Master's Thesis of Mina Cho

It's Good to be Different: How Entrepreneurial Narratives in Videos Affect Initial Coin Offerings

기업 내러티브(Narrative)가 초기 코인 공개(Initial Coin Offering)에 미치는 영향: 콘텐츠 차별화 효과를 중심으로

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It's Good to be Different: How Entrepreneurial Narratives in Videos Affect Initial Coin Offerings

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Abstract

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Initial Coin Offering (ICO) is an innovative method of financing used by blockchain ventures. To overcome inefficiencies caused by information asymmetry, entrepreneurs send signals about the venture's higher quality to potential investors. While scholars have examined non-content determinants of ICO success, there is sparse research on the effect of content features. Synthesizing cultural entrepreneurship theory and signaling theory, we use data mining and natural language processing to explore whether video narrative distinctiveness and technology-related language signal venture quality. Using 4,087 ICOs from ICObench.com, results show that video availability is positively related to ICO success. Also, the effect of video distinctiveness and the moderating effect of technology-related language is positively significant for fundraising success and the amount of funds raised, but insignificant for coin listing success. Our research offers theoretical contributions to the entrepreneurial financing and ICO literature. Additionally, our research has practical implications for entrepreneurs and ICO platforms.

Keywords: Initial Coin Offering, Video Distinctiveness, Entrepreneurship, Cultural Entrepreneurship Theory, Signaling Theory
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Chapter 1. Introduction

Initial Coin Offering (ICO) is an innovative method of financing used by early-stage blockchain ventures. In an ICO, ventures collect funds from investors in return for tokens, which entitle investors to future services or a partial share of ownership (Albrecht et al., 2020). Although ICOs are similar to traditional crowdfunding in that they help young businesses to raise funds, a distinguishing feature is their use of distributed ledger technology (DLT). Having raised US$35 billion in 2016-2020 (Lyandres et al., 2022), ICOs have become an important method of both financing and investment. A unique feature of ICOs is the possibility of subsequently listing and trading tokens in secondary markets created by exchange platforms.

However, ICOs suffer from serious market inefficiencies caused by information asymmetry between investors and entrepreneurs. Due to a lack of institutional and regulatory frameworks, there are barely any formal information disclosure requirements. This makes it difficult for investors to assess the true quality of ventures (Fisch & Momtaz, 2020). Thus, ventures aim to reduce this information asymmetry by sending signals about the venture's higher quality to potential investors (Fisch, 2019).

Information that is used to judge venture quality can be classified into content and non-content features (Majumdar & Bose, 2018). Content features, including text descriptions and video pitches (Frydrych et al., 2014), refer to narratives articulating the venture’ s vision, business plan, and projections. Content features aim to increase the persuasiveness of descriptive narratives, whereas non-content features are not associated with such narratives (Majumdar & Bose, 2018).

Previous studies have focused on examining non-content determinants of ICO performance, such as social media activity, whitepaper availability (Lyandres et al., 2022), and heterogeneity in team knowledge (Xu et al., 2021). However, there is a limited understanding of the impact of content features, especially videos. Synthesizing cultural entrepreneurship theory and signaling theory, we use data mining and natural language processing to answer: (1) *Does the availability of video pitches affect ICO success? (2) What aspects of the video narrative make it an effective pitch?*

Content factors are important because pitching can be understood as a persuasion process where entrepreneurs use narratives to differentiate themselves from competitors (Majumdar & Bose, 2018; Zhou et al., 2018). Among the two primary sources of descriptive narratives (i.e., text descriptions and video pitches)

(Frydrych et al., 2014), we focus on video content.

Although past literature acknowledges that videos play an important role, most studies have simply treated videos as binary variables and have examined whether their existence impacts fundraising performance (Mollick, 2014; Yuan et al., 2016). More recent studies have also considered the number of videos and video length (Yeh & Chen, 2020). However, there is still a lack of research on the content features of video narratives.

Regarding the second research question, we examine the distinctiveness and linguistic style of video narratives. Distinctiveness refers to the degree to which narratives deviate from other ventures in the same category (Taeuscher et al., 2021). Ventures competing for finite funds must persuade investors that they are a better investment than others. According to Porter (1997), differentiation is a strategy to distinguish oneself from competitors to gain a competitive advantage. Accordingly, we posit that ventures with distinctive videos are more likely to attract investments. Since ventures must stand out from the group by convincing investors of their higher quality, we argue that ventures with distinctive narratives will more likely attract investors.

Additionally, linguistic style is another important aspect of entrepreneurial narratives. In particular, we examine a linguistic style that is relevant to the ICO context and test whether it has moderating effects on the relationship between video distinctiveness and ICO performance. Entrepreneurs need to understand what effect distinctiveness and linguistic style of video content have on ICO performance to design competitive video pitches.

In our analysis, we use a Python web crawler to construct a dataset of 4,087 ICOs launched after Jan. 1, 2017, and completed before Dec. 31, 2020, from *ICObench.com*[1]. Our dataset was collected on Jan. 23, 2021. We use Microsoft Azure's speech-to-text service[2] to transcribe the narrative content of videos and then follow Zheng et al. (2020) to measure distinctiveness via *Doc2Vec* cosine distance scores. We used LIWC-22 software[3] to measure the narratives' linguistic features.

Results show that the availability of video pitches is positively related to all three measures of ICO success used in this study: i) fundraising success, ii) amount raised, and iii) token listing success. However, the effect of video distinctiveness and the moderating effect of technology-related language is positively significant for fundraising success and the amount of funds raised

[1] https://icobench.io/
[2] https://azure.microsoft.com/en-us/products/cognitive-services/speech-to-text
[3] https://www.liwc.app/

only, while insignificant for token listing success.

Our study makes meaningful theoretical and practical contributions. The novelty of our research is that we establish a relationship between ICO success and video narrative design. We add to the ICO and entrepreneurial financing literature by empirically demonstrating that video distinctiveness and technology-related language can signal venture quality and reduce information asymmetry. Mitigating uncertainty about venture quality enables better investor decision-making. For practical implications, our study helps entrepreneurs design competitive video pitches that can help them maximize the chances of fundraising success and the amount of funds raised.

