053
SE	0.033	0.031	SE	0.031	0.030
Matchfunding Amount		0.051***	Matchfunding Amount		.020*
SE		0.009	SE		0.009
N_Days		0.527***	N_Days		0.108
SE		0.121	SE		0.120
Word Count		0.411***	Word Count		0.220
SE		0.117	SE		0.116
N_Rewards		0.044***	N_Rewards		0.054***
SE		0.008	SE		0.008
Randstad Dummy		0.013	Randstad Dummy		-0.003
SE		0.027	SE		0.027
Netherlands Dummy		-0.014	Netherlands Dummy		0.045
SE		0.062	SE		0.062
PrepTime		0.006	PrepTime		0.000
SE		0.027	SE		0.027
Age_Artist		0.221*	Age_Artist		0.215*
SE		0.101	SE		0.101
N_Obs	502	502	*N_Obs*	502	502
R^2 Adjusted	**0.046**	**0.253**	***R^2 Adjusted***	**0.034**	**0.184**
ANOVA F	25.312***	19.984***	***ANOVA F***	18.687***	13.669***
AIC	-1119.209	-1234.972	***AIC***	-1160.200	-1237.889
Schwarz-Bayesian Criterion	-1110.756	-1192.707	***Schwarz-Bayesian Criterion***	-1151.746	-1195.623
*p<.05, **p<.01, ***p<.001					

Table C15

Model 3 Results of the Two-step Linear Regression Analysis

Model 3a: DV Amount Raised *Predictors*	**IVs**	**Control**	**Model 3b:** DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	3.610***	0.915*	(Intercept)	1.757***	0.344
SE	0.022	0.427	SE	0.021	0.419
N_CampaignSignals	0.257***	0.112**	N_CampaignSignals	0.270***	0.162***
SE	0.036	0.035	SE	0.034	0.034
Matchfunding Amount		0.047***	Matchfunding Amount		0.013
SE		0.009	SE		0.009
N_Days		0.538***	N_Days		0.135
SE		0.119	SE		0.116
Word Count		0.380**	Word Count		0.166
SE		0.117	SE		0.115
N_Rewards		0.041***	N_Rewards		0.049***
SE		0.008	SE		0.007
Randstad Dummy		0.012	Randstad Dummy		-0.002
SE		0.027	SE		0.027
Netherlands Dummy		-0.006	Netherlands Dummy		0.062
SE		0.063	SE		0.062
PrepTime		0.006	PrepTime		0.005
SE		0.027	SE		0.027
Age_Artist		0.199	Age_Artist		0.172
SE		0.101	SE		0.099
N_Obs	502	502	*N_Obs*	502	502
R^2 Adjusted	**0.090**	**0.266**	***R^2 Adjusted***	**0.111**	**0.217**
ANOVA F	50.402***	21.221***	***ANOVA F***	63.254***	16.424***
AIC	-1131.698	-1232.142	***AIC***	-1196.068	-1252.143
Schwarz-Bayesian Criterion	-1123.260	-1189.956	***Schwarz-Bayesian Criterion***	-1187.631	-1209.957
*p<.05, **p<.01, ***p<.001					

Table 16

Model 4 Results of the Two-step Linear Regression Analysis

Model 4: DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	1.854***	1.306
SE	0.073	0.861
Dynamic Binary	0.244**	0.165*
SE	0.080	0.080
Rhetorical Binary	-0.143	-0.080
SE	0.089	0.080
Matchfunding Amount		-0.011
SE		0.022
N_Days		-0.270
SE		0.227
Word Count		-0.028
SE		0.248
Average Day Ratio		0.219
SE		0.146
Average Likes		0.268***
SE		0.077
N_Rewards		0.049**
SE		0.017
Randstad Dummy		0.085
SE		0.152
Netherlands Dummy		-0.036
SE		0.058
PrepTime		-0.050
SE		0.060
Age_Artist		0.006
SE		0.003
N_Obs	99	99
R^2 Adjusted	**0.069**	**0.318**
ANOVA F	4.655*	4.800***
AIC	-228.558	-250.155
Schwarz-Bayesian Criterion	-220.773	-216.418
*p<.05, **p<.01, ***p<.001		

Table C17

Model 5 Results of the Two-step Linear Regression Analysis

Model 5: DV Number of Donations *Predictors*	**IVs**	**Control**
(Intercept)	1.806***	1.429
SE	0.048	0.845
Number of Dynamic Signals	0.309**	0.262*
SE	0.103	0.101
Matchfunding Amount		-0.004
SE		0.021
N_Days		-0.353
SE		0.226
Word Count		-0.058
SE		0.244
Average Day Ratio		0.107
SE		0.150
Average Likes		0.303***
SE		0.072
N_Rewards		0.044**
SE		0.017
Randstad Dummy		0.110
SE		0.148
Netherlands Dummy		-0.035
SE		0.056
PrepTime		-0.045
SE		0.058
Age_Artist		0.007*
SE		0.003
N_Obs	99	99
R^2 Adjusted	**0.075**	**0.342**
ANOVA F	8.944**	5.641***
AIC	-230.126	-254.693
Schwarz-Bayesian Criterion	-224.936	-223.551
*p<.05, **p<.01, ***p<.001		

Appendix D
Disclaimer on Formatting and General Thesis Structure

I am including this appendix in order to inform the reader that I am aware that this paper features several stylistic variations from the APA and Erasmus University style guide. Among these are not indenting initial paragraphs of sections, as well as adding an additional space at the end of a section. I have opted to format my paper in this manner at the suggestion of my research supervisor, who requested I do so. I agree with the suggestion, so I have opted to do so wholeheartedly, as it allows for a cleaner presentation of an otherwise dense study.

Additionally, the decision to add a chapter before the Theoretical Framework dedicated to establishing context was also done at the behest of my supervisor, and similarly with a separate Discussion chapter before the conclusion. The reason for this is that 1) the need for additional context is essential to forming a well-rounded understanding of the research, yet it would weaken the discussion of theory to include it in the same chapter, and that 2) the size of the data from the regression models entails that much of the findings should focus on analyzing statistical data. As much would remain to be discussed and contrasted with the literature, the decision was made to add another chapter for this specific purpose, with the additional benefit of allowing the conclusion to be focused and concise.

Appendix E

Raw Data

The raw coding data has been uploaded to the Thesis Management System (TMS) as a separate Excel file. As the methodological guidelines for the thesis were unclear on file format, if there is need to have the data converted, email me at 685632mm@eur.nl and I will make it available as soon as possible.