Chapter 2. Literature Review

2.1. ICO Performance, Content, and Non-Content Features

Literature on determinants of ICO success can be divided into two categories: content factors and non-content factors (Majumdar & Bose, 2018). Content factors refer to features related to the persuasiveness of the project's descriptive narratives, whereas non-content factors refer to appeals that are not associated with such narratives (Majumdar & Bose, 2018). Content features include narratives containing the venture's vision, business plan, and future projections, whereas non-content factors are non-narrative appeals. According to entrepreneurship literature, narratives are defined as stories that are told about entrepreneurs and their ventures (Martens et al., 2007).

Previous literature found that the likelihood of ICO success is associated with various non-content-related features, including venture-initiated social media activity, KYC (Know-Your-Customer) availability, and whitepaper availability (Lyandres et al., 2022). Additionally, heterogeneity in team knowledge (Xu et al., 2021) and the availability of source code and presale (Adhami et al., 2018) increased the chances of ICO success. <Table 1> presents a summary of key studies on various non-content features that affect ICO success.

Compared to the extensive literature on non-content features, there is limited research on content features that affect ICO performance. Existing studies have examined the basic properties of project descriptions such as length, readability, and tone (Zhou et al., 2018), while deeper semantic characteristics remain relatively unexplored. Thus, we aim to provide insights into the effect of content features on ICO performance, which will enhance our understanding of the role of entrepreneurial narratives.

<Table 1> Past studies on non-content features of ICO success

Reference	Feature	Title	Main Point
Lyandres et al., 2022	Venture-initiated social media activity	Initial Coin Offering (ICO) Success and Post-ICO Performance	The effect of venture-initiated social media activity on ICO success depends heavily on the type of platform used.
Lyandres et al., 2022	KYC availability	Initial Coin Offering (ICO) Success and Post-ICO Performance	ICOs which have KYC requirements are more likely to be successful in ICO funding.
Lyandres et al., 2022	Whitepaper availability	Initial Coin Offering (ICO) Success and Post-ICO Performance	ICOs with whitepapers available for the audience are more likely to be

			successful in ICO funding.
Xu et al., 2021	Heterogeneity in team knowledge	Prediction of initial coin offering success based on team knowledge and expert evaluation	Heterogeneity in team knowledge contributes to the prediction of ICO success.
Adhami et al., 2018	Availability of source code and presale	Why do businesses go crypto? An empirical analysis of initial coin offerings	There is a higher probability of ICO success when the ICO makes its source codes available and offers a presale.

2.2. Role of Video as an Entrepreneurial Narrative

Two sources of descriptive narratives are text narratives and video pitches (Frydrych et al., 2014). Although still in its infancy, prior ICO literature has examined the role of text narratives, especially whitepapers. Whitepapers are voluntary and unaudited documents provided by ventures typically describing their product, business plan, project roadmap, and team profile. Scholars have analyzed the effect of whitepaper features on ICO success such as informativeness (Florysiak & Schandlbauer, 2022) and length (Fisch, 2019).

In comparison to whitepapers, ICO video pitches have received less attention. To fill this gap, we empirically analyze the effects of video availability and video narrative distinctiveness on ICO success.

2.3. Cultural Entrepreneurship Theory and Signaling Theory

According to cultural entrepreneurship theory, entrepreneurial storytelling acts as a resource-leveraging mechanism during the capital acquisition stage by constructing favorable and comprehensible venture identities (Lounsbury & Glynn, 2001). Narratives can reduce uncertainty, especially in environments where risk is not easily measured such as ICOs. Despite the importance of entrepreneurial narratives, previous studies have focused on exploring non-content determinants of ICO success such as social media activity, whitepaper availability (Lyandres et al., 2022), and heterogeneity in team knowledge (Xu et al., 2021). As narratives play an important role in capital acquisition, the role of content features warrants further investigation.

According to signaling theory (Spence, 1973), information asymmetry inevitably occurs between sellers, who have large amounts of information, and buyers, who have little information. Sellers attempt to overcome such knowledge gaps by conveying information to assist buyers evaluate the quality of products. This information is called a signal. For a feature to be a signal, it must satisfy two criteria: first, it must be observable, and second, it must be costly to realize and imitate. Applying signaling theory to the ICO context, ventures can reduce information asymmetry by sending signals to potential investors about their higher quality (Fisch, 2019). By sending visible and inimitable cues, ventures can distinguish themselves from others and increase their chances of investments.

Chapter 3. Hypothesis Development

This research aims to answer the following two research questions: *(1) Does the availability of video pitches affect ICO success? (2) What aspects of the video narrative make it an effective pitch?*

Video availability refers to whether the focal ICO has made a video pitch available to potential investors, as shown in <Appendix 1>. To measure ICO success, we use three measures borrowed from previous literature: i) fundraising success, ii) amount raised and iii) listing success. Regarding the first measure, an ICO is considered successful when the amount of funds raised is either above the softcap or above $0.5 million (Lee et al., 2022). Secondly, the amount raised refers to the dollar amount raised during the ICO. Lastly, listing success refers to whether the coin was successfully, listed on exchanges after the ICO's completion.

To answer the second research question, we study whether video distinctiveness affects ICO success, measured using the same three measures as before. Video distinctiveness is defined as the degree to which video narratives deviate from other ventures in the same category. Details on how we quantify video distinctiveness will follow.

Additionally, we analyze whether technology-related language has a moderating effect on the relationship between video distinctiveness and ICO success. Technology-related language is the language associated with "scientific and technological devices and inventions" (Boyd et al., 2022). The definitions of the concepts used are summarized in <Table 2>.

<Table 2> Definition of Concepts

Concept	Definition	Reference
Video Availability	Whether the focal ICO has made a video pitch available to potential investors	Mollick, 2014
Funding Success	Whether the amount of funds raised is either above the softcap or above $0.5 million	Lee et al., 2022
Amount Raised	The dollar amount raised during the ICO	Fisch, 2019
Token Listing Success	Whether the coin was successfully, listed on exchanges after the ICO's completion	Lyandres et al., 2022
Video Distinctiveness	The degree to which video narratives deviate from other ventures in the same category	Taeuscher et al., 2021
Technology-Related Language	Scientific and technological devices and inventions	Boyd et al., 2022

3.1. Video Availability

According to signaling theory (Spence, 1973), sellers with large amounts of information send signals to buyers with little amounts of information to overcome information asymmetry. To become a signal, information must first, be observable and second, costly to realize and imitate. We argue that video availability signals high venture quality since video pitches demonstrate a project's preparedness and a venture's means to produce informative content (e.g., financial, and human capital). This leads to our first hypothesis:

Hypothesis 1(H1): *The availability of a video pitch is positively related to ICO success.*

3.2. Video Distinctiveness

Distinctiveness refers to the extent to which narratives deviate from other ventures in the same category (Taeuscher et al., 2021). To stand out from the group, ventures must convince investors of their higher quality and the originality of their projects. We argue that narrative distinctiveness satisfies both criteria of signaling theory. First, distinctiveness is observable through comparison with other ventures. Second, unique business features and their representation in video form are costly to imitate in terms of money, time, and effort. Therefore, distinct video narratives signal higher quality by demonstrating a venture' s innovation and creativity. This brings us to our second hypothesis:

Hypothesis 2 (H2): *Distinctiveness of video narrative is positively related to ICO success.*

3.3. Moderating Effects of Linguistic Features

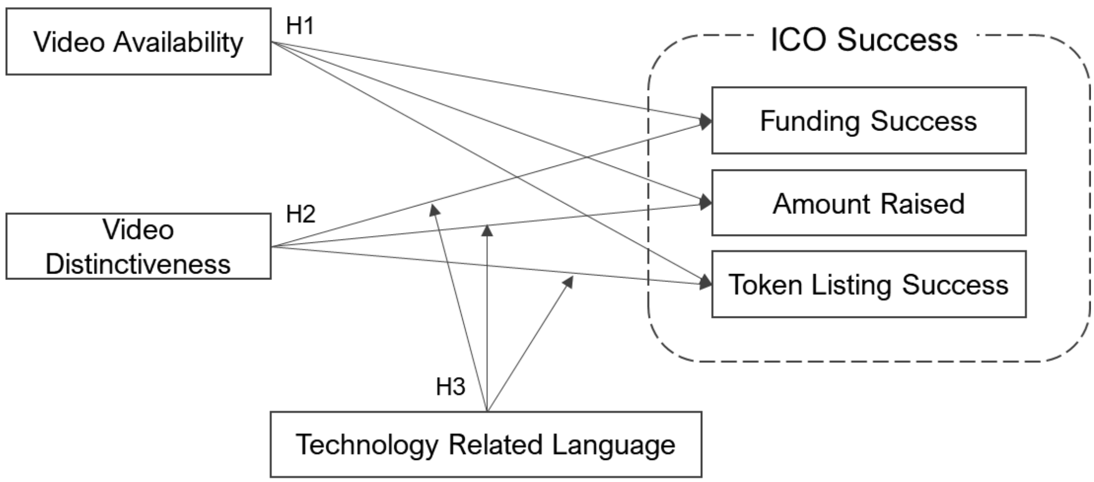
Linguistic style is an important communicative aspect of ICO narratives. In this study, we chose a linguistic style that is relevant to the ICO context, and test whether it has moderating effects on the relationship between video distinctiveness and ICO performance.

Technology is critical for ICO-participating ventures. As blockchain is technology-driven, a venture's future success depends on its ability to utilize complex technology. Therefore, ventures with stronger technical capacities are more likely to receive investments. This is consistent with findings from previous studies, as technological capabilities, measured via technical white papers and high-quality codes, were associated with better ICO performance (Fisch, 2019). Since investors are likely to associate a venture's business potential with its technological capability, we expect higher-quality ventures to highlight their technological proficiencies in their video narratives. This leads to our final hypothesis:

Hypothesis 3 (H3): *Technology-related language has a positive moderating effect on the relationship between video narrative distinctiveness and ICO success.*

Figure 1 presents the research framework for our study.

<Figure 1> Research Framework



Chapter 4. Methods

4.1. Dataset Construction

We used a Python crawler to construct a dataset of 4,087 ICOs launched after Jan. 1, 2017 and completed before Dec. 31, 2020[4]. The main source for our dataset was *ICObench.com*, a database widely used by ICO researchers due to its extensive coverage (Benedetti & Kostovetsky, 2021; Lyandres et al., 2022; Xu et al., 2021). When data were missing, we supplemented information from other platforms including *Icodrops.com*[5], *Icopulse.com*[6], and *Icoholder.com*[7].

We used Microsoft Azure's speech-to-text service to transcribe video narratives into text. A speech-to-text service is a service that converts spoken audio into text format. Among our sample, 1,566 ventures had videos with English-narrated content. All ICOs with non-English narrated content were removed from our dataset.

ICObench.com does not indicate whether the token was successfully listed on exchanges after the ICO's completion.

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[4] Our data was collected on Jan. 23, 2021
[5] https://icodrops.com/
[6] https://icopulse.com/
[7] https://icoholder.com/

Therefore, we collected listing data from *Coinmarketcap.com*[8], which is widely regarded as the most comprehensive source for aftermarket data (Fisch & Momtaz, 2020). Ventures from *ICObench.com* and *Coinmarketcap.com* were matched based on their ticker symbols and project names. When ventures had duplicate data, we manually visited their websites to accurately match them.

4.2. Measures

4.2.1 Dependent Variables

Since there is no consensus about a single measure of ICO success, three variables from ICO literature were used: i) fundraising success, ii) amount raised, and iii) listing success. Following prior studies, fundraising was considered successful if the amount raised was larger than the softcap or above $ 0.5 million (Lee et al., 2022). For the amount raised, we use the log of funds raised plus 1 to reduce skewness (Fisch, 2019; Lyandres et al., 2022). Token listing success is a post-ICO success variable indicating whether the token was listed on *Coinmarketcap.com*.

[8] https://coinmarketcap.com/

4.2.2 Independent Variables

Video Dummy ***(VidDummy)*** indicates whether the venture included a video pitch for its project, as shown in <Appendix 1>. Video narrative distinctiveness ***(VidDistinctiveness)*** represents the degree to which a video narrative deviates from other ventures in the same industry category (Taeuscher et al., 2021). *ICObench.com* has 29 categories (e.g., banking, entertainment, health) and ventures may be assigned to several categories according to their business activities. To quantify video distinctiveness, following Zheng et al. (2020), we first use the *Doc2Vec* model to transform video transcripts into vectors. We then calculate cosine similarity between vectors *i* and *j* in the same category, as shown in eq. (1). ***VidDistinctiveness**$_{ij}$*, is measured as 1 − ***VidSimilarity**$_{ij}$*, and it ranges from 0 to 1, where a higher ***VidDistinctiveness**$_{ij}$* value means the video narrative is more distinct from ventures in the same category. For ventures assigned to several categories, we derive the overall average cosine distance across all categories.

$$VidSimilarity_{ij} = \frac{V^i \cdot V^j}{\parallel V^i \parallel \cdot \parallel V^j \parallel} = \frac{\sum_{k=1}^{K} V_k^i \times V_k^j}{\sqrt{\sum_{k=1}^{K}(V_k^i)^2} \times \sqrt{\sum_{k=1}^{K}(V_k^j)^2}} \qquad (1)$$

$$VidDistinctiveness_{ij} = 1 - VidSimilarity_{ij} \quad (2)$$

Linguistic features were measured using the Linguistic Inquiry and Word Count (LIWC)-22 software, a dictionary-based language analysis tool popular among entrepreneurial finance researchers (Fisch, 2019). LIWC-22 is a text-analysis tool that contains dictionaries containing words reflecting different social and psychological categories such as achievement, certitude, sadness, and politeness. When given a piece of text to analyze, the software compares and matches words in the text with words in the various dictionaries. It then decides the percentage of total words that can be assigned to the social and psychological categories.

We measure technology-related language ***(Tech)*** using LIWC-22. This refers to language related to "scientific and technological devices and inventions" (Boyd et al., 2022).

4.2.3 Control Variables

A wide set of control variables identified by previous literature were included to minimize confounding effects on ICO performance. The distinctiveness of text description

(*TextDisctinctiveness*) was calculated for each venture using the same process as videos. Video length (*VideoLength*), venture rating (*Rating*), number of team members (*Team*), the existence of Github (*Github*), number of social media accounts (*SocialMedia*), and duration of ICO (*ICODuration*) were included. Additionally, the existence of Know Your Customer (*KYC*), an obligation for participants to disclose their identities, Whitelist *(Whitelist)*, a requirement for investors to register in advance, presale (*PreICO*) or bonus (*Bonus)*, advantages given to early investors before the official ICO period, softcap (*Softcap)*, the minimum amount of funds required for the ICO to succeed and hardcap (*Hardcap)*, the maximum amount of funds that can be raised in the ICO were included (Lyandres et al., 2022).

Time-fixed effects (year-quarter) were added to isolate ICO performance from general market trends (Fisch, 2019; Fisch & Momtaz, 2020; Lyandres et al., 2022). We present a summary of all variables and their descriptive statistics in <Table 3> and <Table 4>.

<Table 3> Definition of Variables

Variable		Definition
Dep. Variable	*Fund_Success*	Fundraising success (successful if above softcap or $0.5M)
	Amount_Raised	Log of the amount raised in the ICO plus 1
	Listed	Listing success on *coinmarketcap.com*
Indep. Variable	*VidDummy*	Availability of video pitch
	VidDistinctiveness	The degree to which video narratives deviate from other ventures in the same category
	Tech	Technology-related language
Control Variable	*TextDisctinctiveness*	Distinctiveness of text description
	VidLength	Video length in seconds
	Rating	Venture rating on ICObench.com
	Team	Number of team members
	Softcap	Existence of softcap for ICO
	Hardcap	Existence of hardcap for ICO
	Github	Existence of venture profile on Github
	SocialMedia	Number of venture social media accounts
	Bonus	Existence of bonus for early investors
	KYC	Existence of Know Your Customer
	Whitelist	Existence of Whitelist
	PreICO	Existence of presale
	ICODuration	Duration of ICO in days

<Table 4> Descriptive Statistics

Variable		Mean	SD	Min	Max
Dep. Variable	*Fund_Success*	0.369	0.483	0.000	1.000
	Amount_Raised	6.253	7.500	0.000	22.158
	Listed	0.118	0.323	0.000	1.000
Indep. Variable	*VidDummy*	0.463	0.499	0.000	1.000
	VidDistinctiveness	0.761	0.051	0.408	0.881
	Tech	2.674	1.915	0.000	13.890
Control Variable	*TextDisctinctiveness*	0.554	0.188	0.004	0.854
	VidLength	154.70	143.63	13.000	1460.0
	Rating	3.016	0.716	0.800	5.000
	Team	12.65	8.258	1.00	96.00
	Softcap	0.575	0.494	0.000	1.000
	Hardcap	0.780	0.415	0.000	1.000
	Github	0.387	0.487	0.000	1.000
	SocialMedia	6.345	2.215	0.000	12.00
	Bonus	0.0954	0.294	0.000	1.000
	KYC	0.427	0.495	0.000	1.000
	Whitelist	0.271	0.444	0.000	1.000
	PreICO	0.496	0.500	0.000	1.000
	ICODuration	67.58	75.412	1.000	777.00

Chapter 5. Results

In all regressions, we control for year−quarter and category−fixed effects and show heteroskedasticity−robust standard errors. As shown in <Appendix 5>, except for the interaction terms and their constituent variables, all variance inflation factors (VIF) were below 5, indicating no serious multicollinearity (Jaccard et al., 1990). We use logit models for fundraising and listing success, and OLS models for the amount raised.

<Table 5> shows results for the effect of video availability on ICO success. The coefficient for ***VidDummy*** is positively significant across all columns – (1) fundraising success, (2) amount raised, and (3) listing success. Consistent with existing literature, we see a positive correlation between video availability and ICO success (Thewissen et al., 2022). Our results support H1.

<Table 5> Regression Results 1

Variables	*(1) Fund_Success*		(2) *Amount_Raised*		(3) *Listed*	
	β	Std. Error	*β*	Std. Error	*β*	Std. Error
VidDummy	**0.134***	0.078	**0.423***	0.221	**0.313*****	0.111
Rating	0.992***	0.087	2.738***	0.227	0.889***	0.122
Team	0.045***	0.005	0.132***	0.014	0.026***	0.006

Softcap	0.054	0.091	−0.319	0.256	−0.404***	0.124
Hardcap	0.270**	0.111	0.883***	0.296	0.345**	0.151
Github	0.064	0.085	0.242	0.248	0.401***	0.119
SocialMedia	0.023	0.027	0.104	0.073	−0.085**	0.037
Bonus	−0.173	0.130	−0.340	0.377	−0.062	0.199
KYC	0.118	0.102	0.168	0.272	−0.041	0.150
Whitelist	−0.055	0.100	−0.124	0.281	−0.335***	0.116
PreICO	−0.265***	0.080	−0.690***	0.222	−0.335***	0.116
ICODuration	−0.004***	0.001	−0.011***	0.001	−0.007***	0.002
Year-Quarter FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Log Likelihood/Adj. R^2	−2,168.190		0.223		−1,260.570	
Observations	4,087		4,087		4,087	
Notes. ***p<0.01; **p<0.05; *p<0.10						

<Table 6> shows findings regarding the effects of video narrative distinctiveness (odd columns) and the moderating effect of technology-related language (even columns). The coefficient for ***VidDistinctiveness*** is significantly positive for columns (1) and (3), but not for column (5). Similarly, the coefficient for the interaction term ***VidDistinctiveness * Tech*** is significantly positive for columns (2) and (4), but not for column (6). Hence, H2 and H3 are

supported for fundraising success and the amount of funds raised, but not supported for listing success.

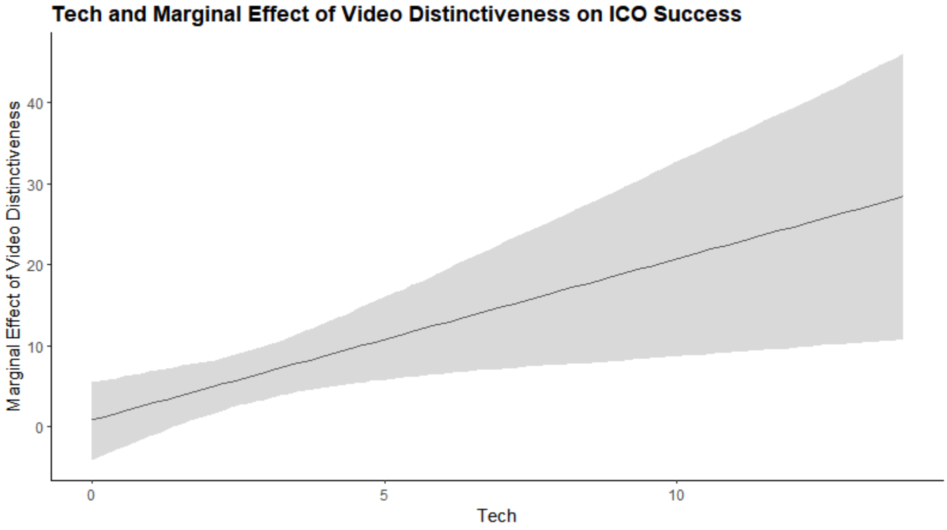
<Table 6> Regression Results 2

Variables	*Fund_Success*		*Amount_Raised*		*Listed*	
	(1)	(2)	(3)	(4)	(5)	(6)
VidDistinctiveness	**5.666*** (1.691)**	0.823 (2.569)	**14.594*** (4.733)**	2.726 (6.827)	3.079 (2.096)	−0.013 (3.024)
Tech		−1.487*** (0.574)		−3.557*** (1.379)		−0.947 (0.673)
*VidDistinctiveness * Tech*		**1.984*** (0.758)**		**4.683** (1.829)**		1.292 (0.892)
TextDisctinctiveness	−0.644 (0.415)	−0.643 (0.417)	−1.889 (1.191)	−1.799 (1.188)	−0.327 (0.537)	−0.340 (0.541)
VidLength	0.0002 (0.0005)	0.0004 (0.0005)	0.001 (0.001)	0.002 (0.001)	0.0004 (0.001)	0.001 (0.001)
Rating	0.954*** (0.148)	0.953*** (0.148)	2.476*** (0.400)	2.451*** (0.400)	0.758*** (0.197)	0.765*** (0.197)
Team	0.046*** (0.009)	0.047*** (0.009)	0.125*** (0.025)	0.129*** (0.025)	0.030*** (0.010)	0.032*** (0.010)
Softcap	−0.006 (0.151)	−0.022 (0.152)	−0.403 (0.424)	−0.429 (0.424)	−0.276 (0.181)	−0.281 (0.182)
Hardcap	0.565*** (0.196)	0.568*** (0.196)	1.739*** (0.530)	1.760*** (0.529)	0.399 (0.248)	0.395 (0.249)
Github	0.216 (0.138)	0.218 (0.139)	0.692* (0.406)	0.692* (0.406)	0.459*** (0.176)	0.449** (0.177)
SocialMedia	0.030 (0.046)	0.034 (0.046)	0.161 (0.130)	0.167 (0.129)	−0.108* (0.057)	−0.107* (0.057)
Bonus	0.005 (0.131)	0.011 (0.131)	−0.110 (0.380)	−0.095 (0.379)	−0.315* (0.172)	−0.317* (0.173)
KYC	−0.127	−0.130	−0.238	−0.249	0.119	0.117

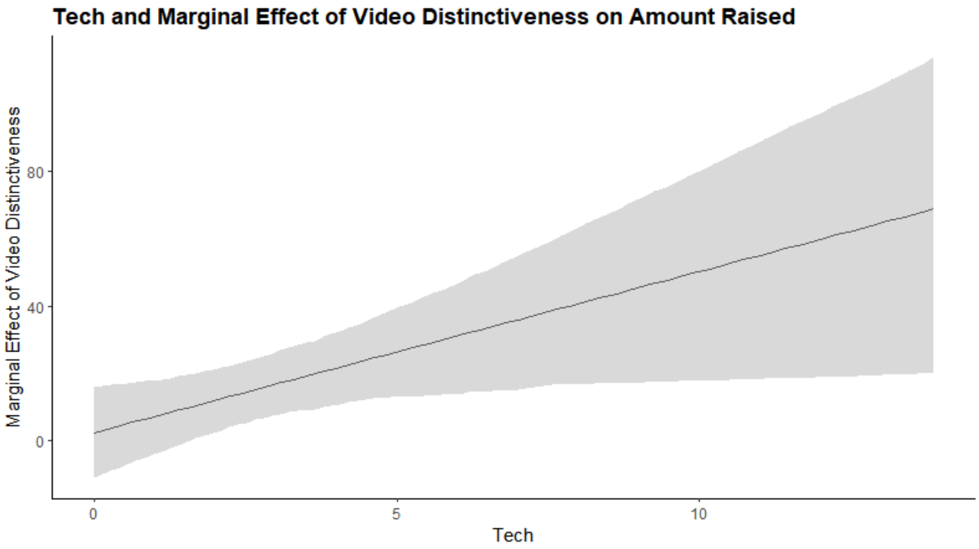
	(0.162)	(0.163)	(0.448)	(0.449)	(0.215)	(0.215)
Whitelist	0.030 (0.150)	0.028 (0.151)	0.249 (0.436)	0.250 (0.435)	−0.030 (0.208)	−0.035 (0.208)
PreICO	−0.347*** (0.132)	−0.363*** (0.133)	−0.939** (0.378)	−0.964** (0.378)	−0.490*** (0.168)	−0.494*** (0.169)
ICODuration	0.0001 (0.001)	0.0001 (0.001)	−0.0002 (0.001)	−0.0001 (0.001)	−0.003 (0.002)	−0.317* (0.173)
Year−Quarter FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Log Likelihood/Adj. R^2	−848.588	−845.038	0.228	0.230	−564.633	−563.496
Observations	1,566	1,566	1,566	1,566	1,566	1,566
Notes. ***p<0.01; **p<0.05; *p<0.10						

To better understand how the effect of video distinctiveness is moderated by technology−related language, we plot the marginal effect of video distinctiveness on the three measures of ICO success (y−axis) at different levels of technology−related language (x−axis). <Figure 3>, <Figure 4>, and<Figure 5> show that the effect of video distinctiveness on fundraising success and the amount of funds raised is reinforced by technology−related content.

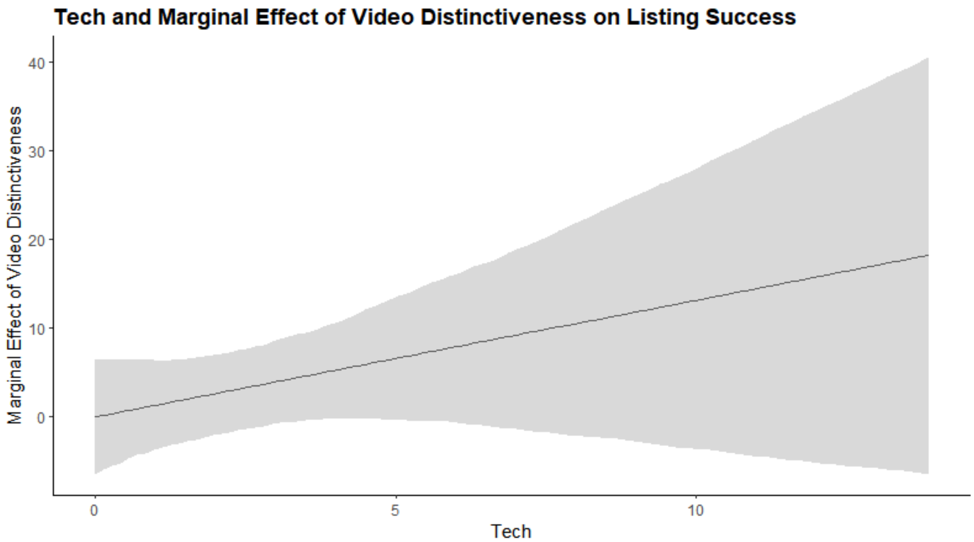
<Figure 2> Marginal Effect of Video Distinctiveness on ICO Success at varying levels of Technology−related Language



<Figure 3> Marginal Effect of Video Distinctiveness on Amount Raised at varying levels of Technology−related Language



<Figure 4> Marginal Effect of Video Distinctiveness on Listing Success at varying levels of Technology−related Language



Chapter 6. Discussion

6.1. Discussion

This research sought to answer two research questions: *(1) Does the availability of video pitches affect ICO success? (2) What aspects of the video narrative make it an effective pitch?* Thus, we studied the effects of video availability and narrative distinctiveness on ICO success. We used three variables to measure ICO success: i) fundraising success, ii) amount raised and iii) listing success.

Using data mining and natural language processing methods to analyze 4,087 ICOs, we found that video availability is positively correlated with fundraising success, the amount raised, and listing success. Furthermore, more distinct narratives in videos are associated with a higher probability of fundraising success and a larger amount of funds raised, and this relationship is reinforced by technology-related language. However, there was no significant relationship between listing success.

A possible explanation for the diverging results is that the effect of video narratives differs between ICO- and post-ICO indicators. Whereas fundraising success and the amount raised are direct outcomes of the ICO itself, token listing happens after the

ICO ends. An exploration of possible explanations may be an area for future research.

6.2. Theoretical and Managerial Contributions

This study offers important theoretical contributions. First, we establish a relationship between ICO success and video narrative design, which to the best of our knowledge, has not yet been examined. Additionally, we contribute to venture financing literature by empirically showing that video distinctiveness and technology-related language reduce information asymmetry by signaling venture quality. Third, we contribute to the literature on signaling theory and cultural entrepreneurship theory by extending them to ICO contexts. Our research reveals that video distinctiveness acts as a quality signal, reducing information asymmetry and enabling more informed decision-making among ICO investors.

In terms of practical contributions, our research is helpful for both entrepreneurs and ICO platforms. Our results suggest that entrepreneurs should highlight the distinctiveness of their ventures in video pitches to maximize investments. We help entrepreneurs design competitive video pitches that maximize chances of fundraising success and the amount of funds raised. Additionally, ICO platforms can identify ventures that are most likely to receive funds by analyzing their video pitches. For example, platforms could display projects with the highest potential at the top of the website to encourage investments.

6.3. Limitations and Future Research Directions

We acknowledge that this paper has several limitations. Firstly, our research is context-specific since *ICObench.com* is one of the many ICO platforms. Nevertheless, *ICObench.com* is a leading platform in the ICO market and may potentially be representative of other ICO platforms. In future research, we can increase robustness by comparing results across multiple platforms, and checking whether the results are consistent across them.

Secondly, a video delivers information not only through its voice-overs but also through visual and auditory aspects. For example, a video's color, resolution, volume, pitch, etc. may affect ICO success. In future research, we should control for visual and auditory characteristics of videos to minimize their confounding effects on ICO outcomes.

Lastly, we collected data by transcribing audio into text, which means our data contained only those videos that had voice-overs. This means we were unable to include videos that had text written out in visual form, but that did not have voiceovers. In future research, we could enrich our data by also including text data presented in visual form. In that case, we would need an additional variable to control for whether the content was presented in visual or auditory form.

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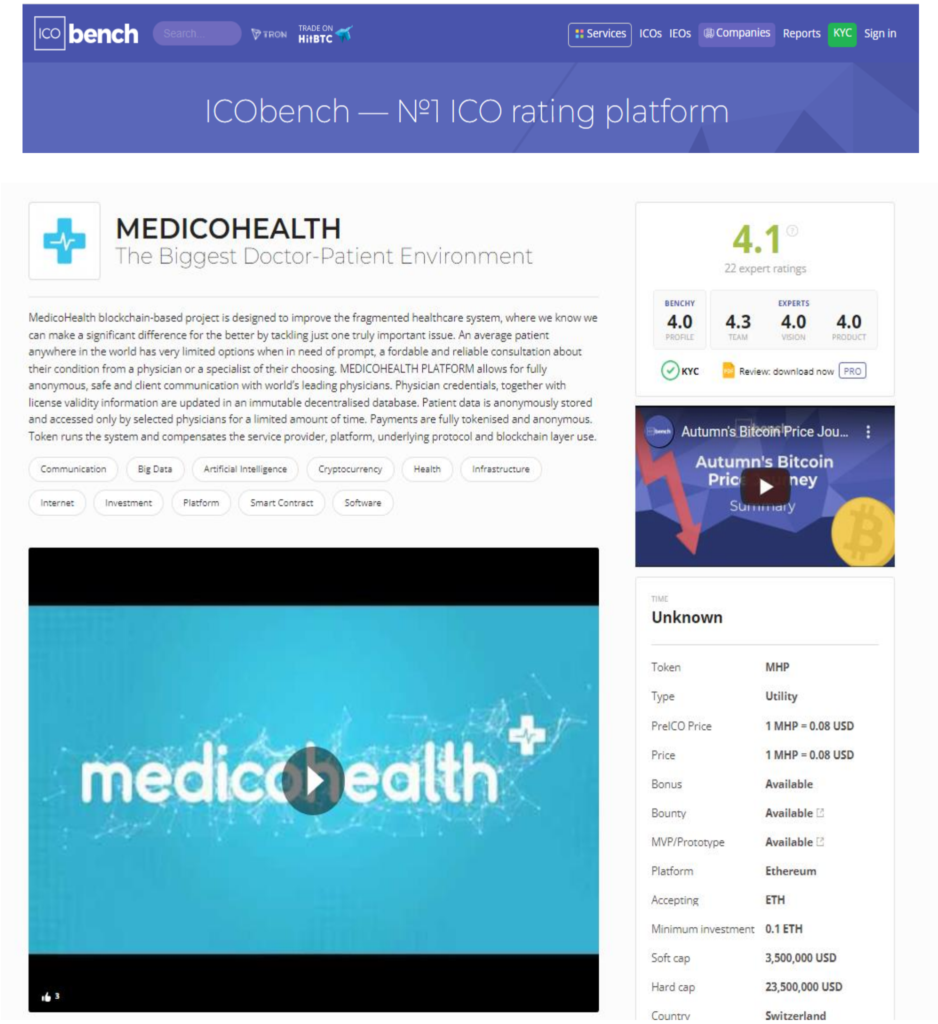
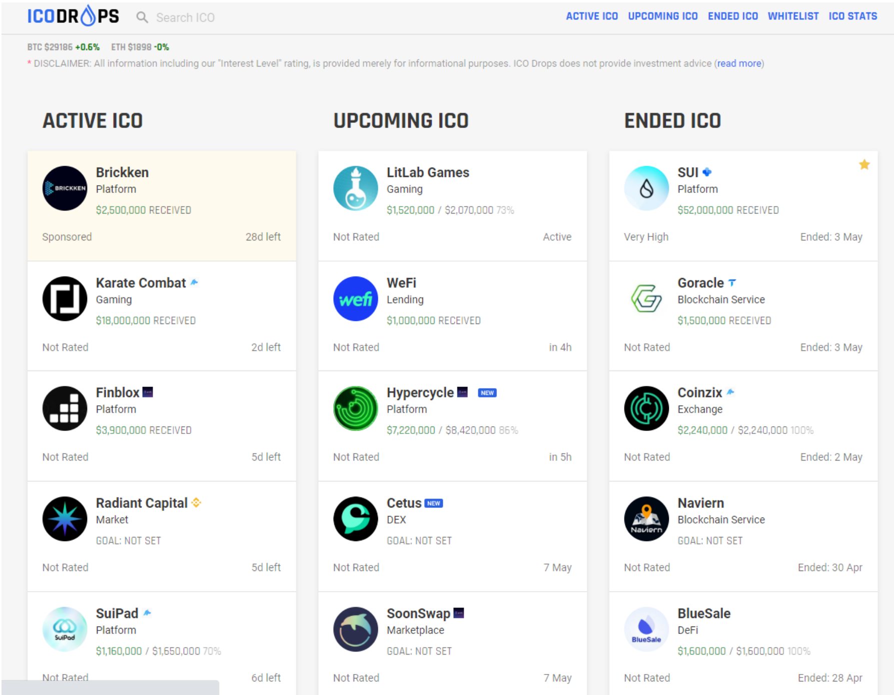
Appendix

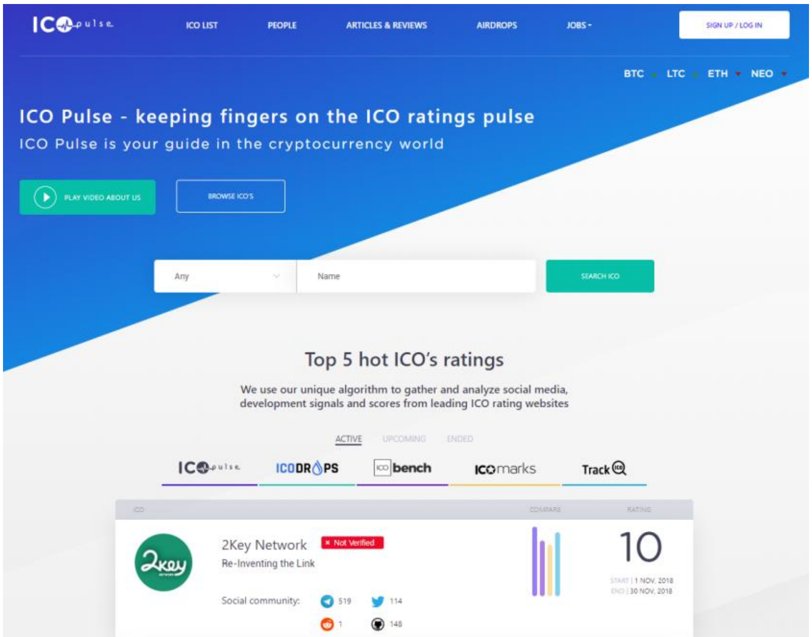
<Appendix 1: ICO bench.com>



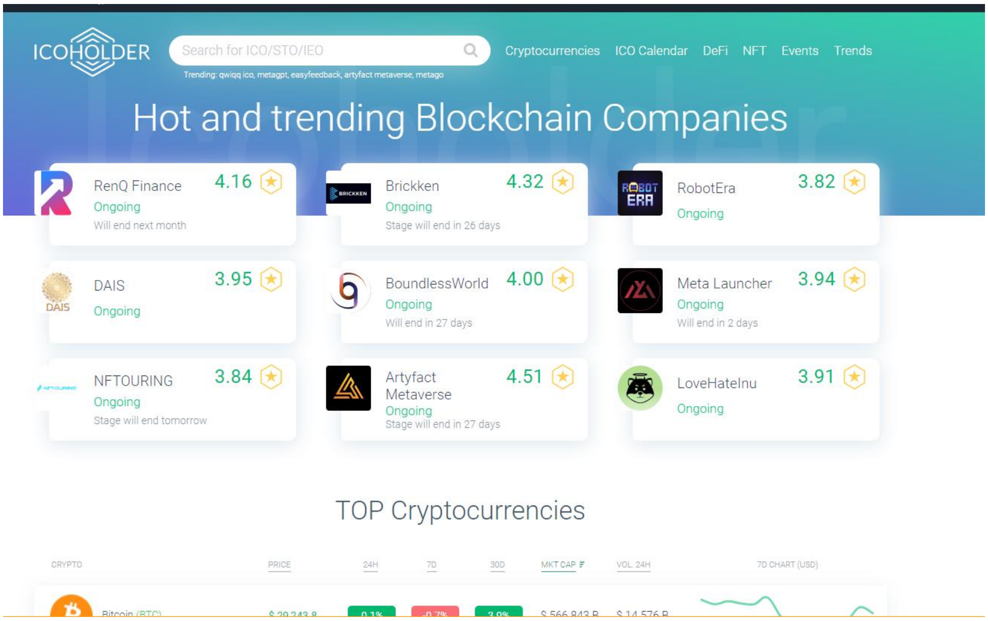
<Appendix 2: ICO Drops.com>



<Appendix 3: ICO Pulse.com>



<Appendix 4: ICO Holder.com>



<Appendix 5: VIF check for multicollinearity>

Dependent Variable: Fundraising Success

Variable	VIF
dist_vid	1.895
dist_desc	1.587
social	2.134
softcap_binary	1.460
hardcap_binary	1.339
bonus	1.204
duration	1.169
preICO	1.189
KYC	1.762
Whitelist	1.427
ratings	2.082
team	1.203
github	1.303
video_duration	1.411

Variable	VIF
video_binary	1.102
social	2.302
softcap_binary	1.439
hardcap_binary	1.366
bonus	1.081
duration	1.068
preICO	1.164
KYC	1.815
Whitelist	1.430
ratings	2.420
team	1.186
github	1.274

Dependent Variable: Amount Raised

Variable	VIF
dist_vid	1.957
dist_desc	1.649
social	2.225
softcap_binary	1.491
hardcap_binary	1.406
bonus	1.228
duration	1.140
preICO	1.190
KYC	1.724
Whitelist	1.418
ratings	2.101
team	1.251
github	1.340
video_duration	1.392

Variable	VIF
video_binary	1.114
social	2.438
softcap_binary	1.480
hardcap_binary	1.433
bonus	1.077
duration	1.059
preICO	1.148
KYC	1.711
Whitelist	1.399
ratings	2.447
team	1.217
github	1.301

Dependent Variable: Listing Success

Variable	VIF
dist_vid	1.970
dist_desc	1.572
social	2.228
softcap_binary	1.431
hardcap_binary	1.354
bonus	1.233
duration	1.203
preICO	1.219
KYC	2.012
Whitelist	1.564
ratings	2.230
team	1.225
github	1.339
video_duration	1.465

Variable	VIF
video_binary	1.098
social	2.415
softcap_binary	1.397
hardcap_binary	1.333
bonus	1.086
duration	1.070
preICO	1.193
KYC	2.020
Whitelist	1.558
ratings	2.494
team	1.209
github	1.304

Abstract in Korean

초기 코인 공개 (Initial Coin Offering)는 블록체인 벤처기업들이 투자 유치를 위해 활용하는 자금조달 방법이다. ICO 관련 규율 및 체계가 미비한 상황에서 ICO 시장 내 정보 비대칭 문제가 발생하고 있다. 정보 비대칭으로 인한 비효율을 극복하기 위해 기업가들은 투자자들에게 벤처의 장점을 부각시키는 긍정적인 신호를 보낸다. 과거 문헌연구는 ICO 성공 요소 중 비콘텐츠 (Non-content features) 결정요인에 집중한 반면, 본 논문은 콘텐츠 결정요인 (Content features)에 대해 연구한다. 본 논문은 비디오 내러티브 (Narrative)의 차별화와 기술 관련 언어가 ICO 성공과 어떠한 연관성이 있는지 탐구한다. 문화적 기업가정신 이론 (Cultural Entrepreneurship Theory)과 신호 이론 (Signaling Theory)에 바탕을 두며, 데이터 마이닝과 자연어 처리를 사용해 ICObench.com 내 4,087개의 ICO를 분석한다. 결과에 의하면 비디오 존재 여부는 ICO 성공여부와 긍정적인 상관관계가 있다. 또한, 비디오 내러티브의 차별화와 기술관련 언어의 조절효과는 모금 성공률 (fundraising success) 와 모금액 (amount of funds raised) 과 긍정적인 상관관계가 있지만, 코인 상장 여부(coin listing success) 와는 유의한 관계성을 보이지 않았다. 본 연구는 창업재무 (entrepreneurial financing) 및 ICO 문헌에 기여한다는 이론적 의의를 가지며, 기업가와 ICO 플랫폼들이 사업을 영위해 나가는데도 실질적인 도움을 줄 수 있다.